Camill Harter

Vulnerability through Vertical Collaboration in Transportation

A complex networks approach

Vulnerability through Vertical Collaboration in Transportation: A complex networks approach

Vulnerability through Vertical Collaboration in Transportation: A complex networks approach

Kwetsbaarheid door verticale samenwerking in transport: Een benadering vanuit complexe netwerken.

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Chapter 1

Introduction

1.1 Motivation

Globalization has led to a drastic increase in the demand for transportation services of goods and people over the last decades. For instance, international seaborne trade carried by container ships has increased from 102m tons in 1980 to 1,834m tons in 2017[1] and the number of airline passengers worldwide has increased from 1,994m in 2004 to 4,543m people in 2019[2]. The consequences are not only higher overall transport volumes and more services, but also more destinations that need to be connected and transportation networks becoming denser and more extensive. The network of intermodal services for hinterland container transport in Europe has expanded from connecting 24 countries and 324 cities in 2016 to 25 countries and 452 cities in 2021, and the global nonstop and one-stop connectivity index for passenger flights grew by 86.3% and 175.8%, respectively, between 1990 and 2012 (Allroggen et al., 2015). Despite a temporary setback due to the Covid-19 pandemic, the demand for transportation is expected to continue in the upcoming decades, which means that the supply needs to grow accordingly.

This can be achieved by investments in transportation infrastructure such as canals, railways, highways, or airports, to provide access to more destinations and allow for higher throughput. Moreover, individual carriers can expand their service network and increase the capacities on existing services to skim the growing market. However, while these solutions are to some extent inevitable, they are expensive, complex, inefficient, and often impractical. Infrastructure in most transportation systems is constrained by geographical and geopolitical aspects and expansion of carrier networks to reach new destinations needs to be in line with their existing service portfolio and overall strategy.

Vertical collaboration is a way to overcome these issues. It involves the sequential execution of transportation services from origin to destination. A sequence of services can involve different carriers and different transport modes providing an integrated service. Through vertical collaboration, the service networks of transport modes and carriers are integrated, leading to larger coverage of destinations and shorter routes. For instance, airlines can expand their destination network through offering connecting flights operated by partner airlines (Cardillo et al., 2013b), and rail and barge services in intermodal hinterland container transport complement each other

[1] Source: https://www.statista.com/statistics/253987/international-seaborne-trade-carried-by-containers/ (Date accessed: February 21, 2022)

[2] Source: https://www.statista.com/statistics/564717/airline-industry-passenger-traffic-globally/ (Date accessed: February 21, 2022)

to overcome geographical obstacles and provide a competitive alternative to trucking (de Langen et al., 2017). Thereby, the transportation system can reach a higher level in terms of transport times, flexibility, resilience, and environmental footprint due to a more efficient use of existing resources and better responsiveness under disruption to the service network (Cardillo et al., 2013b).

However, successful collaboration is subject to a number of conditions, among which are competitive and commercial alignment (Agarwal and Ergun, 2010; Houghtalen et al., 2011; Özener et al., 2011), organizational readiness (Cruijssen et al., 2007b; Sanchez Rodrigues et al., 2015), and sufficient technical infrastructure (Buijs and Wortmann, 2014). If these conditions are not met, collaborations might not yield the expected benefits and can even be prone to failure. In particular, impacts such as legislative or policy changes, conflicts, technical failure, or cyber attacks (Kumar and van Dissel, 1996; Tonn et al., 2019) can lead to the collapse of collaborative systems with adverse impact on the transportation performance. As a result, there is a type of vulnerability created through collaboration, which comes in addition to the physical threats to transportation systems such as low water levels for barges or rail breakdown. A transportation system that makes extensive use of collaboration is heavily reliant on these collaborations being intact (Cardillo et al., 2013b). This vulnerability can have a severe impact, as painfully highlighted in the 2017 (Not)Petya hack, a malware attack in the Ukraine that infected a large number of companies and institutions across the world including several transportation companies such as Maersk/APM Terminals (USD 300m damage) and TNT Express (USD 400m damage), disrupting their operations or even bringing them to a halt (Greenberg, 2018). Throughout this dissertation, the term vulnerability is used to describe the potential impact magnitude of disruption combined with disruption probability (how likely) and susceptibility (how easy to exploit). The term risk is used to describe the probability of a disruption taking place and the term threat is used to describe origins or sources of disruption.

While the benefits of collaboration in transportation systems are extensively covered in the literature, for instance with respect to cost synergies (Adenso-Díaz et al., 2014; Cruijssen et al., 2007a), or carbon footprint reduction (Demir et al., 2016; Lin and Ng, 2012), knowledge on the concomitant vulnerability is rather limited. Existing studies focus on the conditions for successful collaboration and potential causes for failure, e.g. with respect to the alignment of side payments in liner shipping (Agarwal and Ergun, 2010) or truck transportation (Özener et al., 2011), incentivisation schemes

(Houghtalen et al., 2011), organizational readiness (Verstrepen et al., 2009; Zacharia et al., 2011), or the creation of trust (Pomponi et al., 2015), but an integrated perspective on opportunities and threats of collaboration in large scale transportation systems is missing.

In a world of transportation that is becoming evermore reliant on collaboration and consequently more interconnected through information technology, this is a severe knowledge gap. New visions of transportation such as synchromodal transport (van Riessen et al., 2015a) or the Physical Internet (Montreuil, 2011) are heavily dependent on close collaboration between carriers in order to be realized. Moreover, these visions require strong technological integration, including the sharing of large amounts of data and the usage of sophisticated technologies such as sensor technology or smart contracts. It is crucial to understand the vulnerabilities that come with these developments.

Traditional approaches in transportation research often fall short in addressing the complex multi-layered nature of modern transportation systems. Besides presenting an efficient and sustainable solution to cope with increasing demand for transportation, vertical collaboration creates a new level of complexity emerging from the network integration, the transshipments between transport modes and carriers along a path with sequential services, as well as the collaboration and information exchange between autonomous carriers required to provide such services. This complexity is difficult to capture with conventional notions and models used in transportation research. Operational, technical, commercial, and organizational aspects of collaborative transport systems are well researched at the individual and local level (Pan et al., 2019), e.g. the alignment of side payments (Agarwal and Ergun, 2010), partner selection (Verstrepen et al., 2009), intermodal terminal operations (Arango et al., 2011), or the role of IT in joint decision making (Buijs and Wortmann, 2014). At system level, however, individual and local decisions lead to the emergence of a complex adaptive system with non-trivial features. These features are difficult to trace back to the individual level, which leads to low predictability of the impact of changes to the system (Choi et al., 2001).

Understanding the complexity at system-level is fundamental to provide a comprehensive analysis of the impact of vertical collaboration on the vulnerability of a transportation system, which is the core objective of this dissertation. Establishing such an understanding can be achieved through observing changes in individual characteristics emerging from integration, but also through abstraction from individual

instances and focus on structural patterns. This enables a dedicated analysis of the vulnerability induced by collaboration and put it into relation with the benefits.

The remainder of this chapter begins with the provision of background knowledge on some of the most relevant theories, concepts, and methods that are relevant in the context of this dissertation (Section 1.2), namely intermodal transport (Section 1.2.1), collaboration in transportation (Section 1.2.2), and the science of complex networks (Section 1.2.3). In Section 1.3, the research objective and approach are presented. The introduction concludes with an outline of the dissertation including a brief summary of each content chapter in Section 1.4.

1.2 Background knowledge

1.2.1 Multimodal hinterland transport

Despite covering general transportation systems with decentrally operated services, the main reference system of this dissertation is multimodal container transport in the seaport hinterland. Multimodal transport describes the flexible use of alternative transport modes rail and barge, including multi-leg transport chains involving multiple transport modes and carriers. Enabling such transport chains requires vertical collaboration between carriers. The aim of multimodal transport is to provide a more flexible, resilient, and sustainable transport transport systems with little need for truck transport. In Europe, hinterland transport is carried out through a network consisting of a large number of transport services provided by different independent operators and via different transport modes on road, rail, and inland waterways (de Langen et al., 2017). Barge transport, which is inland shipping on rivers and canals, is the cheapest option. However, it is also the slowest option and is naturally limited to existing transport connections. Rail transport is significantly faster, but also limited to the existing rail network and availability of services. In contrast, trucking offers maximum flexibility and short transport times, but comes with the highest costs. The trade-off between these different transport modes has already been addressed in various publications (Bloemhof et al., 2011; Crainic and Bektas, 2007; van Riessen et al., 2015b).

Under the premises of this multimodality trade-off and the limitations of infrastructure, hinterland transport went through a process to adapt to increasing transport demand. For a long time, unimodal transport from the sea port to the final destination with a single transport mode, usually truck, was predominant (de Langen and

Sharypova, 2013). However, congestion of roads through trucks, increased cost pressure for transportation of goods, and environmental considerations have increased awareness and usage of alternative hinterland transport modes such as barge and rail. In addition to that, advances in technology enabled the provision of transport services in sequence with multiple modes and carriers. The fact that shippers not only started using alternative transport modes, but also multiple modes within one transport sequence, gave way to the emergence of a complex network of multimodal transport services. This network exhibits a highly complex structure as it is the product of multiple individual, but interlinked networks formed by the different transport modes. While the backbone of this network was to some extent predetermined by the availability of inland waterways and rail infrastructure, evolution of the network of services was shaped by several influencing factors. Besides the performance attributes speed, price, and reliability of the respective modes, evolution of the network is additionally driven by geographical, geopolitical, and infrastructural factors (Notteboom, 2010).

Throughout the last decade a substantial set of literature has grown on multimodal hinterland transport and the associated concepts of inter- and synchromodal transport. Agamez-Arias and Moyano-Fuentes (2017) provide a comprehensive review on multimodal transport. On the one hand, much of the existing body of knowledge focuses on optimization models for planning on operational, tactical, and strategic level as reviewed in SteadieSeifi et al. (2014). Among those are models for routing, scheduling, or global optimization of container flow. Most of these models have been employed with a limited scale in order to enable optimization. While this approach contributes strongly to the theoretical understanding of the subject, it cannot say much about the structural evolution of the network. On the other hand, many researchers investigated intermodal transport from an economical, political, or competitive perspective. Janic (2007), Vannieuwenhuyse et al. (2003), and Islam et al. (2013) provide approaches to estimate costs of intermodal transport connections and to compare them. Van Der Horst and De Langen (2008) find that coordination is a major enabler for the performance of hinterland supply chains, but its development is hindered by free-riding problems, a lack of contractual relationships, information asymmetry, and a lack of incentives. Ducruet and van der Horst (2009) measure the role of intermediaries in this context.

A number of studies on structure and complexity of intermodal transport from a system perspective contribute to the explanation of emerging system features and

how the evolution of the network reflects in its structure. Veldman and Bückmann (2003) identify a change in port competition stemming from more opportunities for port selection due to the hinterland network becoming more connected. Wang and Cullinane (2016) provide benchmarks for the competitive positions of seaports based on their centrality score in the worldwide maritime sea-shipping network. In a longitudinal study performed on the European container network, Notteboom (1997) concluded the containerisation of transport is not leading to further concentration of ports. Instead, he expected traffic flows to decentralise under the influence of competition between large consortia, the development of hinterland links, and policies from (port) authorities and governments. In his follow-up research in 2010 it became evident this was indeed happening (Notteboom, 2010). Structural aspects can also be found in the design of hinterland corridors, e.g. for the outgoing barge networks in Rotterdam (Konings et al., 2013) or Antwerp (Caris et al., 2012). Ducruet et al. (2010), Ducruet and Zaidi (2012), and Wang and Cullinane (2016) provide evidence of the effectiveness of structural network analysis for an understanding of the functionality of global container transportation system and the role of ports as an interface between foreland/maritime and hinterland networks.

1.2.2 Collaboration in transportation

Collaboration in transportation or collaborative transport describes transport systems, in which carriers or transport modes can leverage their individual transport offering through collaborative provision of services, with the aim to improve the overall service level (destinations, flexibility, transport time) or reduce costs.

Types of collaboration

Collaborative provision of services between carriers can take on various forms, among which are horizontal and vertical collaboration. Horizontal collaboration involves carriers that provide similar services, possibly in competition, for which resources can be shared to enhance capacity or frequency of service. In intermodal transport, horizontal collaboration for instance can include flexible allocation of containers to parallel services operated by different carriers and possibly on different transport modes in order to cope with demand variation or disruption. Vertical collaboration involves carriers providing transportation services that can be executed in sequence to provide a combined transportation service along a path. In between those connecting services, transshipment is required. Vertical collaboration in intermodal transport comprises

the provision of transport chains involving transshipment between services operated on different transport modes or by different carriers. Coordination of transshipment at terminals and enabling integrated booking are key aspects of vertical collaboration in hinterland transport. Despite touching upon certain aspects of horizontal collaboration such as the similarity of services, the focus of this dissertation lies on vertical collaboration with consecutive services and transshipments.

We distinguish vertical collaboration by the type of transshipment, which can be between different transport modes (multi-mode vertical collaboration) and different carriers (multi-carrier vertical collaboration). Transshipment between different transport modes happens for instance in public transportation, where passengers can change between bus, train, metro, and even plane in consecutive fashion at given transshipment points in the network. Multi-mode vertical collaboration often aims at providing a cheaper and more sustainable alternative to an established transport mode like the car for passengers or trucks for cargo, which cause and suffer from congestion on highways. Since travelling by car and transportation by truck is highly convenient with respect to speed, flexibility, and coverage of destinations, multi-mode vertical collaboration needs to provide a cheaper and more sustainable alternative while offering a comparable service level in order to present a competitive alternative. This can be achieved through vertical collaboration. By connecting the networks of different transport modes through the possibility of transshipment, the weaknesses of the respective transport modes can be overcome and their individual strengths can be exploited. In the case of intermodal transport, barges can be used to provide high-frequency and high-capacity services between large hubs in high-demand areas in the hinterland with decent canal infrastructure, from where rail services can be used to serve more remote hinterland destinations. Challenges of vertical collaboration of transport modes centre around the process of transshipment w.r. to infrastructure, revenue management, and operational planning (Agamez-Arias and Moyano-Fuentes, 2017; Caris et al., 2014; van Riessen et al., 2017).

Multi-carrier vertical collaboration, e.g. as part of intermodal transport, mainly aims at providing a more efficient utilization of existing transportation resources, wider network coverage of carriers, as well as shorter and more flexible routes (Cardillo et al., 2013b). The challenges are similar to those of multi-mode collaboration, but additional complexity is added by the fact that vertically collaborating carriers are to some extent collaborators and competitors at the same time. Commercial alignment between carriers, e.g. through side payments (Agarwal and Ergun, 2010; Özener et

al., 2011) or incentivation schemes (Houghtalen et al., 2011) is therefore paramount to guarantee stable coalitions. Moreover, the market structure of carriers within the system needs to be taken into account as heterogeneity in cost structure (Defryn et al., 2016; Padilla Tinoco et al., 2017) and bargaining power (Guajardo et al., 2016) can be barriers for feasible benefit sharing.

The methodology of this dissertation largely abstracts away from the specific type of collaboration to ensure general applicability of findings. Nevertheless, references and examples from the specific context are provided throughout to make the approach and findings tangible

Physical and collaborative level of transportation systems

There is a distinction in collaborative transport systems between the physical and the collaborative level. The physical level describes the actual physical movement of goods or people. It includes the physical transportation services performed by different carriers and different transport modes, as well as transshipment services performed by terminal operators. The collaborative level addresses activities beyond the physical movement of goods, which include non-physical coordination efforts and information exchanges between involved parties required to enable collaboration. Coordination efforts include, for instance, sharing of booking and planning information, redistribution of costs and benefits, tracking of deliveries, and error handling. In intermodal transport, coordination is necessary between a number of parties, especially truck, train, and barge carriers, as well as terminal operators. Basic collaboration could entail sharing of data on schedules and availability capacity on manual request as well as manual coordination of bookings and compensations between carriers. More advanced collaborations come with an interface enabling integrated booking of transportation services involving both carriers at either carrier's platform or even a shared interorganizational information system (van Baalen et al., 2008). These systems can include automated compensation schemes for service sharing and automated coordination of transshipment with terminal operators.

System impact of vertical collaboration: Emerging characteristics, synergies and vulnerability

Emergent patterns in complex supply networks are difficult to grasp as complexity does not allow for creating a direct relationship between changes and outcome (Cardillo et al., 2013a; Choi et al., 2001). While physical and collaborative level

are complex by themselves, it is the interdependence between them that makes the transportation system truly complex. Changes on either level can have an impact on the other level and the system as a whole.

Vertical collaboration can be interpreted as the merging of otherwise isolated transportation networks. Progressive merging of such networks leads to the emergence of structural features that are not present in the single layers and have an impact on the statics of the system (Battiston et al., 2017). For instance, the merging of service networks of national flagship airlines in the European Air Transport network leads to the emergence of a rich-club, a connected subnetwork of highly connected nodes representing the largest European airports (Cardillo et al., 2013a). Emerging network features also affect the positioning of nodes (hubs/terminals in a transportation context) within a network. It is not sufficient to classify them by their connectivity, but also by their connecting role between services of different carriers or transport modes. A node that is central within the network of one mode or carrier can be rather remote in the collaborative network if it has no transshipment connections. In intermodal transport, terminals that have both rail and barge connections benefit disproportionately from vertical collaboration.

The aim of vertical collaboration is to create synergies and improve the overall performance of the system. However, contrary to the widely adopted assumption in transportation research and practice, the complex outcome of vertical collaboration is not always only for the better, but can also have adverse impacts. Besides the creation of synergies, a new type of vulnerability at the collaborative level emerges. The potential synergies of vertical collaboration are relatively intuitive. Synergies through collaboration are created by exploiting unused potential of existing transport service infrastructure. The potential is unused due to constraints in service usage and transshipment, i.e. available multi-leg routes can only be used if involved carriers collaborate to facilitate booking and transshipment. For instance, two adjacent rail services cannot be used in sequence if the operating carriers do not provide integrated booking. Services have to be booked separately, which is inconvenient since transshipment might not be arranged and there is no compensation guarantee for missed connections. As a result, customers might opt for a direct truck service instead, which is more expensive, less sustainable, and would not be necessary if carriers were collaborating. Establishing collaborations reduces these constraints, leading to an increased number of alternative routes, higher network coverage, and shorter transport times. Synergies in collaborative planning can be exploited by maximizing

fill rates (Cruijssen et al., 2007a), reducing empty runs (Adenso-Díaz et al., 2014; Ergun et al., 2007; Lin and Ng, 2012), finding optimal locations to foster participation of carriers Hernández et al. (2011), and optimizing supply network pooling Pan et al. (2013). Improvements are substantial, for instance w.r. to cost synergies (Adenso-Díaz et al., 2014; Cruijssen et al., 2007a), or carbon footprint reduction (Lin and Ng, 2012).

Vulnerability through vertical collaboration is less intuitive. Collaboration does not only create synergies, it also creates a new disruption threat at the collaborative level, which comes on top of the existing physical disruption threats (disruption of physical services, e.g. through low water levels). For instance, collaborating carriers have to rely on each other that information is provided on services, bookings, capacities, transshipments, and that this information is correct. In intermodal transport, coordination is required to deploy intermodal transport chains involving multiple carriers. If carriers fail to provide their partners and involved terminals with the required data or the data is falsified, e.g. resulting from a ransomware attack, transport chains become infeasible. Disruption at the collaborative level can also be caused by strategic misalignment in collaborations, e.g. from a commercial (Agarwal and Ergun, 2010; Houghtalen et al., 2011; Özener et al., 2011), competitive, legislative, or trust perspective (Pomponi et al., 2015). External influences such as new regulations or new physical infrastructure can cause an imbalance of benefits of collaboration between partners, or even to collaborations becoming obsolete for one of the two or both parties. The consequence of disruption at the collaborative level can be the failure of collaboration, and consequently a loss of system performance. Vulnerability at the collaborative level is defined by the potential magnitude of the impact of disruption and how susceptible the system is to this impact.

1.2.3 The science of Complex Networks

Complex networks methods and applications

The study of complex networks has first received attention through Milgram (1967), who discovered in an experiment that people were acquainted to each other by an arbitrary path length of six. The results of the experiment became popular as small-world phenomenon or six degrees of separation. Watts and Strogatz (1998) generalized the findings of Milgram (1967) by introducing a network model to analyze the phenomenon and to generate random graphs with small-world property. Barabasi and Albert (1999) introduced the class of scale-free networks, networks whose node

degree distribution (number of adjacent edges) follows a power law, i.e. there is a small number of nodes with very high degree whereas most nodes are sparsely connected. They discovered that scale-free networks are very resilient to random failure, but very vulnerable to targeted attack against high degree nodes. Since then, network science established itself as a useful approach to study natural and engineered systems with high inherent complexity. The representation of such systems as networks allows for the use of relatively simple metrics to extract information about the nature of the system out of its network structure.

Network science does not only make highly complex networks more tractable, it often fulfills a different purpose than most conventional methods as well. While the focus of for instance operations research is predominantly on the optimization of system parameters to maximize performance, network science aims to carve out general system characteristics and the driving structural forces behind them. For instance, one would not necessarily try to find the optimal set of links to maximize the resilience of a given transporation network instance, but rather search for network characteristics that support resilience and apply to a wider range of networks.

Such analysis has been conducted in empirical studies using extensive data of a wide range of real-world systems including social, biological, or physical systems (Boccaletti et al., 2006; Newman, 2010). Studies on social networks addressed for instance personal acquaintances (Milgram, 1967; Watts and Strogatz, 1998) or opinion dynamics (Shao et al., 2009; Solomon et al., 2000). Socio-economic systems analyzed from a complex network perspective include the internet (Barabasi and Albert, 1999; Siganos et al., 2003), academic citations (Radicchi et al., 2008), or financial networks (Bonanno et al., 2004; Sarantitis et al., 2018). Moreover, analyses of cellular and metabolic networks (Jeong et al., 2000), epidemic spreading (Pastor-Satorras and Vespignani, 2001), immunization strategies (Cohen et al., 2003), and food webs (Williams and Martinez, 2000) were conducted. Among the physical networks studied in a complex networks context are power grids (Strogatz, 2001) and telecommunication networks (Onnela et al., 2007).

The empirical analysis of real-world networks is sometimes not sufficient to derive specific insights on the system impact of certain network characteristics, since these characteristics need to be varied to derive their impact. A suitable alternative is provided by random network models mimicking the structure of real-world networks. Random network models can be used to conduct the desired analysis, either with

an analytical approach or by generating and analysing large populations of networks with tunable network characteristics.

In the field of transportation research, the ample opportunities of network science have not gone unnoticed. The most prominent applications of complex networks analysis for transportation networks are airline networks (Cardillo et al., 2013a; Cardillo et al., 2013b; Du et al., 2016; Guimera et al., 2005; Verma et al., 2014), public transport networks (Ferber et al., 2009; Latora and Marchiori, 2002; Sen et al., 2003), or maritime shipping networks (Ducruet and Notteboom, 2012; Hang et al., 2015; Kaluza et al., 2010; Pais Montes et al., 2012; Wang and Cullinane, 2014).

Multi-layer networks

Most complex systems comprise multiple types of interactions, potentially at different physical or logical levels, or change depending on time. As a consequence, an adequate network representation cannot be achieved in a single network, but the multi-layer nature of these systems needs to be accounted for. Research on multi-layer networks, which is a generalization of conventional network theory, provides a framework and tools to study such systems (Kivela et al., 2014). Multi-layer analysis is nowadays one of the most relevant research streams within the field of network science. Multi-layer systems are dissected into subnetworks, which represent for instance different types of acquaintances (friend, colleague, relative) in a social network or different transport modes (train, car, plane) or carriers in a transportation network (Cardillo et al., 2013a; Cardillo et al., 2013b). These two examples fall into the category of multiplex networks, which are a special case of multi-layer networks. Multiplex networks are node-aligned, i.e. each network layer has the same set of nodes and layers only differ in the set of edges (Kivela et al., 2014). General multi-layer networks have a wider definition. Nodes and edges can represent something different in each layer, which allows for representing more complex functionally interdependent network layers.

Multi-layer network modelling is particularly popular for research on cyber-physical systems such as power-communication coupled systems with a power infrastructure layer and a communication layer. The two layers are coupled to enable smart grid functionality, but they are also closely coupled and therefore highly interdependent. Buldyrev et al. (2010) show that such networks are prone to cascading failure, where failure in one network layer propagates back and forth between layers and can lead to complete disintegration of the network. Moreover, (Parshani et al., 2010) found that

reducing the coupling strength can mitigate the risk of cascading failure in general interdependent networks. In many real-world interdependent systems, layer integration exhibits a trade-off between network functionality and vulnerability. Schneider et al. (2013) developed strategies to select autonomous (immune to failure) nodes to improve resilience of communication-power coupled systems. In a similar context, Korkali et al. (2017) found that the inter-layer coupling mechanism is decisive if an increasing level of layer interdependence increases or reduces the risk of cascading failure.

The versatility of multi-layer modelling and the fact that analyses of related cyber-physical systems have contributed greatly to the understanding of interdependence and vulnerability suggests that this approach bears large potential to expand the knowledge on collaborative transport systems.

1.3 Research objectives and approach

This dissertation attempts to contribute to the understanding of complexity in collaborative transport systems and to explore the impact of vertical collaboration across transport modes and carriers on the emergence of system characteristics. A particular focus is set on vulnerability emerging from collaboration, and how this vulnerability stands in contrast to the synergies of collaboration.

The adoption of vertical collaboration in transportation systems adds a new layer of complexity, which can alter the overall resilience to disruption. The current understanding of vulnerability in transportation is mainly based on the physical disruption threats, which comes short of two essential aspects. First, vertical collaboration leads to the emergence of structural network features and new roles of network components, which can alter the structural static and therefore vulnerability of the system. Second, vertical collaboration creates interdependencies between the actors involved and their operations. These interdependencies produce a new type of vulnerability at the collaborative level, which comes in addition to the physical threats. The new aspects of vulnerability have the potential to offset the synergies created through collaboration, which calls for a careful consideration of both synergies and vulnerabilities in decision making on vertical collaboration.

A conclusive assessment requires an expansion of the system scope beyond the physical level, taking into account the arrangements between stakeholders at the collaborative level as well as the functional interdependence (coupling) between physical

and collaborative level. Expanding the knowledge on vulnerability in complex decentrally operated transportation systems is crucial, since growing transport demand, constrained infrastructure expansion, technological innovation, and increasing need for sustainable solutions will further drive the relevance of collaboration and lead to even higher complexity.

While a complexity angle in transportation systems is not entirely new in the transportation literature, the existing body of scientific knowledge does not sufficiently cover the collaborative aspect and the associated vulnerability. This is due to a lack of appropriate multi-layer models that are able to capture the functional interdependence (coupling) between physical and collaborative level in large-scale transportation systems. Such models have supported a thorough understanding of complexity in other cyber-physical systems such as smart power grids (Buldyrev et al., 2010), and need to be established to enable a similar analysis in collaborative transportation.

The research conducted in this dissertation attempts to fill the knowledge gap on complexity induced by vertical collaboration. The main research objectives are summarized in the following:

- Analyze the emergence of structural network features and roles of network components under vertical collaboration across transport modes and carriers
- Identify key drivers for vulnerability at the collaborative level based on network and market structure
- Identify a trade-off between synergies and vulnerabilities of vertical collaboration
- Develop analytical and simulation tools and provide managerial decision support in vertical collaboration strategy and policy making.

The science of complex networks provides a framework to study large-scale multi-layered systems such as multi-mode and multi-carrier transportation systems. By aggregating data, mapping it in a network, and analysing it with dedicated measures, network science creates a relatively simple interface to explore complex relations at large scale (Newman, 2010) where conventional operations research and optimization models were likely to become intractable. We build a novel multi-layer network model that is able to capture the impact of vertical collaboration and analyse it with a combination of well-known metrics from network science and new methods developed ourselves.

Moreover, a mix of analytical computations and simulation-based methods is applied to establish general findings derived from random network classes and verify them through simulation. The development of random network classes mimicking the structure of real-world transportation systems allows for the systematic variation of system characteristics to identify drivers of vulnerability. The findings are further verified through the analysis of a real-world data set comprising all intermodal transport services by rail and barge in the European hinterland in 2019.

1.4 Outline of the dissertation

This dissertation comprises 5 chapters. Chapter 1 serves as an introduction and motivation for the research. The final Chapter 5 concludes the work and discusses opportunities for future research. Chapters 2-4 contain the research studies conducted as part of this dissertation project.

Figure 1.1 visualizes and describes how the research objectives outlined above are addressed along these chapters. In chapter 2, the notion of connectivity in transportation systems is extended under the emergence of structural network features through integration of transport modes at the example of intermodal container transport in Europe. Chapters 3 and 4 focus on vertical collaboration between carriers. In Chapter 3, a model is established to capture the interdependence (coupling) between physical and collaborative level, and a deep-dive on the structural root causes of vulnerability induced by vertical collaboration is performed. Chapter 4 analyzes the trade-off between synergies and vulnerability depending on the level of collaboration and its impact on physical transportation performance. Chapters 2-4 are briefly introduced in the following.

An extended notion of hinterland connectivity to analyze multimodal integration in European hinterland service networks

This chapter analyzes changes in network structure under vertical integration of multiple transport modes in the European network for hinterland container transport. Hinterland connectivity of a port is mostly treated as a local indicator, describing the number of different hinterland locations served from a port via a direct service. However, with multimodality being on the rise and transfer connections becoming more feasible and common, the existing local notion of connectivity is not sufficient anymore. This chapter extends the notion of hinterland connectivity by non-local

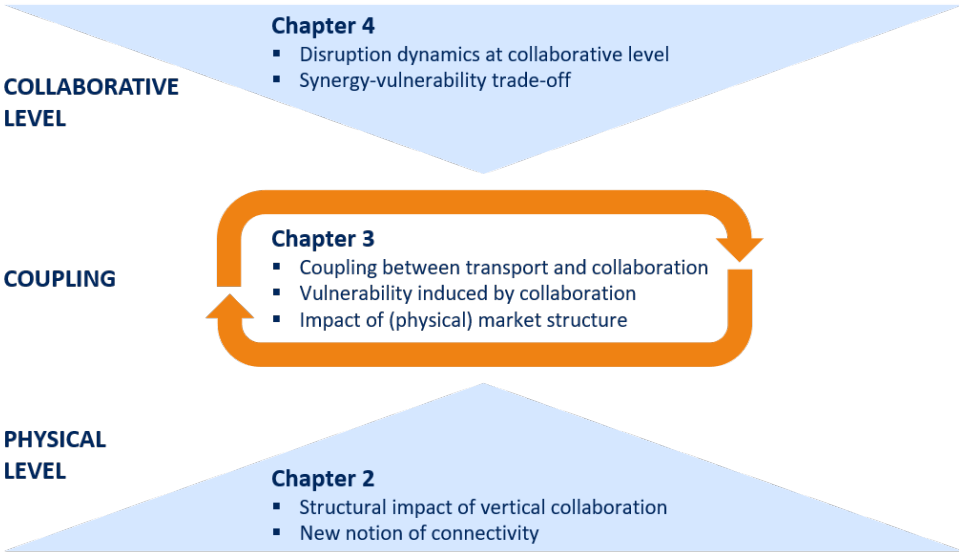


Figure 1.1: The figure shows the different levels of analysis of transportation networks with vertical collaboration in this dissertation and how they are captured by the different chapters. All chapters address both levels and the coupling in a certain way. However, each single chapter contributes something new to the understanding of vertical collaboration, which is reflected in this figure. Chapter 2 deals with the impact of vertical collaboration on the structure of (physical) transportation networks and addresses the need for a new notion of connectivity at the physical level. In Chapter 3, a model is established to capture the coupling (interdependence) between physical and collaborative level. It describes how a given constellation of collaborations impacts the performance of physical transport. Moreover, the impact of changes at the collaborative level on the physical level can be assessed, which allows for an analysis of vulnerability to disruption at the collaborative level. Chapter 4 addresses the dynamics of disruption (propagation) at the collaborative level, and how the resulting vulnerability stands in relation to the synergies of collaboration.

(network) and multimodal aspects, and uses this notion to analyze hinterland connectivity for the European hinterland transport network of scheduled rail and barge services. The following research questions are addressed:

RQ2.1 Does the adoption of (multimodal) transfer connections in hinterland transport require a new notion of connectivity? Which new aspects need to be considered?

RQ2.2 What is the impact on the system capability to perform hinterland transport? What is the impact on the roles and positioning of transshipment hubs in the network?

The results show that overall structural capability to perform hinterland transport assignments increases strongly as transfer connections and multimodal routes are established. Moreover, non-local measures show that ports with poor local connectivity can still be well positioned within a vertically integrated network if they have a connector role between the different network layers. Last but not least, all ports benefit individually from multimodal integration, but some do more than others. For instance, 'Multimodal hubs' are the most important contributors to multimodal integration, but their relative accessibility does not improve much.

Vulnerability of collaborative transport systems: A multi-layer network model

In this chapter we analyze how the market structure of carriers and their positioning in the transport network drive vulnerability at the collaborative level of vertical carrier collaboration. Therefore, the transportation network in our model is complemented by a collaboration network representing the collaboration links between carriers and the system impact of disruption to this new network layer is assessed. The potential synergies of collaborative transport are influenced by the market structure of carriers, i.e. potential is highest if there is a large number of small and medium sized carriers (Cruijssen et al., 2007a). The current body of literature, however, is inconclusive whether market structure has a similar effect on vulnerability, meaning that higher synergies would create higher vulnerability due to a high dependence of the system on collaboration. This leads to the research question

RQ3.1 What is the impact of carrier market structure on the vulnerability of collaborative transport systems?

Instead of demonstrating our results on particular instances of such multi-layer networks, we describe a population of networks by its structural properties, capturing the constraints imposed by collaborations in an analytically tractable way. The analysis is complemented by a simulation study on less tractable, but more realistic networks to verify the analytical findings. The results indicate that market structure, represented by disparity in carrier sizes, has a non-trivial impact on the vulnerability of a collaborative transport network to targeted disruption at the collaborative level, resulting from the interplay between a system's dependence on collaboration and its susceptibility to targeted attack. Networks are most vulnerable if they have intermediate disparity in carrier sizes, i.e. carriers are overall similarly sized, but there is some heterogeneity with a moderate gap between few larger and many smaller

carriers. Networks with perfect uniform distribution of carrier sizes exhibit medium to high levels of robustness whereas highly disparate networks exhibit the highest robustness.

The impact of collaborative connectivity on the risk of failure cascades in collaborative transport systems

This chapter studies the trade-off between synergies and vulnerability through vertical collaboration. Since offering shared routes requires close alignment between parties, collaborations are fueled by the exchange of data and the integration of information systems, which creates disruption threats in the form of technical failure, cyber attacks, or organizational conflicts. Research has shown that failure in interdependent networks can propagate and lead to a cascade of failures, which casts doubt on the claim that more collaboration has a solely positive impact on system performance, and rises the research question:

RQ4.1 Is there a trade-off between synergies and vulnerability from vertical collaboration?

RQ4.2 Can this trade-off be quantified depending on the level of collaborative connectivity?

To answer this question, the network model from the previous chapter is coupled with a model for propagation of cyber/false data disruption, and the impact on network performance under varying levels of collaborative connectivity is observed for random network models, simulated network instances, as well as for a network generated from real-world data on intermodal transport services in the European hinterland. Results show that increasing collaborative connectivity does not have a monotone effect on performance, but there is a maximum at intermediate connectivity levels. Below this threshold level, more collaborations have a mostly positive impact on performance, since unused synergy potential is high while the risk of disruption causing a cascade is low. Above it, failure cascades become larger and more likely while the marginal added synergies are diminishing.

Chapter 2

An extended notion of hinterland connectivity to analyze multimodal integration in European hinterland service networks

2.1 Introduction

Hinterland transport fulfills the first and last stage of global transport of containers, i.e. it comprises the landside transport before and after maritime shipping. Transport in the hinterland differs from maritime transport by shorter distances, less opportunities for pooling due to more individual destinations, and consequently disproportionately higher transport costs (Van Der Horst and De Langen, 2008). In Europe, hinterland transport is carried out via different transport modes on road, rail, and inland waterways (barge transport) (de Langen et al., 2017). Although road transport is still predominant in many places as trucks are available on short notice providing fast and direct transport (Vannieuwenhuyse et al., 2003), alternative transport modes have gained traction in recent years as a result of increasing global trade (European Commission, 2018), cost pressure, congestion on European highways, and environmental aspects (Macharis et al., 2011).

The competitive position of sea ports depends on their capability to forward incoming cargo from overseas to its final destination, and it is an important criterion for port selection (Martínez Moya and Feo Valero, 2017). Such capability is associated with the hinterland connectivity of the sea port. The definition of hinterland connectivity in literature and practice is usually based on direct transport services between the port and inland ports. This simple notion provides a highly relevant connectivity indicator, but is insensitive to more downstream connecting services operated by means of multiple modes and across the hinterland network. Rail and barge transport is mainly fulfilled by scheduled services run by different operators, spanning an extensive decentrally managed multimodal service network across the European hinterland (Van Der Horst and De Langen, 2008). This network exhibits a high natural level of complexity shaped under geographical, (geo-)political, and infrastructural influences (Notteboom, 2010). Complexity in transportation networks comes with non-trivial connectivity features that are often overlooked and require a holistic network connectivity analysis. In multimodal systems, complexity is amplified by the integration of different transport modes. Complex outcomes are not only driven by the the overall network structure, but also by the connectivity across transport modes (Lee et al., 2015).

Analyzing hinterland connectivity with a too simple notion of connectivity could therefore lead to a misjudgement of the positioning of (inland) ports. On the one hand, a port with many direct connections to poorly connected destinations would seem to have great hinterland connectivity, while in reality it is quite isolated in the

overall network. On the other hand, a port with only one connection leading to the biggest transshipment hub in the network is quite well connected. To address these shortcomings, the notion of hinterland connectivity is extended in two ways. First, not only direct services and immediate neighbours are considered. As hinterland transport allows for connections with transshipments, connectivity of a port goes beyond its immediate neighbourhood. Second, the presence of multiple alternative transport modes is captured. The more integrated use of rail and barge services changes the positioning of (inland) ports in the network.

The science of complex networks provides a set of quantitative measures to systematically develop this extended notion of connectivity and apply it to the hinterland transport service network in Europe. By aggregating data, mapping it in a network, and analysing it with dedicated measures, network science creates a relatively simple interface to explore complex relations (Newman, 2010). Using these techniques, we follow a two step approach. In the first step, connectivity on network level is analyzed along selected measures for each of the layers and the aggregated network. Building on the work of de Langen et al. (2017), we derive how structural characteristics of the two transport modes assign them a specific role in the hinterland network and how they jointly create potential for multimodal transport. In the second step, hinterland connectivity is analyzed on individual level. We distinguish between local connectivity, non-local connectivity, and multimodal connectivity. Non-local connectivity provides information about the positioning of (ports) in a wider network context, i.e. their positioning as a start and end point of transport routes and as a transshipment hub. Multimodal connectivity additionally shows how port positioning changes under an increasing share of multimodal routes. An overview of the approach can be found in Figure 2.1.

Our findings are twofold. On the one hand, existing qualitative findings and findings with local scope regarding port development are substantiated through empirical data, e.g. the role of extended gates in the hinterland (Roso et al., 2009; Veenstra et al., 2012) and increasing competition for hinterlands between sea ports due to higher hinterland connectivity (Notteboom, 2010). On the other hand, our extended notion of connectivity creates new findings on hinterland connectivity. Results show how connectivity of the European hinterland transport network changes as transport services grow into a multimodal service network and the shares of transfer connections and multimodal transport routes increase, and how this affects the role and positioning of (inland) ports in the system.

	Local connectivity	Non-local (network) connectivity	Multimodal connectivity
Description	Perspective comprises direct hinterland connections (immediate neighbours)	Perspective comprises (indirect) connections to entire network	Perspective comprises multimodal connections (local and non-local)
Underlying assumption	At most one barge or rail transport leg feasible. Rest is trucking	Transfer connections (rail-rail, barge-barge) are feasible	Rail and barge can be used sequentially in transfer connections
Literature coverage	High, e.g. De Langen, Sharypova (2013)	High (but low for hinterland transport), e.g. Burghouwt, Redondi (2013)	Medium (but low for hinterland transport), e.g. Mishra et al. (2012)
Contribution	-	Positioning of (inland) ports within greater network by - Accessibility (transp. time) - Transshipment centrality	Potential of integrated mode planning at European level and positioning of (inland) ports in a multimodal system

Figure 2.1: In columns, various definitions (or levels) of port connectivity (local, network-wide and multimodal) are given, while in rows, a description, underlying assumptions made, the extent to which the level of connectivity is covered by the existing literature, and the extent to which the progressive level of connectivity contributes by providing more comprehensive insights are shown.

The remainder of this paper is organized as follows. The subsequent section comprises a review of most relevant literature on hinterland transport and network connectivity. Section 4.3 is dedicated to the introduction of the data set used and the methodology. Section 4.4 comprises the results of the analysis, serving as a basis for the discussion in Section 4.5. Section 4.6 concludes and provides an outlook for future research.

2.2 Theoretical background

Hinterland connectivity

Hinterland connectivity of (inland) ports is an important criterion for port choice in container transport, and ports compete based on their ability to cater door-to-door services more than port-to-port services (Martínez Moya and Feo Valero, 2017). Hinterland connectivity, after port costs, is the second most important factor for port competitiveness (Parola et al., 2016) and is expected to become even more relevant (Sdoukopoulos and Boile, 2020). Caballé Valls et al. (2020) find that intermodal hinterland connectivity is a determinant of the market share of a port in the (contested) hinterland. Hinterland connectivity, very often in the context of port performance and port selection criteria, is studied in many different ways, without there being a generally accepted definition. For instance, Tavasszy et al. (2011) use a strategic network choice model to study the relation between port choice and intermodal connectivity, whereas Ferrari et al. (2011) use a gravity model to evaluate hinterland

connectivity by means of accessibility of three Italian ports. Moreover, van den Berg and de Langen (2011) find in a case study with the port authority of Barcelona that active hinterland connectivity strategies by port authorities can attract cargo volumes from distant hinterlands.

In an empirical study, de Langen and Sharypova (2013) analyze hinterland connectivity as a port performance indicator of sea ports in Europe and find that intermodal connectivity is increasing in Europe. However, due to lack of data they can only use measures such as the number of direct connections and services to inland ports. Inland ports, however, are usually not only connected to a single dedicated sea port, but have connections with multiple sea ports and other inland ports. In such a way, they form a network of services, which is illustrated in de Langen et al. (2017). As a result, hinterland connectivity becomes more than just the number and frequency of sea port-to-hinterland connections. It is also about the connectivity of inland ports to other sea ports and to further hinterland destinations. As a consequence of more connected hinterlands, sea ports start to compete for hinterland areas (Notteboom * and Rodrigue, 2005). This is studied in a number of case studies for specific hinterlands, e.g. Spain (Garcia-Alonso et al., 2019), Austria (de Langen, 2007), and Adriatic Sea (Acciaro et al., 2017). Garcia-Alonso et al. (2019) find that the immediate port hinterland remains relatively captive, whereas distant hinterland is fiercely contested. Distant hinterland has not been in focus for a long time when studying intermodal connections, since they were difficult to reach with intermodal services. With hinterland becoming more connected, distant hinterland destinations become more accessible as routes with transfers at intermediate inland ports can be planned. For the study of hinterland connectivity, this means that a broader notion beyond direct services is needed to fully grasp the characteristics of hinterland transport services as a network on a continent-wide scale.

The existing body of literature embracing the network aspects of hinterland transport is very limited, especially regarding empirical studies. Studies of network connectivity exist though for comparable transport networks, e.g. Burghouwt and Redondi (2013) study connectivity in air transport networks, and Ducruet et al. (2010) study connectivity of maritime networks. The work of Mishra et al. (2012) comes closest to our suggested notion of non-local and multimodal connectivity. They use connectivity measures for prioritization in multimodal transit planning and find that transit connectivity varies across nodes, links, transfer centers, and regions. In the context of hinterland transport, Halim et al. (2016) use a multi-objective optimization ap-

proach to generate plausible port hinterland distribution structures for large regions and continents. Studies of hinterland network connectivity incorporating the multimodal aspect, where barge and rail services are fully integrated, are even more rare. de Langen et al. (2017) published the only study that captures both transport modes on a European level in the scope of their work. However, they are only studying the amount and distribution of direct services, but do not looking at the multimodal network connectivity that emerges from the resulting network.

The reviewed studies on hinterland connectivity suggest that hinterland transport needs to be considered at the network level, and that multiple transport modes need to be considered integrally, although this adds complexity. However, most studies do not fully capture both of these aspects, and if they do, only for a very limited geographical scope. Our work aims at filling this gap through a comprehensive study of hinterland connectivity at European level with intermodal services interpreted as an integrated multimodal system.

Network science as a tool to study hinterland connectivity

The science of complex networks provides us with the suitable tools for such an analysis. Starting with two fundamental models revealing that small-world networks feature short average path length (Watts and Strogatz, 1998) and scale-free networks are robust-yet-fragile (Albert et al., 2000), it has developed into a powerful framework to analyze the complex topology of real-world systems. As network science became more sophisticated, more applications to a large number of social (Radicchi et al., 2008), ecological (Jeong et al., 2000), economical (Bonanno et al., 2004), or physical real-world (Buldyrev et al., 2010) systems were studied. Prominent applications for transportation networks are airline networks (Cardillo et al., 2013b; Du et al., 2016; Guimera et al., 2005), public transport networks (de Domenico et al., 2014; Latora and Marchiori, 2002; Luo et al., 2019), or maritime shipping networks (Calatayud et al., 2017; Ducruet and Zaidi, 2012; Kaluza et al., 2010).

In recent years, the study of multiplex networks faced increasing popularity as it allows for a more accurate mapping of many real-world systems, e.g. multi-mode public transport systems (de Domenico et al., 2014), multi-operator airline networks (Cardillo et al., 2013b), and seaport-airport networks (Parshani et al., 2010). Multiplex networks are a type of multi-layer networks, where each network layer shares the same set of nodes, but the set of links is different. Multiplexity has a non-trivial impact on a system's structure and function, as connectivity between the layers am-

plifies complexity of the system (Lee et al., 2015). Multimodal transport networks are multiplex since each transport mode forms a separate layer. An analysis of how layers mutually enhance each other and the overall system requires careful assessment of connectivity within and between the layers.

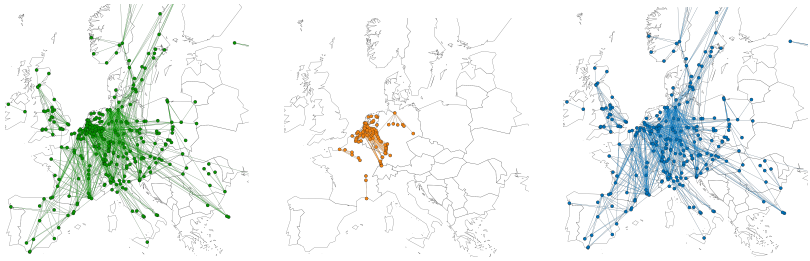
Modeling the network of intermodal hinterland transport services as a multiplex networks, we obtain an instrument to study network connectivity of European hinterland services and fill the research gap outlined above.

2.3 Methodology

Dataset

For our analysis we use a data set containing all intermodal services scheduled in the European hinterland including transport mode, transport time, and number of weekly services. Alternative transport modes are barge and rail. All ports/terminals within a city are grouped into a single transshipment area that serves a single market and is represented by a node in the network. We use the term node to avoid confusion and to be in line with network terminology. It stands for an area where multiple terminals may reside.

In 2019, the dataset comprises 26 countries, 337 cities, 496 terminals and 111 transport operators. The intermodal links data set is a highly suitable tool to study the European hinterland network from a structural perspective as scheduled services are a good proxy for available transport links and routes. The data set is rather complete for the covered regions, as indicated by de Langen et al. (2017) based on a benchmarking of the actual container throughput volume and the capacity implied by the data set. Moreover, the data is accurate as it is collected and verified with two independent sources, intermodal carriers and ports/inland terminals. Nevertheless, resulting from the exclusive route planning with barge and rail services only, some illogical routes can arise for connections where shippers would always use other transport modes such as truck or even sea vessel. Most notably, there are some routes from central Europe via Spain to the UK. The data set is visualized in Figure 2.2 and more information about data collection, validation, and preparation can be found in Appendix 2.A.



(a) Full network **(b)** Barge **(c)** Rail

Figure 2.2: Visualization of hinterland service network. Barge services form a dense network along major inland waterways in Northwestern continental Europe. Rail service span across the entire continent.

Description of approach

The methodology applied to this data set comprises a systematic analysis of hinterland transport connectivity on a European level by using measures from network science. There is a large number of articles and books providing a summary of these tools and how they can be used efficiently, see Newman (2010) for an overview. For multiplex networks, Boccaletti et al. (2014) and Battiston et al. (2017) are useful. We use a combination of measures suitable for standard and multiplex networks to provide answers to the questions raised in the previous sections.

Our analysis comprises the network of rail and barge services in the European hinterland. Even though truck services are a competitive alternative for almost any transport assignment in the hinterland, they are not included in the analysis. Trucking can either be a competing mode with scheduled multimodal services or a mode used mostly for first or last mile. In both cases, trucking does not need to be incorporated explicitly to perform a meaningful analysis since it is either part of the competitive environment, or when focusing on (inland) port to (inland) port transport, it is out of scope. The core of the analysis is connectivity of multimodal hinterland networks and how such a network of scheduled services can possibly provide an alternative to direct truck transport.

Network connectivity - Network layer description and multimodal interface

In an initial step, connectivity on network level is analyzed for rail and barge networks separately as well as for the joint multimodal network representation. This allows for

a characterization of the two network layers and how they jointly form a multimodal network. The analysis covers network size dimensions (number of services, number of connections), service attributes (frequency, duration, distance), as well as structural and intra-layer connectivity aspects ('density': ratio of services to nodes, 'rich-club': density among highly connected nodes, 'assortativity': preference of nodes to attach to nodes of similar degree). Most importantly, shortest-path-connectivity, i.e. the transport time between two arbitrary nodes in the network with intermodal services, is analyzed for both layers and for the integrated network. It comprises the two measures efficiency (reciprocal of average shortest path length) and interdependence (share of all shortest paths that include multimodal transshipment) provide insights about the potential of multimodal integration. An interpretation of these measures and formulae used are found in Appendix 2.C.

After the general description of layer characteristics, focus shifts to multimodal connectivity, i.e. the nodes where the two layers are connected. These nodes are crucial for enabling intermodal transport, which is why they receive particular attention. The set of nodes connected by multimodal links is called multimodal interface. Our analysis of the multimodal interface reveals to what extent and where the service networks overlap.

Node connectivity - Local, non-local and multimodal

The focus of the second part is hinterland connectivity on node level. We distinguish between local, non-local, and multimodal connectivity. Local connectivity describes connectivity in the immediate neighbourhood of a node, assuming that transport is only happening on direct connections without transshipments. It is measured by the node degree, i.e. the number of nodes that a node is connected to by a direct service. Non-local connectivity describes the positioning of a node within the entire network. It is based on the assumption that routes can be planned along multiple links via transshipments. We distinguish between accessibility and transshipment attractiveness. Accessibility describes how well a node can be reached through intermodal services from an arbitrary node in the network. It is measured by the network measure closeness centrality, which is computed by the shortest path length between a node and all other nodes in the network (Newman, 2010). Transshipment attractiveness describes the positioning of a node as a transshipment hub, i.e. how often logistics service providers will plan a route including a transshipment at that node. The network measure betweenness centrality is used to determine transshipment attractiveness. It is computed as the share of shortest paths between all pairs

of nodes that cross the respective node (Newman, 2010). The connectivity measures used are formally defined and interpreted in more detail in Appendix 2.D. Each of these measures has a unimodal and a multimodal version. The unimodal versions are calculated based on the assumption that routes can only be planned using services of the same transport mode (combined unimodal), whereas in the multimodal version, mixed mode routes are feasible.

The analysis starts with a categorization of local node connectivity adopted from Battiston et al. (2017). It is derived from two local measures. First, the number of distinct services, which is referred to as (overlapping) degree. Overlapping degree is used to refer to the total degree of a node in a multiplex network, as opposed to the layer degree, which only counts links in the respective layer. Second, a participation coefficient is calculated, measuring the spread of connectivity across rail and barge services, i.e. the homogeneity of layer degrees. The combination of these two measures allocates nodes to categories with similar role in the network. A formal definition of the categorization approach is shown in Appendix 2.D.

In the next step, non-local connectivity is benchmarked against local connectivity in order to show how the additional information gathered from non-local measures is relevant to accurately assess the positioning of a node in a multimodal network. Similarly, multimodal connectivity measures are benchmarked against their unimodal counterpart to illustrate how nodes can improve their connectivity if multimodal transshipments are established. Last but not least, accessibility and transshipment attractiveness of nodes are compared to show what their profile is within the network. Usually being the start and end point of intermodal routes, sea ports will mainly care about their position in the network in terms of accessibility, whereas inland ports might rather want to position themselves as land-to-land transshipment hubs on intermodal routes.

2.4 Results

2.4.1 Network connectivity - Network layer description and multimodal interface

The analysis of network connectivity comprises an isolated view on the two layers with regard to network characteristics and similarities, as well as a multimodal view with regard to joint functionality and multimodal service interface.

Measure \ Instance	Barge	Rail	Multimodal
Number of weekly services	6,901	12,743	19,644
Number of direct connections	366	1,309	1,609
Avg. number of weekly services	18.86	9.73	12.21
Avg. service duration [days]	2.67	2.14	2.36
Avg. aerial distance [km]	183	637	548
Efficiency	0.03	0.18	0.28
Interdependence	-	-	0.40
Density	0.039	0.017	0.015
Rich club coeff. [≥ 5]	0.44	0.10	0.10
Rich club coeff. [≥ 25]	1.00	0.47	0.47
Degree assortativity	-0.60	-0.22	-0.28
	Barge	**Rail**	**Intermodal interface**
Overlap - Nodes	0.29	0.83	0.12
Overlap - Edges	0.23	0.81	0.04

Table 2.1: Network connectivity analysis per layer and as an integrated multimodal system. Key findings: 1) Efficiency (a measure for connectivity by shortest path lengths) increases disproportionately through multimodal integration, i.e. it is higher than the sum of the barge and rail scores. 2) Interdependence (share of shortest paths that contain multimodal transshipment) shows that 40% less shortest paths are available without multimodal transshipment 3) Multimodal transshipment is only possible at 12% of all nodes (Overlap - Nodes)
.

The network is visualized in Fig. 2.3 and results are shown in Table 2.1. Barge services are intended to shift container load away from congested connecting sea ports to extended gates (Notteboom, 2010; Veenstra et al., 2012) and other inland terminals. From these inland terminals, containers can be further transported by rail or truck. Thereby, pressure on road infrastructure in these regions can be relieved. This shows in the data, where barge services are limited to central western Europe, i.e. the Netherlands, Belgium, Germany, and France. Barges provide high-frequency, short to medium-haul services (137km average distance) that aim at flexible and cost-efficient transportation in areas with the highest transport demand, which reflects in high network density (0.039).

Rail services form an extensive network connecting both central and remote areas in the hinterland, and providing fast, long-haul connections (637km average) to more remote destinations, which comes with a lower service density (0.017). In terms of weekly services and distinct connections served, the rail network is much larger than

the barge network with 12,743 weekly services serving 1,309 connections, compared to 6,901 weekly barge services serving 366 connections. It provides an alternative to truck transport almost all the way to the final destination of containers.

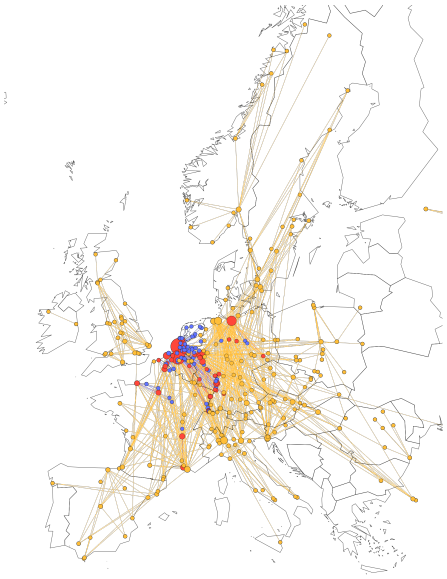


Figure 2.3: Visualization of hinterland network in Central Europe in 2019. Nodes with barge services only are coloured in purple, rail nodes in dark yellow, and multimodal nodes (rail and barge services offered) in red. Node size indicates total number of weekly services. The majority of multimodal activity is happening in Northwestern continental Europe, where multimodal nodes connect the high frequency, short-haul barge network with the long-haul train network.

The potential of multimodal integration for network connectivity shows by efficiency of the integrated network. Efficiency describes the connectivity by shortest path lengths between all OD pairs in the network. The multimodal score (0.28) exceeds the barge (0.03) and barge (0.18) score disproportionately, showing the large potential. This is strengthened by the fact that 40% of shortest paths in the fully integrated system would include a multimodal transshipment, shown by the interdependence measure. The multimodal interface of nodes with both rail and barge services is formed by only 12% of all nodes. Given the highly complementary service structure and specific role of transport modes, it becomes evident that these 12% are crucial for the connectivity of the network in multimodal transport. See Appendix 2.C for a more extensive interpretation of these results.

2.4.2 Node connectivity - Local, non-local and multimodal

Node categorization - Local vs. multimodal connectivity

With this refined picture of the network layers and their role for European hinterland connectivity on network level, our focus shifts towards node connectivity under the extended notion of hinterland connectivity.

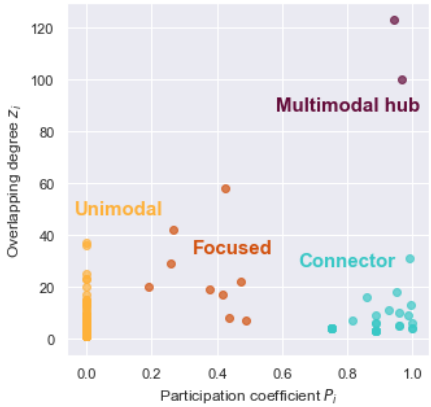


Figure 2.4: The graph shows a node categorization by overlapping degree z_i (local connectivity) and participation coefficient P_i (multimodal split). Four categories emerge from the (P_i, z_i)-values of nodes: Multimodal hub, Focused, Connector, Unimodal. Without the participation coefficient P_i measuring the multimodal service split of nodes, 'Unimodal', 'Focused', and 'Connector' could not be distinguished.

In the first step, local connectivity is benchmarked against multimodal connectivity. Therefore, a node categorization adopted from Battiston et al. (2017) is used. It is defined by the overlapping degree z_i (sum of rail and barge degrees) representing local connectivity and participation coefficient P_i representing the multimodal connectivity split. P_i becomes 1 if a node has the same degree across all network layers and 0 if all layer degrees are 0, except for one layer, i.e. a node has either only rail or only barge connections. A scatter plot of the (P_i, z_i)-pairs in the 2019 network is shown in Figure 2.4. Multimodal connectivity reveals four different clusters, which provide information about the positioning of nodes beyond their degree. Most nodes are in the 'Unimodal' category of nodes with $P_i = 0$, i.e. nodes served by one mode only. The remaining nodes with $P_i > 0$ represent the multimodal interface, which divides into three categories. The category 'Focused' contains nodes whose connections are primarily offered by the same mode plus a few other connections with the other mode. They tend to play a central role in their focus layer, but are as well access

points to the other layers. The 'Connector' category is connected to a similar extent in both layers. Their overlapping degree is on average a bit lower than that of the 'Focused' cluster though. Thus, these nodes do not necessarily have an important hub role, but mainly a transshipment role between the layers. The last category is called 'Multimodal hub' as the nodes in this category are highly connected hubs with balanced participation across both layers. There are only two multimodal hubs, Rotterdam and Antwerp. Since these two are also covering large parts of the maritime inbound container flow, they have an outstanding role for both modes and the whole system. A sketch of the multimodal structure of each node category is sketched in Figure 2.5.

Figure 2.5: Sketch of node categories 'Unimodal' (1), 'Focused' (2), 'Connector' (3), and 'Multimodal hub' (4). The categories are distinguished by their multimodality, by the number of direct connections they offer in total and by the split of these connections between transport modes.

Geographical positioning of node categories

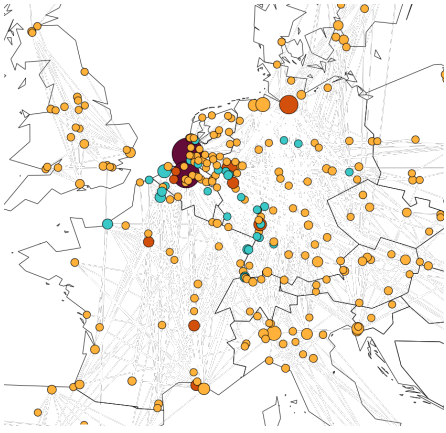


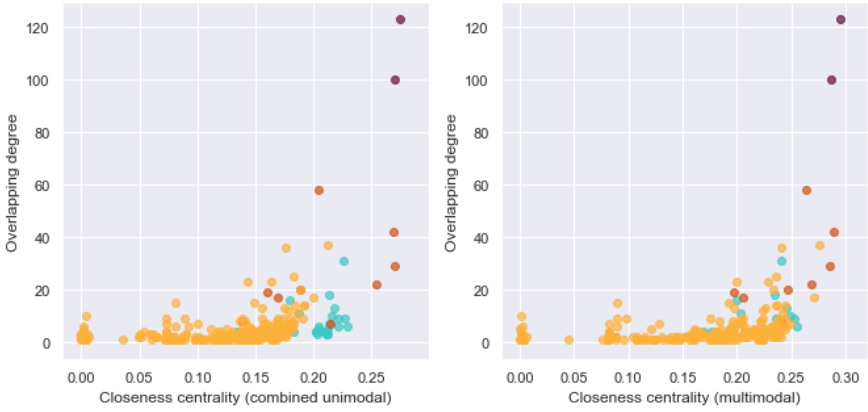
Figure 2.6: Snapshot of 2019 hinterland network in central Europe. Same color code (by node category) as in Fig. 2.4: Purple - 'Multimodal hub'; Red - 'Focused'; Turquoise - 'Connector'; Yellow - 'Unimodal'. Node size by overlapping degree. 'Multimodal hubs' can clearly be identified as Rotterdam and Antwerp. 'Focused' and 'Connector' nodes are mainly found along major inland waterways Rhine, Meuse, and Scheldt.

Figure 2.6 shows the hinterland network with nodes coloured by their role. As pointed out before, most nodes are 'Unimodal', whereas multimodal nodes can only be found in central/western Europe. 'Focused' nodes are mainly found along major inland waterways Rhine (Duisburg, Cologne, Ludwigshafen), Rhône (Fos-sur-Mer, Lyon), Elbe (Hamburg), and Zeekanaal Gent–Terneuzen (Ghent, Terneuzen). Interestingly, all these nodes have their focus on rail connections, despite being located at major inland waterways. In fact, many of them act as dry ports (Roso et al., 2009) or extended gates (Veenstra et al., 2012) that are connected by barge to sea ports and by many different rail connections to their further hinterland. They collect the large influx coming from ports in multi-port gateway regions (Notteboom, 2010) via barge and distribute it to their final destinations after a transshipment to truck or rail services. According to the generic framework for intermodal transport network design developed by Woxenius (2007), structure around 'Focused' nodes follows a corridor design (cf. Figure 1 in Woxenius (2007)).

'Connectors' are mostly smaller (inland) nodes in the Rhine-Meuse-Scheldt delta (e.g. Liège, Tilburg), along the river Rhine (e.g. Andernach, Mannheim, Strasbourg) and some smaller rivers or canals (e.g. Trier/Mosel, Hanover/Leine, Riesa/Elbe). Moreover, there are a few larger 'Connector' nodes such as Amsterdam, Zeebrugge, and Le Havre. In a unimodal network, most nodes in this category would have no special significance, but their access to both rail and barge services gives them a special role in a multimodal network. Together with the dominant hubs in the region, the large number of 'Connector' nodes clustered in northwestern continental Europe creates alternative choices for intermodal routes. Without these transshipment opportunities, alternatives would be limited and more truck transport is required if there is disruption in 'Multimodal hubs' or 'Focused' nodes. Such flexible routing opportunities are in high demand as observed in Notteboom (2010). In the framework by Woxenius (2007), this network structure falls in the dynamic routing category, which in hinterland shipping terms is known as synchromodal transport.

Non-local connectivity

In the next step, non-local connectivity is analyzed. The existing node categorization is kept in order to track the change induced by non-local measures. Figure 2.7 shows relation between the local measure overlapping degree and the non-local measure closeness centrality, which describes the accessibility of a node in a network as a start and end point of routes. It becomes apparent that low degree nodes can have high closeness, showing that accessibility cannot be deduced from local measures

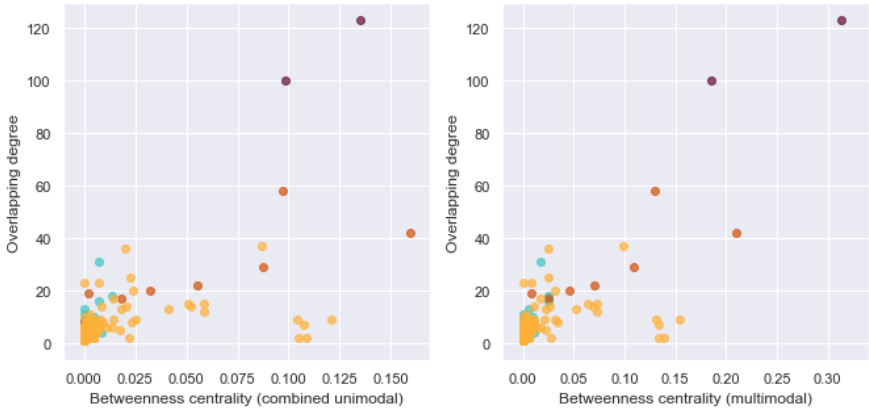


(a) Unimodal **(b)** Multimodal

Figure 2.7: (a) Local (degree) vs. non-local (closeness centrality) node connectivity. The graph shows how node positioning differs between local and non-local perspective (closeness/accessibility). Among nodes with low local connectivity (degree < 15), non-local connectivity can be very different. Accessibility depends a lot on the connectivity of the neighbours of a node. (b) shows the same plot, but with the multimodal version of accessibility. Same color code (by node category) as in Fig. 2.4.

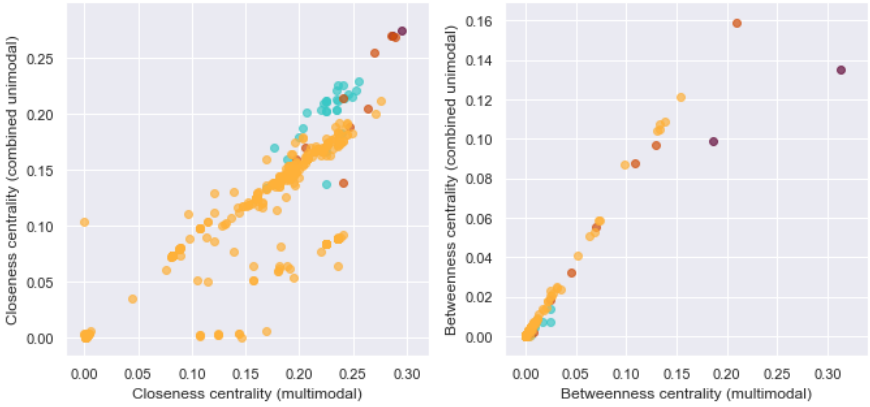
only. For instance the city of Poznan (Poland) has only two direct connections, but these two lead to Rotterdam and Duisburg, which are two of the most central hubs.

In Figure 2.8, instead of closeness/accessibility we analyze betweenness, which describes a node's attractiveness as a transshipment hub. Betweenness/transshipment attractiveness scores are more in line with the degree, suggesting that a large number of distinct connections supports the positioning of a node as a transshipment hub. There are some exceptions, most notably Bilbao, Valencia, and Barcelona in Spain, as well as Barking and Daventry in the UK, which form the small cluster of 'Unimodal' nodes (yellow) with high transshipment attractiveness and degree <10. In the case of Barcelona, this is due to the node being a sort of bridge between Spain and large European hubs such as Antwerp, Milano, and Ludwigshafen. The rail service Valencia-Barking is the only direct connection between the UK and mainland Europe, thus every route going to/from the UK would go through these two nodes, giving them a bridge function as well. This needs to be put into perspective though, given that shippers would most likely not send a container to the UK via Valencia, but rather book a vessel or a direct truck service.



(a) Unimodal **(b)** Multimodal

Figure 2.8: (a) Local (degree) vs. non-local (betweenness centrality) node connectivity. The graph shows how node positioning differs between local and non-local perspective (betweenness/transshipment attractiveness). Degree and transshipment attractiveness are correlated, but there are a number of exceptions with low/medium degree, but high transshipment attractiveness in the right lower part of the graph. These nodes often have a bridge function between sparsely connected regions, e.g. Barcelona for Spain and the rest of mainland Europe. (b) shows the same plot, but with the multimodal version of transshipment attractiveness. Same color code (by node category) as in Fig. 2.4.



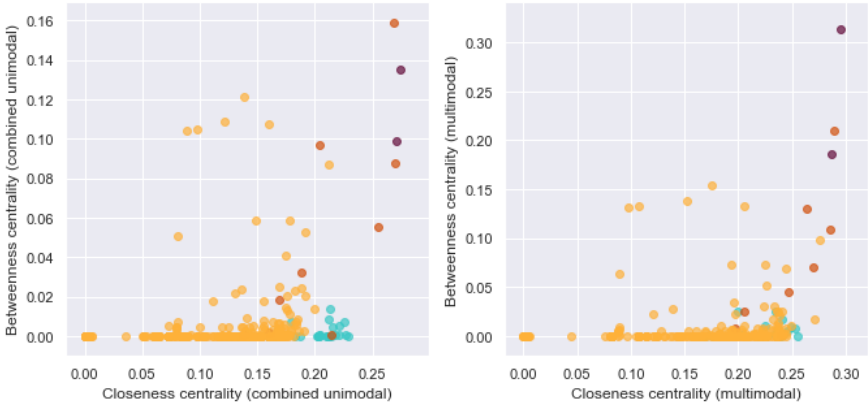
(a) Closeness/accessibility

(b) Betweenness/transshipment attractiveness

Figure 2.9: Unimodal vs. multimodal connectivity (non-local). The graph shows how non-local connectivity changes if multimodal transport is established. A node's benefit from multimodal transport can be interpreted by how far to the right of the $(x = y)$-line it is located. Same color code (by node category) as in Fig. 2.4. (a) For closeness/accessibility, most 'Unimodal' (yellow) nodes get a disproportional benefit. (b) For betweenness/transshipment attractiveness, the two 'Multimodal hubs' strengthen their position the most.

Multimodal connectivity

The analysis of multimodal connectivity reveals how the positioning of nodes changes if routes containing services by both transport modes can be planned. Figure 2.9 visualizes how nodes compare in their unimodal and multimodal positioning. In general, scores increase under multimodal transport, since more opportunities for routing are available. For accessibility (Figure 2.9 (a)) 'Unimodal' nodes seem to make the biggest leap, which seems surprising considering that 'Unimodal' nodes by definition are not even active in both modes, but benefit the most from intermodal transport. This is a result of the small multimodal interface. Nodes at the multimodal interface have the privilege to be already connected to both subnetworks, especially 'Multiplex hubs' play central roles as distributing hubs in both, being easily reachable from anywhere. 'Unimodal' nodes, however, are only connected by transport services of the same mode, thus they are not reachable from the other mode network and therefore have to rely on intermodal links. In the case of transshipment attractiveness, most nodes seem to improve their score in a similar way, except the 'Multimodal hubs' Rotterdam and 'Antwerp', which strengthen their position as a transshipment hub disproportionately.



(a) Unimodal **(b)** Multimodal

Figure 2.10: Comparison of different non-local positionings of nodes (closeness/accessibility vs. betweenness/transshipment attractiveness). Same color code (by node category) as in Fig. 2.4. (a) shows unimodal positioning. 'Multimodal hubs' and most 'Focused' nodes are both accessible and attractive for transshipment. 'Connector' nodes are accessible, but not so well positioned for transshipment. (b) shows multimodal positioning. Similar picture, only 'Unimodal' nodes become more accessible.

Positioning of nodes - Accessibility vs. transshipment attractiveness

The relevance of accessibility and transshipment attractiveness for ports differs depending on their role in the system. For sea ports, accessibility is most important, since they are usually start or end point of a trip and short distances to other nodes in the network are crucial for their competitive positioning. For inland ports it is more important to be in the center of many transport routes as a transshipment hub, thus transshipment attractiveness is more relevant.

Figure 2.10 illustrates the positioning in terms of betweenness/transshipment attractiveness and closeness/accessibility. It shows that multimodal nodes ('Connector', 'Focused', 'Multimodal hub') tend to be at the higher end of accessibility as well as transshipment attractiveness. However, 'Connector' nodes have relatively low transshipment attractiveness, even lower than many 'Unimodal nodes, which is surprising given their position at the multimodal interface and many of them being inland ports. In a multimodal system, poor transshipment attractiveness despite having access to both transport modes indicates a weak competitive positioning. It is also worth mentioning that Duisburg exhibits the highest transshipment attractiveness in the unimodal setup, even higher than Rotterdam and Antwerp. For inland ports

like Duisburg, transshipment positioning is more important than for sea ports, which are usually start or end points of routes. Nevertheless, Rotterdam has the highest transshipment attractiveness in the multimodal setting, indicating that it could theoretically function as a hinterland transshipment hub as well. If short-sea shipping was added to the data, Rotterdam would certainly live up to that role.

2.5 Discussion

In this paper we analyzed connectivity of the European hinterland transport network on node and network level. The paper partly adds to the findings of de Langen et al. (2017), who conducted the first and only other empirical exploration of this network on a Europe-wide scale, on the role and characteristics of the different transport modes and the joint functionality as a multimodal transport network. Moreover, the paper extends the existing predominantly local notion of hinterland connectivity by non-local and multimodal aspects. The results yield some relevant conclusions for (inland) port and terminal operators, but also policy making entities.

The European hinterland container transport network is an extensive network of scheduled transport services carried out via barge or rail. The network exhibits a hub-and-spoke structure around the two dominant global hubs Rotterdam and Antwerp, and a number of smaller hubs. The two transport mode layers are complementary and fulfill specific roles in the network in terms of geographical coverage and service structure. The barge network provides high volume short to medium-haul connections in regions of high transport demand, i.e. northwestern continental Europe. The rail network provides long-haul connections across the entire European hinterland. As a result, multimodal nodes, which are active in both networks, are only found in northwestern continental Europe.

The multimodal version of the network exhibits high structural capability to perform hinterland transport assignments. Integrating the two mode networks does not only create a larger joint network, functionality is also amplified by the opportunity to perform intermodal transport. For instance, intermodal transport increases the number of available shortest paths by 67% (interdependence of 40%, cf. Table 2.1) and the shortest-path-connectivity (efficiency) increases from 0.03 (barge) and 0.18 (rail) to 0.28 (multimodal). However, even though the two mode networks provide greater structural functionality in an intermodal setting, they are only connected through a relatively small set of multimodal transshipment nodes (12%). As a consequence,

this small multimodal interface plays a crucial role in tapping the full potential of the network. The potential of intermodal transport has been shown in a number of previous works, for instance on intermodal network design (van Riessen et al., 2015b) or pricing of intermodal services (Kim and van Wee, 2011). A characterization of multimodal hinterland transport by means of a complex networks approach, and a quantification of the potential of multimodal integration on a Europe-wide scale, is however novel in this field, substantiating and extending previous studies empirically.

On node level, we gather new information from our data about the positioning of nodes in a non-local and multimodal context using the extended notion of hinterland connectivity. Given the increasing number of transfer connections and multimodal transshipment opportunities in the hinterland (European Commission, 2018), these are important insights complementing the existing knowledge about local and unimodal hinterland connectivity.

We found four categories of nodes characterizing their local positioning by local and multimodal connectivity: three categories of nodes that are at the multimodal interface plus 'Unimodal' nodes as fourth category. Just by adding the split of multimodal connections, we were already able to refine the connectivity notion and gather meaningful complementary information. The role of Rotterdam and Antwerp as 'Multimodal hubs' would become visible only by looking at the total number of connections. However, the role of 'Focused' nodes, which are multimodal, but with a focus on one of the two modes, would not become apparent without looking at multimodality. The fact that these nodes are mainly found along major inland waterways acting as extended gates (Veenstra et al., 2012) by collecting container influx from few high-frequency barge connections to sea ports and distributing it to the further hinterland by rail or truck would require actual qualitative knowledge about the respective (inland) ports. Similarly, the role of 'Connector' nodes is only discovered with data on multimodality and 'Unimodal' could not be distinguished from the other categories.

Adding a non-local (network) perspective further refines the understanding of how nodes are positioned in a multimodal system. If only local connections are looked at, the fact that all these services form a complex network and connectivity goes beyond local positioning is missed, for instance in de Langen and Sharypova (2013). Nodes that seem relatively poorly connected due to few direct connection, can actually be quite well positioned within the network. For instance, the node Poznan has only two connections, but they lead to the hubs Rotterdam and Duisburg, which results in high accessibility for Poznan, being easily accessible from the whole network via these

two hubs. Similarly, the node Barcelona has few direct connections, but connects Spain and (indirectly) the UK with the rest of mainland Europe as a sort of bridge, which results in a high transshipment attractiveness that is not visible in the local perspective. These network connectivity aspects will further grow in relevance when sequential use of multiple intermodal transport services as alternative to long-haul truck transport becomes more of a standard procedure in hinterland transport. Port authorities can use this type of analysis for their hinterland strategies. For instance, the hinterland strategy of the port of Barcelona (van den Berg and de Langen, 2011) could have used more advanced information about the role of rail connectivity in their attempt to attract distant hinterland.

By combining non-local and multimodal aspects, information is gathered about the change of roles of nodes if unimodal networks are integrated and become a multimodal system. Interestingly, the most crucial nodes to establish a multimodal network, i.e. the nodes at the multimodal interface are not necessarily the ones that strengthen their position the most. For instance, Rotterdam and Antwerp improve their accessibility only by an amount proportional to other multimodal nodes. Most 'Unimodal' nodes though face a disproportionately high accessibility increase. Their positioning improves as they get access via the multimodal nodes to their non-native mode network that they are not directly connected to. In turn, multimodal nodes strengthen their position as transshipment hubs, above all Rotterdam and Antwerp. This is a delicate finding given the fact that the large sea ports are designed for transshipment from sea-to-land, but not land-to-land, so they do not really act as transshipment points on hinterland routes. The only land-to-land transshipment at sea ports takes place in the form of container exchange between sea ports by barge transport. The data, however, suggests that sea ports could take on a multimodal hub role if the required infrastructure was available. If short-sea connections were added to the data, they would certainly live up to that role. The only node with transshipment attractiveness on the same level as Rotterdam and Antwerp is Duisburg. Duisburg probably makes a better hub for land-to-land transshipment for reasons that are not captured in the data, such as the more central geographical location in the European rail and waterway infrastructure network, port strategies (van den Berg and de Langen, 2011), or European corridor strategies as part of the Ten-T programme (European Commission, 2018). The latter provides an interesting connection between the service network discussed in this work and the backbone network of intermodal infrastructure (railways, inland waterways, transshipment facilities), which defines the set of connections, on which a service can be offered. For

intermodal infrastructure development programmes like Ten-T, it should be possible to express the objectives of infrastructure investments in the Ten-T network in terms of our connectivity indicators, which is interesting for European policy makers.

These results are subject to a number of assumptions and limitations. The paper employs a pure network perspective, which comes short some operational aspects like congestion, disruption, or reliability of services. This is partly inherent to the methodology, but also a consequence of a lack of data on capacities and demand. The scope of this paper, however, is on network characteristics based on available transport services, and less on the fulfillment of demand.

Assumptions were also made on service connections and transshipments. The maturity level of intermodal transport varies strongly across Europe, hence some of the service connections discussed do not really exist (yet) in practice. Nevertheless, intermodal transport is strongly promoted by European policies to become a central element of the cargo transportation of the future. Since we define nodes as transshipment areas, in which multiple terminals can reside, operational difficulties can arise with transshipment between two services and even more so if they are operated by different means of transport. In the best case, containers can be transshipped within one dedicated intermodal terminal with only one operational step. In the worst case, a truck has to be used to move the container to a different terminal where the subsequent transport service starts. The larger ports have within-port shuttle services between their terminals, which can be used for transshipment. Moreover, many hinterland services stop at multiple terminals within a port, which reduces the number of complicated transshipments. The integration of modes could further be hindered by issues related to information exchange and collaboration between carriers. The planning of routes with transfer connections requires that the carriers involved collaborate to some extent to facilitate transshipments. These difficulties might create a small bias towards routes with more transshipments in our analysis. The number of shortest routes with more than 2 transshipments is however very limited.

In the absence of truck transport, routes that seem illogical from a geographical perspective such as Madrid-Rotterdam-Milan can be shortest paths, if transport time on each leg is short. We argue that such routes are indeed conceivable in an integrated multimodal system with flexible routing, if spare capacity can be used cost-efficiently and the delivery deadline allows for it. Such routes are for instance often seen in air passenger transport. Last but not least, we do not distinguish between different types of nodes in our analysis, even though in practice it makes a

difference if a node is also a sea port or located in the hinterland. This resulted in some interesting findings such as the perfect structural positioning of Rotterdam and Antwerp for land-to-land transshipment.

2.6 Conclusion

This paper has addressed connectivity in European hinterland transport from a complex networks perspective, focusing on how connectivity of the network increases as hinterland transport services continue to grow into a multimodal service network and how this affects the role and positioning of nodes in the system. Therefore, the notion of connectivity, a so far predominantly local measure in the hinterland context, has been extended by non-local (network) and multimodal aspects.

The results comprise several findings about the non-local and multimodal aspects of hinterland connectivity in Europe, some of which are established beyond pure structural terms. First, overall structural capability to perform hinterland transport assignments without the use of trucks increases tremendously as transfer connections and multimodal routes are established. Integrating the rail and barge networks creates a connectivity boost that goes beyond the sum of their individual layer connectivity.

Second, in contrast to networks without transfer connections, nodes in a multimodal system need to care about their positioning in terms of their accessibility within the network and their role as a transshipment hub. Nodes can have a high local degree, but still be poorly connected if their connections lead to irrelevant destinations or if they are located in the network periphery with few chances of being part of multimodal routes. Nodes with low degree in turn can be very accessible if they are connected to well connected nodes. All nodes benefit from multimodal integration, but some do more than others. On the one hand, 'Multimodal hubs' are the most important contributors to multimodal integration, but their relative accessibility does not improve much. On the other hand, 'Unimodal' nodes that used to be limited to one transport mode get indirect access to new destinations through multimodal transshipment and improve their connectivity greatly.

These findings are relevant for two groups of stakeholders. First, terminal and transport operators are interested in the competitive positioning of the port they are located in and the ports they serve, respectively, as it directly affects their success. Hinterland connectivity is an important port indicator, but the existing notions do

not capture the network and multimodal aspects even though these will become more relevant as hinterland becomes more connected. By including accessibility and transshipment attractiveness, our extended notion provides an instrument to capture these aspects and allows terminal and transport operators to make better informed strategical and tactical decisions.

Second, policy making entities are made aware that there can be a mismatch between contribution and benefit when establishing a multimodal system. This can result in a misalignment of incentives, which is a big issue in a system that would rely on collaboration and trust between all actors involved according to Van Der Horst and De Langen (2008), who find that free-riding problems, a lack of contractual relationships, information asymmetry, and a lack of incentives are major barriers for the performance in decentral hinterland supply chains. A careful analysis of accessibility and transshipment attractiveness is therefore highly recommended for intermodal infrastructure and corridor planning.

Even though the European hinterland network is relatively unique due to its manifold shades of complexity, the approach and the extended notion of connectivity apply generally. Some of the learnings of this work could be generalized to a broader category of multiplex networks. Hinterland container networks in other regions suggest themselves, but also other multimodal transport networks such as urban public transport networks (e.g. bus, tram, metro, light rail) or interregional passenger transport networks (airplane, train, bus) are logical choices.

This paper provides groundwork on hinterland connectivity from a complexity and network angle. There are several interesting research directions to further develop the results of this work. By integrating an extended data model including for instance demand data, trucks, or short-sea shipping services, our results could be better established beyond structural terms, enhancing their practical relevance. Moreover, a longitudinal perspective on the development of the services over time would be useful to assess the network's relation with the backbone infrastructure network and to track the impact and target achievement of multimodal corridor and infrastructure investment programmes over time. Last but not least, the hinterland service network could also be studied as a multi-carrier network. Establishing multimodal transport in the hinterland necessarily requires the integration of services by different carriers, who might be competitors or simply not willing to integrate their services and share data. This opens up a whole new challenge for policy makers, for instance with regards to alignment of incentives and information infrastructure.

Appendix

2.A Dataset

Data collection

Data is collected in collaboration with intermodal carriers and transshipment terminals. The data set is updated continuously in two ways. First, newly offered services are added and terminated services are removed from the data set over time. Second, the geographic coverage of the data set is expanded. We possess one instance of the data set per year retrieved in spring season. The data set comprises origin and destination terminal of each transport service in the European hinterland and the transport mode used for this service. Furthermore, carrier company, recurring weekly schedule, number of weekly services, and transport time in days are available for each entry in the data set.

Data validation

On the one hand, the data set is rather complete for the covered regions, as indicated by (de Langen et al., 2017) based on a benchmarking of the actual container throughput volume and the capacity implied by the data set. On the other hand, the data is accurate as it is collected from two independent sources. First, connections and schedules are collected from intermodal carriers constituting the backbone of the data set. Second, the data is verified and refined in collaboration with ports and inland terminals as they have information on arrival and departure of intermodal hinterland services.

Data preparation

The data is prepared for network analysis along two steps. First, origins and destinations are aggregated from terminal to city level as cities are considered transhipment areas and terminals are serving a single market defined by the transhipment area they are in. As a consequence, all terminals within a city's boundaries are represented by a single node and therefore intra-city connections become redundant self-loops and are removed from the data set. Second, all parallel services are aggregated in order to avoid parallel edges, unless they are on different transport modes. Thus, there can be at most two edges between two cities and only if there is a transport link by

barge and by rail. As services are being aggregated, the sum of service frequencies is taken and in case of different transport times the minimum is taken.

2.B Notation

We define a multiplex graph $G = (V, E, L)$ with a set of nodes V representing cities in the European hinterland, a set of edges E representing transport connections, and a set of layers $L = \{\alpha, \beta\}$ representing the two transport modes rail (α) and barge (β). The set of nodes with rail access is denoted by V^α and the set of nodes with barge access by V^β. Nodes serving both modes form the multimodal interface defined by the set $V^{\alpha\cap\beta} := V^\alpha \cap V^\beta$. Further $V_{k\geq x}$ denotes the set of nodes with degree $\geq x$ and V_i the set of nodes that are reachable from node i, i.e. the connected component that i is part of. N describes the number of nodes in V. A similar notation is used for the number of nodes $(N^\alpha, N^\beta, N^{\alpha\cap\beta}, N_{k\geq x}, N_i)$ the subsets of V.

The set of edges E divides into E^α and E^β, which describe the set of transport connections in the rail and the barge layer, respectively. $E^{\alpha\cap\beta}$ is the set of direct connections that have parallel edges in the two transport modes. M $(M^\alpha, M^\beta, M^{\alpha\cap\beta})$ are the number of edges in the respective (sub-)set of E. Edges have attributes indicating transport time (τ) and weekly service frequency (ρ). For an edge $(i,j) \in E^\alpha(E^\beta)$, $\tau^\alpha_{ij}(\tau^\beta_{ij})$ describes the transport time on this edge with the respective mode and $\rho^\alpha_{ij}(\rho^\beta_{ij})$ describes service frequency. For the multimodal instances (3) and (4), we use the minimum of transport times $\tau^{\alpha\vee\beta}_{ij} := min(\tau^\alpha_{ij}, \tau^\beta_{ij})$ and the sum of frequencies $\rho^{\alpha\vee\beta}_{ij} := \rho^\alpha_{ij} + \rho^\beta_{ij}$.

For a node $i \in V$, $k^\alpha_i(k^\beta_i)$ describes its degree by connections in the rail (barge) layer. Multiplex degrees are denoted by $k^{\alpha\vee\beta}_i$ for the total number of different connections (excluding double counts of parallel services) or $k^{\alpha\wedge\beta}_i$ for the total number including parallel services. The latter is known as overlapping degree. Weighted node degree is defined as the number of weekly services ρ run on edges adjacent to a node, and is denoted analogously to the unweighted degree by $k^{\alpha,\rho}_i(k^{\beta,\rho}_i, k^{\alpha\wedge\beta,\rho}_i)$.

Shortest paths and their lengths differ depending on the network instance considered, which needs to be accounted for in the notation. We write $\sigma^\alpha_\tau(i,j)$ $(\sigma^\beta_\tau(i.j))$ for the set of shortest paths between nodes $i, j \in V$ rail (barge) layer, which is relevant for network instances (1) and (2). Further, $\sigma^{\alpha\vee\beta}_\tau(i,j)$ describes the set of shortest i-j-paths consisting of unimodal trips only, i.e. each shortest path must be either a pure rail or a pure barge trip. This corresponds with the combined unimodal instance (3).

Measure/Instance	Barge	Rail	Multimodal
Number of weekly services	$\sum_{(i,j)\in E^\beta} \rho_{ij}^\beta$	$\sum_{(i,j)\in E^\alpha} \rho_{ij}^\alpha$	$\sum_{(i,j)\in E} \rho_{ij}^{\alpha\wedge\beta}$
Number of direct connections	M^β	M^α	$M^\alpha + M^\beta - M^{\alpha\cap\beta}$
Avg. service duration [days]	$\frac{1}{M^\beta}\sum_{(i,j)\in E^\beta} \tau_{ij}^\beta$	$\frac{1}{M^\alpha}\sum_{(i,j)\in E^\alpha} \tau_{ij}^\alpha$	$\frac{\sum_{(i,j)\in E^\alpha} \tau_{ij}^\alpha + \sum_{(i,j)\in E^\beta} \tau_{ij}^\beta}{M^\alpha + M^\beta}$
Avg. service distance [km]	Avg. aerial distance between cities [km]		
Efficiency	$\frac{1}{N(N-1)}\sum_{i\neq j\in V} \frac{1}{d_*^\beta(i,j)}$	$\frac{1}{N(N-1)}\sum_{i\neq j\in V} \frac{1}{d_*^\alpha(i,j)}$	$\frac{1}{N(N-1)}\sum_{i\neq j\in V} \frac{1}{d_*^{\alpha\wedge\beta}(i,j)}$
Interdependence	$\frac{1}{N-1}\sum_{j\in V_i} \frac{\lvert\sigma_\tau^{\alpha\wedge\beta}(i,j)\rvert - \lvert\sigma_\tau^{\alpha\vee\beta}(i,j)\rvert}{\lvert\sigma_\tau^{\alpha\wedge\beta}(i,j)\rvert}$		
Density	$\frac{2M^\beta}{N^\beta(N^\beta-1)}$	$\frac{2M^\alpha}{N^\alpha(N^\alpha-1)}$	$\frac{2M}{N(N-1)}$
Rich club coeff. $[k \geq x]$	$\frac{2M^\beta_{k\geq x}}{N^\beta_{k\geq x}(N^\beta_{k\geq x}-1)}$	$\frac{2M^\alpha_{k\geq x}}{N^\alpha_{k\geq x}(N^\alpha_{k\geq x}-1)}$	$\frac{2M_{k\geq x}}{N_{k\geq x}(N_{k\geq x}-1)}$
Degree assortativity	Pearson correlation of node degree and avg. neighbour degrees		

Table 2.2: Calculation formulae used for network connectivity.

Measure/Instance	Barge	Rail	Full
Overlap - Nodes	$\frac{N^\beta}{N}$	$\frac{N^\alpha}{N}$	$\frac{N^{\alpha\cap\beta}}{N}$
Overlap - Edges	$\frac{M^\beta}{M^\alpha+M^\beta-M^{\alpha\cap\beta}}$	$\frac{M^\alpha}{M^\alpha+M^\beta-M^{\alpha\cap\beta}}$	$\frac{M^{\alpha\cap\beta}}{M^\alpha+M^\beta-M^{\alpha\cap\beta}}$

Table 2.3: Calculation formulae used for multimodal interface analysis.

For the multimodal instance (4), we use $\sigma_\tau^{\alpha\wedge\beta}(i,j)$, which extends the shortest path notation by including intermodal trips in the set. Shortest paths are measured by transport time, which is why we use τ in the notation. For shortest paths by number of transport legs, τ is omitted. The number of shortest paths corresponding to the shortest path sets σ is denoted by $|\sigma_\tau^\alpha(i,j)|$ ($|\sigma_\tau^\beta(i.j)|, |\sigma_\tau^{\alpha\vee\beta}(i,j)|, |\sigma_\tau^{\alpha\wedge\beta}(i,j)|$) and their length (total transport time) is denoted by $d_\tau^\alpha(i,j)$, $d_\tau^\beta(i,j)$, $d_\tau^{\alpha\vee\beta}(i,j)$, and $d_\tau^{\alpha\wedge\beta}(i,j)$.

2.C Details: Network connectivity

Formulae

See Appendix 2.B for relevant notation. Table 2.2 and 2.3 show an overview of the formulae used for the network connectivity analysis.

Interpretation of network connectivity measures

The measures cover network size (number of services, number of connections), service attributes (frequency, duration, distance), as well as structural and intra-layer connectivity aspects (density, rich-club, assortativity). The size measures purely describe the size of the network and the mode subnetworks. Number of weekly services

shows the total number of actual shipments, whereas the number of direct connections describe how many distinct point-to-point connections exist in the network. Service attributes frequency, duration, and distance provide information about the differences in service structure of the different modes. Connectivity measures reveal the level of interconnectedness, i.e. the share of node pairs with a direct connection. Density comprises interconnectedness of the entire network instance. Results allow for statements on the required average frequency of transshipments in intermodal routes as high density means that many containers can be delivered directly, whereas low density requires more transshipments. The rich-club coefficient describes density among nodes with a degree greater or equal to a certain number. Thus, if higher than general density, it shows that large terminals are more likely to connect to each other. Even though high rich-club coefficients seem logical from a network design perspective, low coefficients can sometimes be observed in competitive transportation networks, in which different operators run their isolated network with a central hub, while hubs of different operators are rarely connected. Degree assortativity measures the correlation between the degree of a node and the average degree of its neighbours in the same layer, thereby showing if nodes tend to connect to nodes of similar degree or not. Most importantly, shortest-path-connectivity, i.e. the transport time between two arbitrary nodes in the network with intermodal services, is computed for both layers and for the integrated network. The two measures efficiency (average shortest path length) and interdependence (share of all shortest paths that include multimodal transshipment) provide insights about the potential of multimodal integration. Interdependence is a measure to quantify the added value of modal integration by analyzing the dependence of the network on intermodal routes. For a specific node, interdependence describes the share of all shortest paths to all nodes, in which more than one transport mode is used. Nodes with high interdependence are dependent on the availability of integrated multimodal services as their accessibility would suffer if transport modes were isolated. On network level, interdependence is defined as the average over all nodes, showing the general relevance of intermodal connections in the network.

Expanded results of network connectivity

Results of the layer characterization are shown in Table 2.1. In terms of weekly services and distinct connections served, the rail network is much larger than the barge network with 12,743 weekly services serving 1,309 connections compared to 6,901 weekly barge services serving 366 connections. This doesn't necessarily mean

that rail is simply more attractive as these numbers have to be viewed relative to the available infrastructure. While there are 217,081 km of active railways in the EU-28 countries, inland waterways only cover a length of 40,895 km as of 2018 (European Commission, 2018). Despite shorter duration of services, the rail network serves much longer distances of 637 km compared to the barge network (183 km), indicating that rail transport is significantly faster.

These figures make clear that the rail and barge network are both relevant, but they have a different service structure, which suggests that they serve different types of transport assignments. Barge provides high-frequency, short to medium-haul services that aim at flexible and cost-efficient transportation. Rail can make use of an extensive network and provides fast, long-haul connections to more remote destinations.

The different structure of the two mode networks reflects as well in the connectivity figures. With a density of 0.039 in 2019, the barge network is more than twice as dense as the rail network (0.017), which supports the idea of a highly connected, high frequency network of services with focus on areas with the highest transport demand. Density of the rail network is lower due to the different character of the network serving point-to-point long-haul connections across the entire continent.

The potential of multimodal integration for network connectivity shows by efficiency of the integrated network. Efficiency describes the connectivity by shortest path lengths between all OD nodes in the network. The multimodal score (0.28) exceeds the barge (0.03) and barge (0.18) score disproportionately, showing the large potential. This is strengthened by the fact that 40% of shortest paths in the fully integrated system would include a multimodal transshipment, shown by the interdependence measure.

The rich-club coefficient describes the connectivity between nodes with a degree over a certain threshold (McAuley et al., 2007). Rich-club figures confirm that the barge network is more densely connected than the rail network, in particular between highly connected nodes. Among nodes of degree $k \geq 5$, only the barge network shows rich club behaviour, whereas among nodes of degree $k \geq 20$, both networks form a rich-club. The $k \geq 20$ rich-club of the barge network is even fully connected, but it contains only two nodes, Rotterdam and Antwerp. Rich-club behaviour of the aggregated network is comparable to that of the rail network, whereas density is lower than in both mode networks. Thus, aggregation of transport modes results in a better connectivity between hubs, whereas connectivity of the full network becomes

Measure/Instance	(1) Barge	(2) Rail	(3) Combined unimodal	(4) Multimodal
Degree	k_i^{β}	k_i^{α}	$k_i^{\alpha\vee\beta}$	$k_i^{\alpha\wedge\beta}$
Degree - weighted	$k_i^{\beta,\rho}$	$k_i^{\alpha,\rho}$	-	$k_i^{\alpha\wedge\beta,\rho}$
Closeness	$\frac{N_i-1}{N-1}\frac{N-1}{\sum_{j\in V_i} d_\tau^{\beta}(i,j)}$	$\frac{N_i-1}{N-1}\frac{N-1}{\sum_{j\in V_i} d_\tau^{\alpha}(i,j)}$	$\frac{N_i-1}{N-1}\frac{N-1}{\sum_{j\in V_i} min(d_\tau^{\alpha}(i,j),d_\tau^{\beta}(i,j))}$	$\frac{N_i-1}{N-1}\frac{N-1}{\sum_{j\in V_i} d_\tau^{\alpha\wedge\beta}(i,j)}$
Betweenness	$\frac{1}{(N-1)(N-2)}\sum_{u,v\in V}\frac{\lvert\sigma_\tau^{\beta}(u,v\lvert i)\rvert}{\lvert\sigma_\tau^{\alpha\wedge\beta}(u,v)\rvert}$	$\frac{1}{(N-1)(N-2)}\sum_{u,v\in V}\frac{\lvert\sigma_\tau^{\alpha}(u,v\lvert i)\rvert}{\lvert\sigma_\tau^{\alpha\wedge\beta}(u,v)\rvert}$	$\frac{1}{(N-1)(N-2)}\sum_{u,v\in V}\frac{\lvert\sigma_\tau^{\alpha\vee\beta}(u,v\lvert i)\rvert}{\lvert\sigma_\tau^{\alpha\wedge\beta}(u,v)\rvert}$	$\frac{1}{(N-1)(N-2)}\sum_{u,v\in V}\frac{\lvert\sigma_\tau^{\alpha\wedge\beta}(u,v\lvert i)\rvert}{\lvert\sigma_\tau^{\alpha\wedge\beta}(u,v)\rvert}$

Table 2.4: Calculation formulae for nodal measures applied to each network instance.

more sparse, suggesting that the barge network mainly supports the rail network in densely connected areas where many rail hubs are located.

The network exhibits slightly negative degree assortativity, i.e. nodes of high degrees tend to connect to nodes of low degree. This shows that a lot of services go through hubs, which distribute the traffic to less central destinations. In particular the barge networks is quite strongly disassortative, which shows that it relies strongly on its hubs, primarily Rotterdam and Antwerp.

2.D Details: Node connectivity

Formulae

See Appendix 2.B for relevant notation. Table 2.4 shows an overview of the formulae used for the calculation of measures for the analysis of node connectivity.

Local node categorization

The definition of the measures for node categorization is adopted from Battiston et al. (2017) and is based on the general connectivity of a node assessed by its overlapping degree $z_i = k_i^{\alpha\wedge\beta}$ and a participation coefficient P_i, which helps to distinguish if a node is relevant for the entire multiplex network or only locally for one mode:

$$P_i = 2\Big[1 - \Big(\frac{k_i^{\alpha}}{k_i^{\alpha\wedge\beta}}\Big)^2 - \Big(\frac{k_i^{\beta}}{k_i^{\alpha\wedge\beta}}\Big)^2\Big].$$

P_i becomes 1 if the number of edges contributing to the overlapping degree $k_i^{\alpha\wedge\beta}$ are equally distributed across the layers and 0 if all edges are in the same layer.

Interpretation of measures

In the following the nodal characteristics used in the analysis in Section 2.4.2 and the measures to test them are introduced in more detail as well as their application over the four instances.

Local connectivity/degree of a node is indicated by degree values, i.e. the number of direct connections of a node to other nodes. In the hinterland context, degree describes the number of transshipment area that a transshipment area is connected to by a direct service. In multiplex networks, each node has multiple types of degrees. In accordance with the network instances defined in Section 4.3, we distinguish between barge (1), rail (2), aggregated (combined unimodal/3), and overlapping (multimodal/4) degree. The difference between aggregated and overlapping degree is the double counting of parallel edges, which is only done for the overlapping degree.

Accessibility of a node is quantified by closeness centrality, which is based on shortest transport times to other nodes. It describes how well a node can be reached through intermodal services from an arbitrary node in the network. It is computed as reciprocal of the sum of shortest path distances from the node to all other nodes in its connected component normalized by the size of the connected component. Shortest paths weighted by transport time are used, since it is more realistic than assuming equal transport time for each service. The four network instances are distinguished by the set of edges available for routing. For the mode networks (1)-(2), only edges of the respective modes can be used. For the combined unimodal network (3), both modes are available, but routes need to be unimodal. The multimodal instance (4) allows for intermodal routes.

Transshipment attractiveness of a node is measured by betweenness centrality, revealing its importance for the network as a transshipment point. It is computed as the share of all shortest paths between all pairs of nodes that go through that node. As for closeness centrality, we consider shortest paths weighted by transport time and the four network instances are distinguished by the set of edges available for routing. However, the reference number of all shortest paths is always based on the multimodal network (4) in order to obtain comparable results across instances. In contrast to closeness, which is a performance indicator both on nodal and aggregated level, betweenness centrality does not have strong performance implications when analyzed on network level, but it is a good indicator for the relevance of a node or a group of nodes for the functioning of the network as a whole. The significance of betweenness for hinterland connectivity therefore lays in the identification of those

nodes that strengthen their role as transshipment points in a multimodal network, thereby playing a crucial role in leveraging the potential of other nodes and the network as a whole.

Chapter 3

Vulnerability of collaborative transport systems: A multi-layer network model

3.1 Introduction

3.1.1 Motivation

Carriers can combine their individual transport offerings through collaborative provision of services, with the aim to improve the overall service level (destinations, flexibility, transport time) or to reduce costs. Collaboration among carriers is known to be an important lever to reap the potential of decentrally operated transportation systems as it enables the integration of otherwise isolated proprietary transport networks, facilitating the flow of goods and creating a more efficient and flexible transportation system (Cardillo et al., 2013b; Cruijssen et al., 2007b). Examples of collaborative transport can be found in container shipping, air passenger transport, and public transport.

However, successful collaborative transport is subject to a number of conditions, among which are competitive and commercial alignment (Agarwal and Ergun, 2010; Houghtalen et al., 2011; Özener et al., 2011), organizational readiness (Cruijssen et al., 2007b; Sanchez Rodrigues et al., 2015), and sufficient technical infrastructure (Buijs and Wortmann, 2014). If these conditions are not met, collaborations might not yield the expected benefits and can even be prone to failure. In particular, impacts such as legislative (antitrust) or policy changes, conflicts, technical failure, or cyber attacks (Kumar and van Dissel, 1996; Tonn et al., 2019) can lead to the collapsing of collaborative systems with adverse impact on the transportation performance. As a result, vulnerabilities are created through collaboration, which come in addition to physical threats such as low water levels for barges or rail infrastructure breakdown for train sets. These vulnerabilities are often associated with threats emanating from information systems that are used in support of the collaborative arrangements. A transportation system that makes extensive use of collaboration is heavily reliant on these collaborations being intact (Cardillo et al., 2013b).

Dependencies induced by collaboration can have severe impacts, as painfully highlighted in the 2017 (Not)Petya hack, a malware attack in the Ukraine that infected a large number of companies and institutions across the world including several transportation companies such as Maersk/APM Terminals (USD 300m damage) and TNT Express (USD 400m damage), disrupting their operations or even bringing them to a halt (Greenberg, 2018). Even after shipping companies improved their response mechanisms to such disruption, the frequency of incidents increased (Tonn et al., 2019) and the issue stayed high on the agenda of transportation managers and gov-

erning parties. In 2020, CMA CGM suffered from a ransomware attack, and despite being able to limit the impact on their own operations, they had to cut all external access to their IT applications and booking systems [1].

In the light of this potentially severe impact of disruption, it is crucial to understand the inherent vulnerability created through collaboration transport systems are facing, and to identify drivers of vulnerability in order to be able to assess the need for preventive measures.

3.1.2 Theoretical background

Collaborative transport may be horizontal or vertical. Horizontal collaboration involves carriers that provide similar services, possibly in competition, for which resources can be shared to enhance capacity or frequency of service. Vertical collaboration involves carriers providing transportation services that can be executed in sequence to provide a combined transportation service along a path. In between those connecting services, transshipment is required.

The existing body of literature extensively shows potential synergies of collaborative transport including ways and conditions to realize them. e.g. through maximizing fill rates (Cruijssen et al., 2007a), reducing empty runs (Adenso-Díaz et al., 2014; Ergun et al., 2007; Lin and Ng, 2012), finding optimal locations Hernández et al. (2011), Teye et al. (2017), and Teye et al. (2018), and optimize supply network pooling (Pan et al., 2013). Potential synergies of collaborative planning in general are substantial, for instance with respect to cost synergies (Adenso-Díaz et al., 2014; Cruijssen et al., 2007a), or carbon footprint reduction (Demir et al., 2016; Lin and Ng, 2012).

Research on vulnerabilities in transportation systems focuses mainly on physical threats. Bottlenecks in road networks are identified using weighted spectral analysis (Bell et al., 2017), disaster response is addressed by finding optimal depot locations (Bell et al., 2014), and parameters to measure the impact of shocks such as strikes, collaboration, or schedule changes are derived with econometric methods (Gillen and Hasheminia, 2016). As stated above, collaborative transport is not only facing the threat of disruption to physical services. Offering intermodal services in hinterland transport, for instance, requires extensive alignment, synchronization, and planning between carriers and terminal operators, with an increasing need for decision support (Agamez-Arias and Moyano-Fuentes, 2017). This highlights that vertical collabora-

[1] Source: https://www.offshore-energy.biz/cma-cgm-confirms-cyber-attack/

tion does not only happen at the physical level, but also at the digital and information level through connected systems (Altuntaş Vural et al., 2020). The rise of information and communication technology in the form of RFID, sensor, and blockchain technology will further contribute to this development (Harris et al., 2015). As a result, there is a growing need to consider vulnerabilities of transport systems beyond those of the physical systems and include vulnerabilities of the highly interdependent collaborative (information) systems that are progressively used in transportation.

3.1.3 Aim of research and introduction to approach

The knowledge gap with regard to vulnerabilities induced by collaboration in transportation is not simply a consequence of lack of awareness, since the aforementioned incidents have already put these vulnerabilities in the spotlight. However, in order to capture the complex interdependence between physical transportation and collaboration from a system perspective, while allowing for a systematic assessment of the drivers of vulnerability, appropriate models are needed. We argue that such models are currently lacking.

In this paper, we propose to build such models based on the science of complex networks. This discipline provides a proven approach to analyze the vulnerability of large-scale networked systems, including systems with multiple interdependent layers (Kivela et al., 2014). In fact, complex networks scientists first looked at interdependent systems from the vulnerability angle before even incorporating the benefits of network layer integration in their models. For instance, Buldyrev et al. (2010) show that such systems are prone to cascading failure, where failure in one network propagates back and forth between network layers and can lead to complete disintegration of the network. In many real-world interdependent systems, e.g. communication-power coupled systems, layer integration exhibits a trade-off between network functionality and vulnerability, depending on the inter-layer coupling mechanism (Korkali et al., 2017). Schneider et al. (2013) developed strategies to select immune nodes to improve resilience of communication-power coupled systems.

In this paper, we will use complex network models to analyse vulnerabilities emerging from collaborative transportation and we will present results. In particular, we develop a new multi-layer network model of transportation systems with vertical collaboration between carriers, who each operate their own proprietary network of transport services. In this system, carriers have the possibility to establish dyadic collaborations, enabling them to provide shared sequential transportation chains in-

cluding transshipments. Transportation services and collaborations between carriers are represented in a network with two separate network layers. The collaboration layer comprises carriers as nodes and their dyadic collaborations as edges. The physical layer is defined by attributed edges representing transportation services associated with the operating carrier, and nodes representing transshipment points, e.g. ports or inland terminals. Our focus is on vertical collaboration. Despite touching upon certain aspects of horizontal collaboration such as the similarity of services, the core of our analysis addresses vertical collaboration with consecutive services and transshipments.

3.1.4 Contribution

In order to analyse vulnerabilities that emerge from large-scale collaborative transportation systems, we develop an integrated transportation-collaboration model. Our model derives relationships between vulnerabilities emerging from bilateral carrier collaborations and general system characteristics such as market structure. The model is sophisticated enough to capture the complex interdependencies between transport services and carrier collaborations including the associated transport performance. At the same time, it is simple enough to be applied to large random network populations and allow for the systematic assessment of the impact of varying network structures on vulnerability. Verification of the model is achieved by showing consistency of results across two different random network classes representing collaborative transportation systems at different levels of proximity to real-world networks with an analytical and a simulation-based approach.

Our model can provide useful insights for policy making on vertical collaboration in real-world networks and supports the prioritization of preventive measures. In the scope of this work, we show that the market structure of carriers, i.e. the disparity in number of services operated, has a non-monotone impact on vulnerability to targeted disruption against the collaborations of selected carriers. There is no clear intuition as to what is the impact of an increase in carrier size on vulnerability. On the one hand, it can have a positive impact as less collaboration is required if there is only a few large carriers, hence the magnitude of collaboration disruption is smaller. On the other hand, having a large number of small and medium sized carriers balances the disruption threats and thereby mitigates the risk of creating a single point of failure. By means of a quantitative assessment, we find that networks are most vulnerable if they have intermediate disparity in carrier sizes, i.e. carriers are overall

similarly sized, but there is some heterogeneity with a moderate gap between a few larger and many smaller carriers. Networks with perfect uniform distribution exhibit medium to high levels of robustness, whereas highly disparate networks exhibit the highest robustness. Vulnerability under variation of market structure is therefore not a monotone curve, but has a minimum at intermediate disparity levels. Our findings substantiate the conjecture that a comprehensive analysis of collaborative transport should not only account for the potential synergies, but also for the concomitant vulnerabilities. In particular, the role of market structure should be considered carefully as it has a different effect on vulnerabilities as compared to synergies.

3.1.5 Outline

The remainder of this study is organized as follows. Sections 3.2 is dedicated to the introduction of the model alongside relevant concepts and assumptions. Section 3.3 is about the evaluation and verification of the model to produce meaningful results. Section 4.4 presents and discusses the results of the analysis of market structure. Section 4.6 concludes and provides an outlook for future research.

3.2 Model formulation

3.2.1 Concepts

Before formulating the model, we define a number of relevant concepts and illustrate them in the context of intermodal transport in the seaport hinterland, which is also our domain of application. Intermodal transport involves the flexible use of alternative transport modes train and barge, possibly resulting in transport chains involving multiple transport modes and carriers. Enabling such transport chains requires vertical collaboration between carriers. The aim of intermodal transport is to provide more flexible, resilient, and sustainable transport systems with little need for truck transport.

3.2.1.1 Collaborative and physical level

We distinguish between the physical and the collaborative level of a collaborative transportation system. The physical level describes the network of physical transportation and transshipment services, and the carriers that operate these transportation services. For simplicity purposes, we abstract away from detailed physical transshipment processes between consecutive transportation services in a transport chain

as well as from collaboration between terminal operators involved in these transshipment processes. Disruption at the physical level comprises the unavailability of physical transport services, as a result of for instance low or high water levels, or (un)planned rail maintenance.

The collaborative level addresses activities beyond the physical movement of goods, which include non-physical coordination efforts and information exchanges between involved parties required to enable collaboration. In intermodal transport, coordination is necessary between a number of parties, especially truck, train, and barge carriers, as well as terminal operators. Coordination efforts include, for instance, sharing of booking and planning information, redistribution of costs and benefits, tracking of deliveries, and error handling.

In our network model, the collaborative level and the concomitant coordination efforts are formalized through bilateral carrier collaborations mapped in a separate network layer consisting of carriers as nodes and collaborations as edges. We define a collaboration between two carriers as a dyadic agreement between two carriers to provide a joint portfolio of transport routes built from shared transport services on consecutive network legs. Collaborations come at least with basic coordination efforts and information exchanges to ensure feasibility of transshipment, but can be more advanced. In intermodal transport, a basic collaboration could entail sharing of data on schedules and availability capacity on manual request as well as manual coordination of bookings and compensations between carriers. More advanced collaborations come with an interface enabling integrated booking of transportation services involving both carriers at either carrier's platform or even a shared interorganizational information system (van Baalen et al., 2008). These systems can include automated compensation schemes for service sharing and automated coordination of transshipment with terminal operators.

3.2.1.2 Synergies, vulnerability, and disruption

Vulnerabilities are inevitably linked to the synergies that are created through collaboration, as these synergies are at risk. In the context of this work, synergies through collaboration are created by exploiting unused potential of existing transport services. The potential is unused when carriers provide their services in isolation. Services of multiple carriers can only be offered as part of joint transport routes when the involved carriers facilitate integrated booking and transshipment between consecutive transport services. This comes with the need to jointly plan transport services to

avoid unnecessary waiting times between arrivals and departures of consecutive transport services. Also, when integrated bookings are provided, there is a need to, for example, redistribute costs and benefits among participating carriers and to provide compensation for missed connections. When such collaborative arrangements are made, the performance of intermodal transport improves. Indeed, when more (joint) transport routes are offered, there are more options to transport freight efficiently, frequently and timely between origins and destinations. As a result, intermodal transport becomes more competitive as compared to direct truck transport.

We define vulnerability by the probability and the impact of disruptions on network performance, and we focus on disruptions at the collaborative level. For instance, while coordinating intermodal transport chains, intermodal carriers depend on each other for the quality of exchanged information on service schedules, bookings, available capacities, transshipment plannings, and so on. If carriers fail to provide their partners and involved terminals with the required data or if the data is of poor quality, e.g. resulting from a cyber security breach or poor data management, transport chains performance deteriorates or even collapses. Disruption at the collaborative level can also be caused by strategic misalignment in collaborations, e.g. from a commercial, competitive, legislative (antitrust), or trust perspective. External influences such as new regulations or new physical infrastructure can lead to an imbalance of benefits of collaboration between partners, or even to collaborations becoming obsolete for one of the two or both parties. The consequence of disruption at the collaborative level can be the failure of collaboration links. Vulnerability at the collaborative level is driven by the potential magnitude of the impact of disruption and how susceptible the network is to this impact.

3.2.2 Problem setting

Before we develop our model for the analysis of vulnerability induced by vertical collaboration in a transportation system and the role of specific system characteristics, we formulate a number of model requirements.

First, the interdependence between collaborative and physical level needs to be captured by our model, i.e. the impact made by specific collaborative arrangements on transportation performance needs to be represented. We choose a multi-layer network approach with a physical and a collaboration layer, since complex networks have successfully been used to analyse vulnerability of large-scale multi-layer systems under variation of specific characteristics. However, collaborations and physical transport

services in collaborative transport systems are interdependent (coupled) in a way that is different from the standards for multi-layer networks defined in Kivela et al. (2014), which requires the development of a new model with a physical layer of transport services and a collaboration layer, in which dyadic carrier collaborations are mapped. Typically, layers are connected through bidirectional node-to-node mappings. In communication-power coupled systems, for instance, communication servers rely on a power station for energy supply, whereas power stations rely on a communication servers for control (Buldyrev et al., 2010).

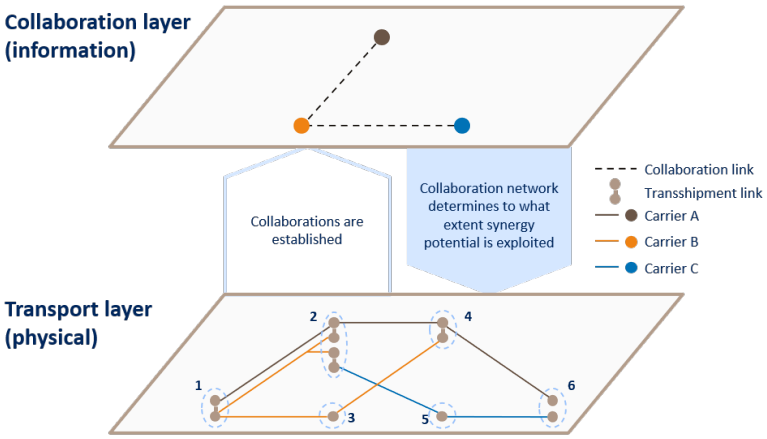


Figure 3.1: The figure shows both network layers and their dependence according to the model. The connectivity of the transport layer depends on the presence of links in the collaboration layer. While carrier B can offer shared transport routes with both other carriers, carriers A and C can only do that with carrier B, but not with each other. As a result, connection 1-2-5 (if 1-2 is operated by carrier A) and 4-6-5 are not feasible, despite the existence of transport services on these connections. The effect of disruption is twofold. Failure of collaboration links leads to more infeasible connections, however not all collaboration links are equally critical to transport functionality. If A-B fails, it would cause more impact than if B-C fails, since A-B enables a higher number of multi-carrier paths. Moreover, since disruption is assumed to happen to carriers, causing them to lose all their collaboration links, disruption at carrier B would be most severe causing the loss of both existing collaboration links.

In our setup, carriers in the collaboration layer are associated with the services they operate in the physical network, and the capability to use these transport services in an efficient collaborative fashion depends on the presence and constellation of collaboration links. As a result, nodes in the collaboration layer (carriers) are mapped to edges (transport services operated by the respective carrier) in the transport layer in a 1-to-n fashion. If there is a link between two carriers in the collaboration network,

paths formed in the transport network can include successive services operated by the two carriers connected through transshipments. Failed or non-functional collaboration reduces functionality as the set of available routes is curtailed (Cardillo et al., 2013b). See Figure 3.1 for a visualization and a descriptive example of the interdependence between collaborative and physical level

Second, a suitable method to carve out the vulnerability impacts of specific system characteristics needs to be found. Real-world transportation systems are rarely designed from scratch, but rather emerge decentrally under certain surrounding conditions, which leaves limited freedom to adjust inherent system characteristics through policies. Optimizing network design in such large-scale systems is not only computationally challenging, it is also less meaningful than creating knowledge on general relationships between system characteristics and vulnerability. Therefore, rather than finding optimal network designs, we aim to provide a tool to estimate vulnerabilities based on given network characteristics. In order to achieve this, the model needs to be applicable to large random network populations with varying system characteristics in order to derive the impact of specific characteristics on vulnerability. The need for such an experimental set-up with tunable system characteristics makes it difficult to conduct the analysis with real-world transportation network data, since the required amount of data on hundreds of different networks is not available. As an alternative, we use random network classes to create populations of proxy networks representative of real-world collaborative transportation networks. These networks can be randomly generated in large quantity and with the desired characteristics. The method is described in Subsection 3.2.4.

Third, we need to measure transportation performance to meaningfully compare the vulnerability of collaborative arrangements on networks. From a system perspective, the aim of collaborative transport, in particular of vertical collaboration, is to create more feasible transport routes in order to connect more origins and destinations and to connect them through faster and more flexible services while achieving a higher utilization of existing transport infrastructure. Specifically in intermodal transport, a flexible and fast collaborative transport system with train and barge services is aimed at in order to reduce the environmental footprint and to reduce congestion on highways by providing a competitive alternative to unimodal truck transport. We need performance measures that reflect the level of achievement of these goals and can be evaluated with low computational effort. The definition of these measures

and an evaluation approach to compute them under the different random network classes is provided in Subsection 3.3.1.

Fourth, the change of transportation performance under disruption needs to be captured, which requires plausible assumptions regarding the disruption mechanisms. These are discussed in Subsection 3.2.3. Moreover, a method to evaluate the impact of disruption on network performance for the given random network classes is described in Subsection 3.3.2.

3.2.3 Model assumptions

Our network model is designed for a rather general and high-level type of analysis and omits operational details at the physical and the collaborative level. The purpose is not to derive explicit action points for decision makers to reduce vulnerability, for instance related to collaboration network design or information link choice, but to provide a general understanding of the relation between collaboration and physical transport and the concomitant vulnerabilities. Findings apply to a wide range of different collaborative transport networks, but are subject to a number of modelling assumptions, which are discussed in the following.

The model is limited to a single type of collaboration links, i.e. collaborations are bilateral and there is no distinction in terms of system impact or disruption risk. In reality, carriers could as well form multilateral alliances, which in our model could be represented by bilateral collaborations between all parties involved. However, disruption in the collaboration layer in the presence of alliances might follow a different mechanism and have different impact compared to what our modeling dictates. For the focus on system vulnerability to collaborations, it is not necessary to make a sophisticated analysis of the value and impact of different types and complexities of collaborations. A basic rule for what a collaboration entails in terms of the capability to provide joint transport routes, and a plausible mechanism for selecting links to generate the collaboration network, are sufficient to get a meaningful mapping between transport and collaboration layers.

Further assumptions are made on the type and the impact of disruptions at the collaborative level and the subsequent failure of collaborations. We assume that disruptions are triggered at individual carriers, i.e. disruptions occur at the nodes in the collaboration layer. The rationale behind this assumption is that most disruptions that lead to a collaboration failure, including false data/cyber-induced disruptions and strategic misalignments, emanate from information systems at (carrier) orga-

nizations. The type of disruption with respect to cause or duration is not further specified in order to ensure generality of the model. Regarding the impact of a disruption, there is a distinction between physical operations of a carrier, which in case of disruption might be unaffected such as in the CMA CGM ransomware attack, and its collaborations, which are prone to failure. While facing a disruption, carriers' first priority is to protect their own operations, whereas external links might even be cut deliberately to protect the own operations or prevent a disruption from spreading. Therefore, the consequences of disruption at a carrier node in the collaboration layer are modeled by the loss of all collaboration links of the respective carrier, i.e. the capability to offer transport chains involving other carriers, while the transport services of the carrier remain unharmed. In reality, physical operations of the affected carrier can be disrupted as well, as shown by the (Not)Petya case. Therefore, our assumption is plausible but rather conservative in terms of disruption impact. Lastly, disruption is assumed not to propagate through the collaboration network. In the case of cyber attack, it would be reasonable to assume that disruption spreads in the network, so this should be considered for future research. Incorporating disruption propagation would even more emphasize the role of the collaborative structure, so it is more suited for an analysis of varying collaboration setups and not varying market structures.

3.2.4 Network definition

Systematically deriving the impact of a specific network characteristic on vulnerability without the need for extensive network data requires a network model, which plausibly represents real-world networks, but comes with tunable network characteristics and a suitable evaluation approach. We address this with two random network classes serving a complementary purpose. First, a probabilistic network class, which is solely described by a set of parameters without the need for generating actual networks, is developed. Within certain boundaries of tractability, this network class allows for an analytical evaluation of the network model and is therefore suitable to establish general relationships between specific network characteristics and vulnerability. Second, a simulation-based network class is developed, featuring realized networks generated from a random graph process, which induces the specified network characteristics. The simulation-based class is more representative of real-world collaborative transportation systems, which facilitates verification and generalization of results to a wider range of networks and associated structural characteristics. Pop-

ulations of the two random network classes are referred to as probabilistic networks and realized networks, respectively.

3.2.4.1 Notation

The multi-layer network model $G = (G^T, G^C)$ consists of two network layers mapping the dependencies between transport service network and carrier collaborations. The first layer is a transport network $G^T = (V^T, E^T)$ with a set V^T of transshipment areas as nodes and a set E^T of transport services as edges. In addition to the nodes $v_1, v_2 \in V^T$ it connects, each edge $e = (v_1, v_2, c) \in E^T$ is attributed to a carrier $c \in V^C$ that operates the service. The same pair of nodes can be served by multiple carriers, which makes G^T a multigraph with parallel edges. The second layer $G^C = (V^C, E^C)$ describes the collaborations between carriers. The node set is the set of carriers V^C. The set of edges E^C maps dyadic collaborations between carriers. The size of the sets is denoted by $N^T = |V^T|$, $M^T = |E^T|$, $N^C = |V^C|$, and $M^C = |E^C|$.

3.2.4.2 Transport layer

The transport network layer can be interpreted as a backbone transport infrastructure network, which comes alive through one or more carriers operating services on it. A realistic random model for collaborative transport networks has to capture both the structure of the backbone transport infrastructure and the structure of the individual carrier service networks. There are numerous factors that can influence the structure of a transport network, e.g. spatial embedding, transport modes, geopolitical constraints, or the competitive landscape, which leads to a large and heterogeneous range of network structures. A general characteristic found across different types of real-world transport networks, e.g. air transport (Guimera et al., 2005) or public transport networks (Ferber et al., 2009), is the scale-free property, i.e. a degree distribution following a power law with few high-degree nodes (hubs) and many low-degree nodes. The structure of the individual carrier networks is a driver by itself for the overall transport network structure, as the full network is a composition of the single carrier networks. Carriers usually have a connected service network, and may also have a scale-free structure, particularly the larger carriers.

In order to accommodate for the most important network features, while keeping the model simple and general, the transport network is defined as a composition of individual scale free carrier networks with power-law degree distribution $P(k) \sim k^{-\gamma}$. The $N^c \leq N^T$ nodes of these carrier networks are randomly matched with the N^T

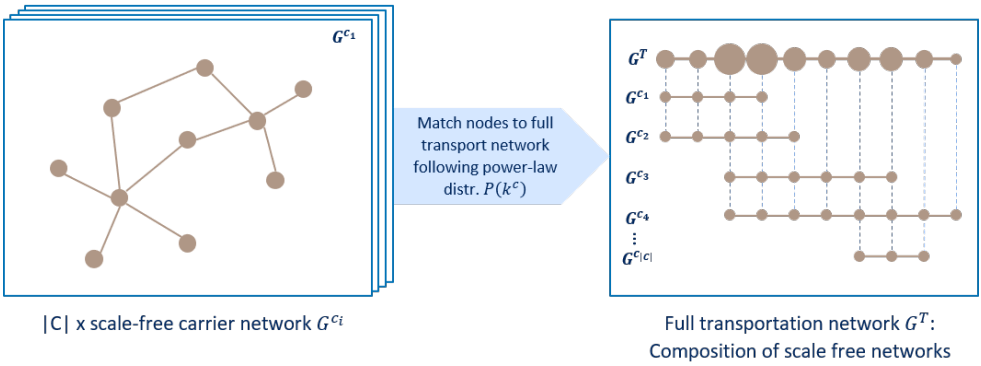


Figure 3.2: The figure visualizes how the individual scale-free carrier networks are composed into an approximately scale-free full transportation network. Networks on the right-hand side of the figure are drawn as a horizontal line to facilitate visualization. The actual structures of the networks are more complex as indicated on the left-hand side for the individual carrier networks.

nodes of the full transportation layer such that it follows a power-law distribution $P(k^c)$ in terms of the number of times k^c a node from a carrier network is matched with a certain node in the full network, i.e. the number of distinct carriers that operate a service adjacent to that node. Under the assumption that the degree distribution of the individual carrier networks is independent of $P(k^c)$, i.e. the carrier network degree of a node is not correlating with the number of distinct carriers operating from that node k^c, the actual degree distribution $P(k)$ of the full network is also approximately power-law distributed (Sun and Zhuge, 2011).

A random graph process to generate networks satisfying these conditions can easily be generated for the simulation-based network class by repeatedly using the Barabasi-Albert model (Barabasi and Albert, 1999). See Figure 3.2 for a visualization and Appendix 3.B for details. The setup of an analytically tractable probabilistic random network class is less straightforward. There are limitations in calculating foundational metrics such as the expected average shortest paths, given that not every path is feasible depending on the presence of collaborations. Therefore, we resort to Erdos-Renyi networks $G(N^T, p)$ (random network with Poisson distributed degrees) with N^T nodes and the probability p for the existence of an edge between each pair of nodes. Each carrier $c \in V^C$ operates a service on each edge e with a probability p^{ξ}_{ec} (some connections can have services run by multiple carriers, but there is also a chance that an edge is not served at all), which is defined per carrier and is constant over all edges, i.e. $p^{\xi}_{c} := p^{\xi}_{ec_i}$ for all $e \in E^T$ and all $c_i \in V^C$.

3.2.4.3 Collaboration layer

The structure of the collaboration layer can take on any arbitrary form, but we propose that such a network will be driven by the structure of the underlying transport network and the positioning of carriers in it. For instance, two carriers whose transport services 'meet' at many destinations (adjacent services), are more likely to establish a collaboration since they can leverage the complementarity of their services to extend their transport offering. A collaboration between carriers with no adjacent services would not add any value to the system. Moreover, there might be constraints with respect to link setup costs or complexity, so carriers would carefully select their partners. The choice of collaboration layer structure is a compromise between accurate representation of reality and the capability of network models to map this representation, especially for analytical computations.

For the present study, collaboration networks are defined through the existence of a link between all pairs of carriers that have at least one transshipment point (adjacent service) in the transport layer. This results in all transshipments being actually feasible and paths can be formed as if there were no transshipment restrictions. It is a neat way to enable an analysis of the full magnitude of vulnerability, while ensuring that the collaboration layer has a meaningful structure resulting from plausible collaboration links. For the simulation-based network class, which features realized transportation layers, the corresponding collaboration layer is constructed in a straightforward manner as described above. The probabilistic network class, however, features probabilistic transport services, which means the existence of adjacent services between two carriers is also probabilistic. The assumption that there is a collaboration links between all carriers with adjacent services in the pre-disruption collaboration network can therefore not be upheld. Instead, a collaboration probability $p^{\kappa}_{c_1 c_2}$ between two carriers c_1 and c_2 is introduced to describe the network. Due to the Erdos-Renyi structure of the physical network, $p^{\kappa} = p^{\kappa}_{c_1 c_2}$ is a constant parameter for $c_1 \neq c_2$, while $p^{\kappa}_{c_1 c_2} = 1$ if $c_1 = c_2$. As a result, the collaboration layer itself is equivalent to an Erdos-Renyi network $G(N^C, p^{\kappa})$.

3.2.4.4 Dependence between layers - Transshipment constraints

The dependence between layers is defined in Section 3.2.2 and visualized in Figure 3.1. While collaborations in practice create synergies through enabling otherwise infeasible transshipments, their non-existence can also be viewed as constraints, limiting the set of theoretically possible paths given by the transport service infrastructure.

For the analysis we use the term transshipment or routing constraints to describe the gap to a transportation network with unconstrained transshipment. Transshipment constraints at a hub depend on whether collaborations between the carriers serving the incoming edges and carriers serving the outgoing edges exist or not. In the simulation-based network class with realized physical networks and realized collaborative networks, transshipment constraints are deterministic. Operating carriers on incoming and outgoing routes are explicitly known, which means feasible transshipments as well as feasible paths can be explicitly determined. This is not possible if the network layers are probabilistic, since the feasibility of transshipments becomes probabilistic as well. Therefore, we translate transshipment constraints into a probability $p^{\theta}_{e_1,e_2}$ representing the occurrence of a feasible transshipment calculated based on available carriers and their collaborations, i.e. the probability that a pair of adjacent edges e_1, e_2 can form a consecutive part of a path. Given the assumptions on physical and collaboration layer structure with constant p and p^{κ}, each potential transshipment is independent and feasible with a constant probability

$$p^{\theta} = 1 - \prod_{\substack{c_q, c_r \in V^C \\ q \neq r}} \left(1 - p^{\kappa} p^{\xi}_{c_q} p^{\xi}_{c_r}\right) \prod_{\substack{c_q, c_r \in V^C \\ q = r}} \left(1 - (p^{\xi}_{c_q})^2\right) \tag{3.1}$$

The derivation of p^{θ} is found in Appendix 3.A. p^{θ} is very powerful, as it combines multiple relevant parameters into a single one. It is able to capture both the structure of the collaboration network and transshipment constraints in a collaborative system, which facilitates the manipulation of network characteristics in the probabilistic network class. Under the assumption of Erdos-Renyi network layers, the probabilistic network class can fully be described by $G(N^T, p, p^{\theta})$ as p^{θ} is a function of p^{κ} and p^{ξ}. Moreover, the impact of disruption can be expressed through a change in p^{θ}, as will become apparent in our analysis.

3.3 Model evaluation

3.3.1 Performance measurement

We choose two measures that reflect the impact of collaborative transport in terms of system performance. The first measure 'Efficiency' is based on path distance, which indicates the amount of distance or time it takes to transport freight from

origin to destination along an intermodal route. Average path distance over all OD pairs is a very common and basic indicator for the performance of transportation networks. Especially in intermodal transport, where the collaborative systems aims to mitigate the need for unimodal truck transport, short transport times are key to provide a competitive alternative to the fast and flexible trucks. The measure 'Efficiency' additionally captures network coverage by discounting disconnected OD pairs, and thereby accounts for another core aim of collaborative transport. The second measure 'Almost shortest paths' (asp) is based on path availability. Adhering to deadlines or providing reliable transport services is crucial in many transport systems, especially in freight transport. Depending on the specifics of the network, delivering an item on time can be more important than the actual transport time. Therefore, it is important for a collaborative transport networks to have a transport offering that ensures high reliability for the delivery. 'Almost shortest paths' addresses this through counting the number of alternative shortest or almost shortest paths. The higher the number of these paths per OD pair, the more flexible and responsive the system is to disruptions.

The specifics and the novelty of our network model require some methodological advances in order to be able to evaluate the chosen performance measures. Analyzing vulnerability comprises the computation of these measures at different stages of disruption. In our case, different levels of network disintegration through node removal are examined in the collaboration layer, whereas the impact of disruption on network properties is measured in the physical layer, since transportation performance is of interest. The impact of the collaboration layer on the physical layer reflects in the transshipment constraints, which need to be integrated into the evaluation of performance measures. The probabilistic network class allows for evaluation of expected vulnerability using an analytical approach, whereas the whole population of realized networks needs to be evaluated and aggregated in the simulation-based network class.

3.3.1.1 Path distance (Efficiency)

The average shortest path length $\phi^{sp}(G) = \frac{1}{N(N-1)} \sum_{\substack{i,j \in V, \\ d(i,j)<\infty}} d(i,j)$ is a very common metric for single-layer networks $G = (V, E)$, but it is not a very suitable measure for networks with disconnected node pairs. Omitting disconnected node pairs leads to very short path lengths in networks with many small fragmented components, conveying a falsely positive impression of basically dysfunctional networks. Discon-

nected node pairs are even more likely in networks with transshipment constraints. Therefore, we resort to a slightly modified version $\phi^{eff}(G) = \frac{1}{N(N-1)} \frac{|\{i,j \in V, d(i,j) < \infty\}|}{\phi^{sp}(G)}$ of the 'Efficiency' measure by Latora and Marchiori (2001), using the reciprocal value of the shortest paths, which is 0 if $d(i,j) = \infty$. If, for instance, 60% of OD pairs in a network are connected, the 'Efficiency' score will be 40% lower than in a network with the same average distance, but all OD pairs connected.

Transshipment constraints induced by the collaboration layer G^C have a non-trivial impact on the length of shortest paths in the transportation layer G^T, as feasibility of paths depends on the feasibility of transshipments along the path. This requires an adjustment of existing methodologies. For realized network populations, calculating ϕ^{sp}_{real} and ϕ^{eff}_{real} requires a minor adjustment to breadth first search, storing carriers who operate feasible services on incoming edges from nodes on the previous level, for each visited node. Transshipment feasibility is assessed between these carriers and carriers operating a service on outgoing edges.

For probabilistic networks, existing shortest path approximations can be made use of, but need to be adjusted as transshipment constraints introduce additional stochasticity. A path $(e_1, ..., e_k)$ formed based on edges from E is only feasible with a probability of $p^{\theta}_{e_1,e_2} \cdot ... \cdot p^{\theta}_{e_{k-1},e_k}$. With decreasing p^{θ}, path lengths generally increase due to a higher chance of paths being infeasible. The analysis of distances or shortest paths and their distribution in different types of random network models has received considerable attention in the literature (Albert and Barabási, 2002; Blondel et al., 2007; Chung and Lu, 2001; Fronczak et al., 2004; Katzav et al., 2018; Katzav et al., 2015). Katzav et al. (2015) developed the Recursive Shell Approach (RSA) for the derivation of the shortest path distribution of Erdos-Renyi graphs $G(N,p)$. RSA is based on a recursive equation

$$F_d = F_{d-1}(1-p)^{(N-1)(F_{d-2}-F_{d-1})}, \tag{3.2}$$

where F_d describes the probability that a randomly selected node is at a distance greater than d from the source. Moreover, it is robust to a wide range of average degrees pN. Robustness to parameter variation is crucial since we want to assess vulnerability through the impact of failure on average distances, which is expressed by a change of parameters. Equation (3.2) can be adjusted such that transshipment constraints expressed by p^{θ} can be captured with moderate additional complexity. With transshipment constraints, an edge on a path can only be taken with probability p^{θ} unless it is the first edge in the path ($d = 1$). Therefore, $F_0 = 1$ and $F_1 = 1 - p$

remain unchanged in the adjusted recursion formula F_d. Beyond the first edge ($d > 1$), the possibility of infeasible transshipments needs to be accounted for. The recursion formula (3.2) becomes

$$F_d = F_{d-1}(1 - pp^{\theta})^{(N-1)(F_{d-2}-F_{d-1})}. \tag{3.3}$$

Equation (3.3) allows the calculation of all $f_d = F_{d-1} - F_d$ representing the probability that the distance from the source is exactly d, and the average distance for the Erdos-Renyi network class with transshipment constraints ϕ^{sp}_{prob} can be derived:

$$\phi^{sp}_{prob}(N, p, p^{\theta}) = \frac{\sum_{d=1}^{\infty} df_d}{\sum_{d=1}^{\infty} f_d}. \tag{3.4}$$

The shortest path with unconstrained routing is obtained by setting $p^{\theta} = 1$. The denominator is needed since $\sum_{d=1}^{\infty} f_d < 1$ if c is below the threshold $ln(N)$ at which the random network is almost surely connected (Bollobás, 2001). In this case, the asymptotic value $F_{\infty} < 1$, $1 - F_{\infty}$ describes the probability that a node pair is not connected, and equation (3.4) describes the average shortest path for an arbitrary node pair given it is in the same connected component. Using this, the 'Efficiency' ϕ^{eff}_{prob} can be derived by devaluing the networks' average distance by the level of their connectivity $(1 - F_{\infty})$:

$$\phi^{eff}_{prob}(N, p, p^{\theta}) = \frac{(1 - F_{\infty})}{\phi^{sp}_{prob}(N, p, p^{\theta})} \tag{3.5}$$

A full derivation of average distance and 'Efficiency' in networks with transshipment constraints as well as an assessment of the accuracy of the approach is found in Appendix 3.C.

3.3.1.2 Path availability (Almost shortest paths)

We define 'Almost shortest paths' with notation ϕ^{asp}_h as the number of paths of length at most h units longer than the shortest path in a non-constrained transport network that are feasible under the given collaboration constellation. Let Π_h be the set of paths between all OD pairs that are at most h units longer than the shortest path in a non-constrained setup. We denote the basic ASP measure by $\phi^{asp}_h = |\Pi'|$, where $\Pi' \subseteq \Pi_h$ is the subset of almost shortest paths that are feasible under the given collaboration network. ϕ^{asp}_h is further refined in order to account for cases, in which it can be misleading, i.e. a decreasing marginal contribution of additional

paths between the same OD pair and the level of disjointness of alternative paths are factored in the score. See Appendix 3.D for details. For simplicity, we set $h = 0$ for the rest of this work and define $\phi^{asp} := \phi_0^{asp}$. ϕ^{asp} can only be computed for realized networks, but not for probabilistic networks, and we write ϕ_{real}^{asp}.

3.3.2 Disruption and robustness

Disruption is simulated by the removal of nodes (carriers) and their links with other nodes from the collaboration network. A disrupted carrier can still operate its own services in the transport network, but loses the ability to offer transshipment connections with other carriers, i.e. only single-carrier routes are available for this carrier. A measure adopted from Schneider et al. (2011) is used to quantify vulnerability, computing the average of an arbitrary performance metric ϕ over every stage of disruption in a sequential removal of all N^C nodes (carriers) in G^C:

$$R = \frac{1}{N^C + 1} \sum_{u=0}^{N^C} \phi(u). \tag{3.6}$$

Here $\phi(u)$ describes the score of the performance metric after removal of u nodes. R is a combined measure averaging different stages of disruption while ensuring comparability of results across different networks. Along the removal of nodes, functionality drops from its level in an undisrupted network $\phi(0)$ to the level in a system without any collaboration and no feasible multi-carrier paths $\phi(N^C)$. Equation (3.6) can be applied to all variants of functionality metrics efficiency ϕ^{sp}, ϕ^{eff}, and ϕ^{asp}. We use the notation R^{eff} and R^{asp} accordingly. Disruption mechanisms differ by the order by which carriers (nodes in the collaboration network and their links with other carriers) are removed. The order of node removal has a strong impact on R, since not all carriers have the same relevance for the functionality of the system. If the order of node removal is chosen in a purposeful way, e.g. by descending size of carriers (number services operated) or by number of links with other carriers (degree in the information layer), functionality decreases more quickly than for random removal, resulting in lower R.

If the physical layer is a realized network, ϕ_{real}^{eff} and ϕ_{real}^{asp} can simply be recalculated for each stage of disruption based on the updated collaboration layer to get R_{real}^{eff} and R_{real}^{asp}. If the physical layer is probabilistic, the change in functionality is driven by a change in transshipment probability p^{θ} caused by lost collaboration links. If the first u carriers $(c_1, ..., c_u)$ are disrupted in the chosen order of removal, their collaboration

probabilities with all other carriers become zero. This results in $p^{\kappa}_{c_q c_r} = 0$ if $q \leq u$ or $r \leq u$ if $q \neq r$. The probability that an arbitrary transshipment is feasible after u carriers have faced disruption becomes

$$p^{\theta}_{u}(p^{\kappa}, p^{\xi}_{c}) = 1 - \prod_{\substack{c_q, c_r \in V^C \\ q \neq r \\ q,r > u}} \left(1 - p^{\kappa} p^{\xi}_{c_q} p^{\xi}_{c_r}\right) \prod_{\substack{c_q, c_r \in V^C \\ q = r}} \left(1 - (p^{\xi}_{c_q})^2\right). \tag{3.7}$$

The efficiency $\phi^{eff}_{prob}(N, p, p^{\theta}_{u})$ of the network for a specific p^{θ}_{u} is given by (4.1). Following (3.6), robustness then calculates as

$$R^{eff}_{prob}(p^{\kappa}, p^{\xi}_{c}) = \frac{1}{N^C + 1} \sum_{u=0}^{N^C} \phi^{eff}_{prob}(N^T, p, p^{\theta}_{u}(p^{\kappa}, p^{\xi}_{c})). \tag{3.8}$$

See Appendix 3.C for details. R^{eff}_{real} and R^{eff}_{prob} are the same metric, they only differ in how they are computed based on the network class they are applied to. Therefore, we write R^{eff}.

3.4 Results

3.4.1 Model application

We show the value of our new model through an analysis of the impact of carrier market structure on the vulnerability to disruption at the collaborative level. Market structure, expressed for instance through heterogeneity in cost structure (Defryn et al., 2016; Padilla Tinoco et al., 2017), bargaining power (Guajardo et al., 2016), or flow characteristics (Palhazi Cuervo et al., 2016), can play an important role in collaborative transport. Angeloudis et al. (2016) study the formation of container service designs in oligopolistic networks, and show that carriers tend to focus on different areas in the network to avoid competition. This leads to higher connectivity and better overall service level compared to the monopoly case, in which it is more economical for the monopolist to not serve the full network. Cruijssen et al. (2007a) find that synergies in joint route planning are moderated by market structure, i.e. they are highest if there is a large number of small or medium-sized flow-controlling entities. The influence of market structure on the vulnerability of the system is rarely studied. For such a study, formation and structure of sub-coalitions and bilateral alliances, i.e. the network of collaborations, need to be taken into account. The only relevant study in this context by Audy et al. (2012) finds that the formation of col-

laborating groups with sequential bilateral agreements reaches stability in a subgame perfect Nash equilibrium of individual benefits depending on the underlying business model. Our multi-layer network model provides a suitable framework to address this gap, since the 1-to-n mapping between carriers in collaboration network and their services in the physical network directly represents the distribution of services per carrier.

We can model different market structures by manipulating the distribution of carrier service probabilities p_c^{ξ}. Zipf's law, a discrete version of the power law which describes the relative frequency of the i-th element in a given set of N^C ranked elements by $f(i, b, N^C) = \frac{\frac{1}{i^b}}{\sum_{j=1}^{N^C} \frac{1}{j^b}}$ (Newman, 2005), can be used to derive heterogeneous carrier service probabilities $p_c^s = f(c, b, N^C)$ (probabilistic network class) as well as the absolute number of services operated per carrier (simulation-based network class). Here $b \geq 0$ is a tunable parameter determining the level of disparity. If $b = 0$, $f(i, b, N^C)$ describes a uniform distribution representing a balanced market structure, whereas larger b leads to concentration of services at fewer carriers. Instead of $p^{\theta}(p^{\kappa}, p_c^{\xi})$ and $R(p^{\kappa}, p_c^{\xi})$ we can write $p^{\theta}(p^{\kappa}, b)$ and $R(p^{\kappa}, b)$ as the service probabilities p_c^{ξ} can be fully expressed by b, which is our main variable of interest.

Results are divided in four parts. First, two drivers of vulnerability, collaboration dependence and susceptibility, are identified and assessed in detail by observing the decay curve of system functionality for different market structures as nodes/carriers are disrupted one by one, and dissecting the two drivers under variation of carrier size disparity. Second, the general relationship between market structure and vulnerability under targeted and random disruption is established for the probabilistic network class and the results are validated using network instances generated from this class. Third, findings are verified in more transport-related setups, using realized network populations from the simulation-based network class, and applying a different measure that better captures the functionality criteria in transport networks. Fourth, the findings and their contribution are positioned within the existing body of knowledge. We use the word vulnerability when referring to the concept that is studied, whereas robustness is used to describe the measure R, which is used to quantify vulnerability. High vulnerability corresponds with a low robustness score.

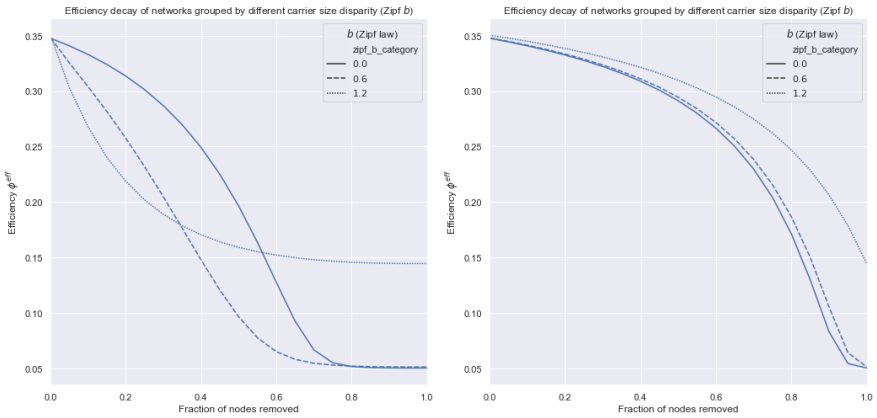
3.4.2 Dissecting the role of market structure

Synergies in joint route planning are moderated by the market structure of carriers, i.e. they are highest if there is a large number of small or medium-sized flow-

controlling entities (Cruijssen et al., 2007a). However, the obvious conclusion that systems become more vulnerable the more they are distributed would be myopic. Vulnerability is not only about the potential magnitude of functionality loss represented by the difference in functionality between a fully-collaborative and a non-collaborative scenario, but also about susceptibility to disruption, i.e. to what extent can certain types of disruption exploit the dependence on collaboration and realize a functionality loss. Susceptibility to random and targeted disruption in a complex network depends on the distribution of node criticality. For instance, networks with few dominating nodes, corresponding with a centralized market structure in collaborative transport, are highly susceptible to targeted disruption (Albert et al., 2000).

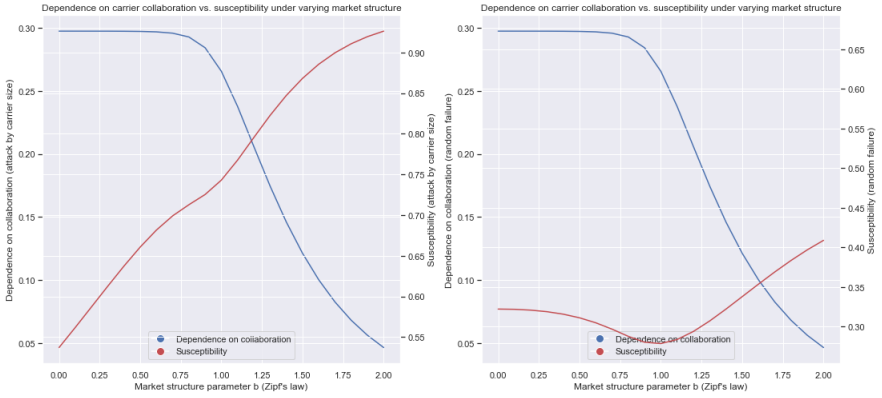
In Figure 3.3, we illustrate how collaboration dependence and susceptibility depend on a system's market structure. The average decay of system functionality is presented as the collaboration network is dismantled node-by-node for three exemplary network parameter configurations: Low (Zipf law parameter $b = 0$), medium ($b = 0.6$), and high ($b = 1.2$) carrier size disparity. Under targeted disruption by carrier size (number of services operated) (Figure 3.3(a)), the network with high disparity faces a steep decay of functionality after the first few nodes are disrupted. However, even after full removal, it maintains decent functionality higher than that of the other two networks. The network with fully balanced carrier sizes ($b = 0$) faces a flatter decay curve, but is a lot more impacted at full removal than the high disparity network. The medium disparity group gets the worst of both worlds and therefore comes out with the lowest robustness score.

Figure 3.3 shows that two different effects emerge as market structure is varied, having a contrary impact on collaboration dependence and susceptibility. If there is high carrier size disparity, the presence of one or few dominant carriers decreases the dependence on collaboration as the big carriers can serve a large share of paths by themselves. As a result, the total magnitude of disruption of information links decreases with increasing carrier size disparity. However, the more a number of carriers stands out from the rest, the easier they can be identified as critical players for a targeted disruption, fostering susceptibility. With number of services being a good indicator of a carrier's criticality, higher carrier size disparity leads to increased effectiveness of targeted disruptions. If all carriers have similar size, the network is highly dependent on carrier collaboration, but not susceptible as targets for a disruption are hard to identify.



(a) ϕ^{eff} under targeted disruption **(b)** ϕ^{eff} under random disruption

Figure 3.3: The figure shows the average decay curve under node removal of three configurations of the random network class $G(200, 0.05, p^{\theta})$ (N^C = 20, p^{κ} = 0.8) with different market structure (carrier size disparity) under targeted disruption by carrier size (a) and random disruption (b). (a) Network 3 (b = 1.2, dotted line) experiences a heavy decay after removing the first few nodes, but stabilizes at a high level without further losses very early. Network 1 (b = 0.0), permanent line) has a flat decay but goes down to a much lower path availability level than network 3. Network 2 (b = 0.6, dashed line) has both steep decay and low outcome level at full disruption. (b) All networks follow a similar curve, higher b leads to less steep decay.



(a) Targeted disruption (carrier size) **(b)** Random disruption

Figure 3.4: The figure shows collaboration dependence and susceptibility of the probabilistic network class (same parameters as in Fig. 3.3) in relation to their market structure under targeted disruption by carrier size (a) and random disruption (b). Dependence on carrier interaction is quantified by the difference between undisrupted functionality and the functionality after full dismantling of the information network $\phi(0) - \phi(N^C)$. It indicates the dependence of a network to have functioning carrier interactions by quantifying the loss in case all collaborations failed. Susceptibility is quantified by $1 - \frac{R-\phi(N^C)}{\phi(0)-\phi(N^C)}$. It describes the relative surface of the base rectangle with height $R - \phi(0)$ compared to the base rectangle with height $\phi(N^C) - \phi(0)$. The smaller this relative surface, the more efficient is the disruption as its full magnitude is reached quicker. We take the complement of this value to get a measure of susceptibility.

This is quantitatively confirmed in Figure 3.4, which shows the contrary effects of varying market structure on the two drivers of vulnerability under targeted disruption, and visually dissected in Fig. 3.5. The figures also indicate why this effect only shows under targeted disruption. While collaboration dependence is purely defined by the market structure (direct effect), susceptibility additionally depends on the order of node removal (indirect effect), i.e. to what extent the heterogeneity in carrier criticality induced by market structure is exploited in the disruption strategy. If the order is chosen randomly, susceptibility becomes much less sensitive to market structure. Carrier criticality is not only influenced by market structure, but also by other aspects such as the structure of the collaboration layer, which is not varied in this study. However, since collaborations usually emerge based on the positioning of the carrier's services in the physical network, the role of collaboration network structure is expected to correlate strongly with the role of market structure.

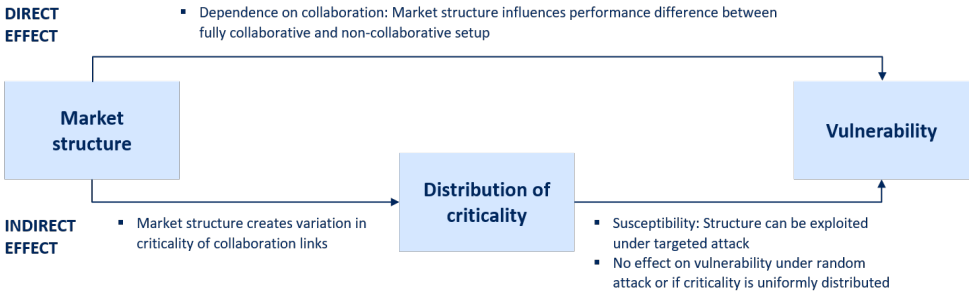
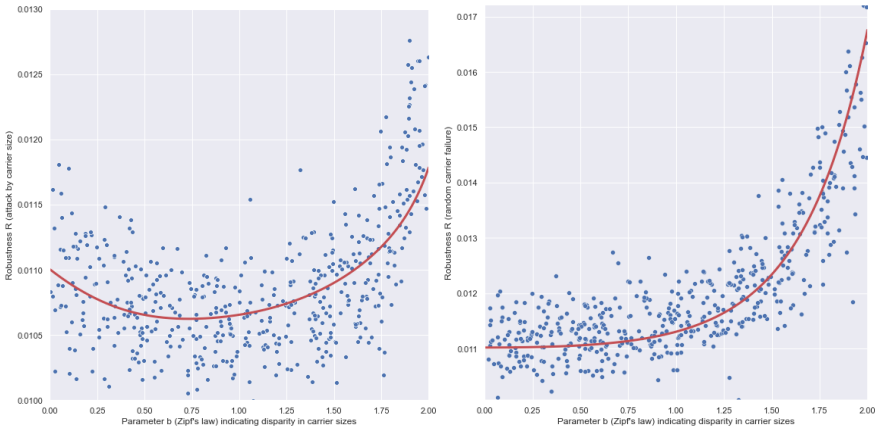


Figure 3.5: Direct and indirect effect of carrier market structure on vulnerability against disruption at the collaborative level. The two effects are contrary under increasing carrier size disparity.

3.4.3 Vulnerability under variation of market structure

3.4.3.1 Analytical results with probabilistic network class

In the next step, the actual vulnerability, being a synthesized outcome of the two observed drivers, is analyzed. Figure 3.6 shows the expected robustness $R^{eff}(p^{\kappa}, b)$ for $b \in [0,1]$ and $N^C = 20$ carriers with default collaboration probability $p^{\kappa} = 0.8$ in a probabilistic network $G(200, 0.01, p^{\theta})$. Moreover, it shows the results of a Monte-Carlo simulation with 1000 realizations of $G(200, 0.01, p^{\theta})$ networks with a random b drawn from a uniform distribution in $[0,1]$. The graph shows that under targeted disruption, the carrier disparity does not have a monotone effect on the vulnerability of multi-carrier transport systems, but takes on a U-shape with a minimum at



(a) R^{eff} under targeted disruption **(b)** R^{eff} under random disruption

Figure 3.6: The figure shows the robustness $R^{eff}(0.8, b)$ for a routing constrained network $G(200, 0.01, p^{\theta})$ with $N^C = 20$ carriers. The red line presents the analytical results of $R^{eff}(0.8, b)$ under variation of b, whereas the blue dots are the outcome of a Monte Carlo simulation. Robustness is computed based on (a) targeted disruption by carrier size and (b) random order of disruption.

intermediate disparity. While centralized setups (high b) with one or few carriers providing almost all services are most robust to disruption, and fully distributed setups (low b) with uniformly distributed carrier sizes exhibit decent robustness as well, intermediate setups (intermediate b) with both larger and smaller carriers are most vulnerable with a minimum around $b = 0.75$. In the case of random disruption (Fig. 3.6 (b)), the result is in turn monotone. Networks are more robust the more services are concentrated at a small number of carriers. The Monte Carlo outcomes are seemingly in line with the analytical results, projecting a similar curve despite considerable variance.

Figure 3.7 shows the shape of the robustness curve (targeted disruption) for different physical network densities p and collaboration probabilities p^{κ}. The basic shape at intermediate values is similar for all combinations of parameters. For increasing b, robustness declines from a medium value until it reaches a minimum. From there, it increases relatively steeply, and then starts to flatten, converging towards the upper robustness bound, which is reached if one carrier operates a service on each single edge. Robustness is generally higher for denser networks (higher p), simply because there are more options for routing. However, the minimum of R^{eff} is reached at smaller b for denser networks, around $b = 0.5$ for $p = 0.05$ compared to $b = 1.4$ for

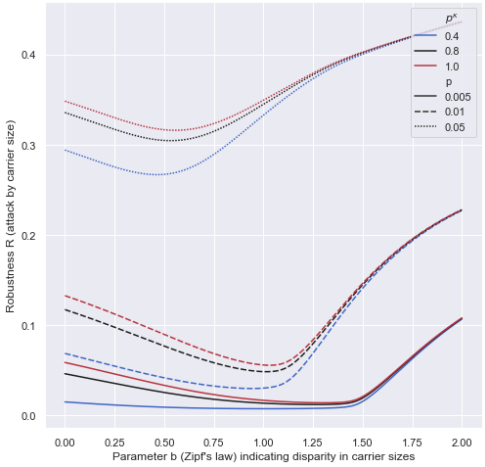
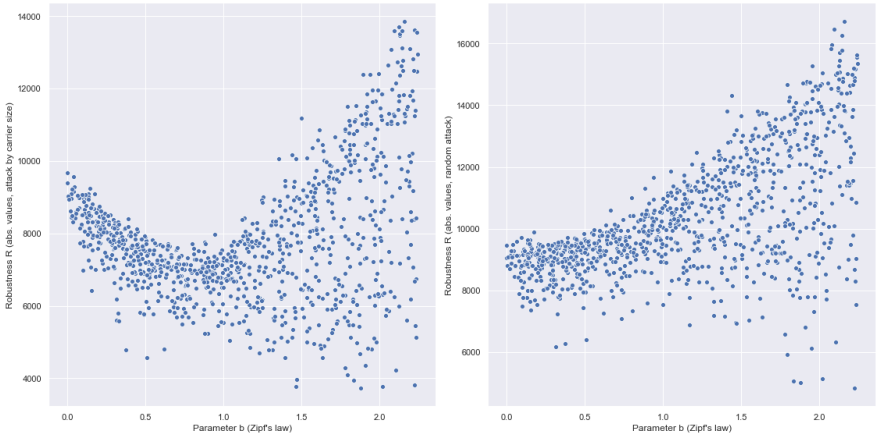


Figure 3.7: The figure shows the robustness curve R^{eff} (targeted disruption by carrier size) under variation of market structure (carrier size disparity) for a probabilistic ER network $G(1000, p, p^\theta)$ with $p \in [0.005, 0.01, 0.05]$, $N^C = 50$ carriers, and collaboration probability $p^\kappa \in [0.4, 0.8, 1.0]$.

$p = 0.005$. As a result, with increasing network density, the range of robust networks is mainly on the disparate market structure end. The relative sensitivity to market structure is highest for the medium density $p = 0.01$ level with R^{eff}. While the curve is comparably flat for $p \in [0.005, 0.05]$, the medium density goes through a deep valley at around $b = 1.1$. This shows that especially for non-extreme networks, $p = 0.01$ corresponds with an average number of distinct services per node of 10, the market structure is a real indicator for vulnerability. The lower p^κ, the less the advantage of a fully balanced network over a intermediate network. In networks with balanced market structure, collaboration is more important than elsewhere, which is why a low (pre-disruption) level of collaboration between carriers leads to poor results even before disruption. The gap between networks differing by collaboration probability p^κ declines with increasing b as the collaboration dependence decreases.

3.4.3.2 Results with realized networks from simulation-based network class

Figure 3.8 shows the robustness results R^{asp} under the path availability measure ϕ^{asp} of simulations for 1000 generated networks ($N^T = 150$ nodes, $M^T = 600$ edges, $N^C = 20$ carriers) with varying market structure parameter b under targeted (a) and random (b) disruption. Despite different network class and different functionality



(a) Removal by carrier size **(b)** Random removal

Figure 3.8: (a) The Figure shows the robustness R^{asp} of 1000 randomly generated networks (N^T = 150 nodes, M^T = 600 edges, N^C = 20 carriers) with varying market structure expressed by parameter b of the services operated per carrier. The carriers' service networks, the overall service network, and the collaboration network are generated as explained in Section 3.2.4. (b) Same figure, but R^{asp} has been determined using random order of node removal.

measure, robustness R^{asp} under variation of b exhibits a similar shape, suggesting that the discovered relationship between market structure and vulnerability is robust to transport and carrier network structure. Comparing the simulations in Figures 3.8 and 3.6, the most striking difference is that there is less variance in the simulation outcomes for medium and small b, indicating that the vulnerability under a given market structure can be predicted even better with the simulation-based network class. For large b, the variance in the realized network instances is much wider, due to networks being more likely to be disconnected if there are few dominant players. The path availability measure punishes disconnected nodes strongly, which is why there are some networks with poor functionality in the large b-range.

3.4.4 Positioning in literature

The identification and integrated analysis of the two contrary effects of market structure constitutes an important addition to the existing body of knowledge in collaborative transport. Cardillo et al. (2013b) find that if collaboration for sharing routes fails or is not functional (no collaboration in place), the network is much more vulnerable to physical disruption. Our results indicate that this physical vulnerability

becomes real if the network can be disrupted effectively at the collaborative level (disparate distribution of carrier criticality), and it can be amplified if the network is very dependent on collaboration. Regarding the role of market structure, Cruijssen et al. (2007a) show that synergies in joint route planning are highest if there is a large number of small or medium-sized flow-controlling entities. Using populations of random networks instead of constructed benchmark cases, our study reproduces their finding that potential synergies of collaborative transport (performance difference between no collaboration and collaboration) are highest with many small/medium companies. However, The potential loss is also very high due to a high dependence on collaboration, especially since carriers tend to put their service focus on different areas in the network to avoid competition (Angeloudis et al., 2016). Moreover, the actual composition of small and medium players needs to be assessed in a more nuanced way. If it is close to a uniform size distribution, the network cannot be disrupted in an effective way, but if there are some medium and some small companies, the system is vulnerable to targeted disruption.

3.5 Conclusion

While the great potential of collaboration between carriers in transport systems to enable efficient use of decentral transport resources is well known and undisputed (Cruijssen et al., 2007b), this paper identified the need to also take a perspective on the vulnerabilities induced by collaboration. This study aimed to establish an understanding of collaborative transport as a complex interdependent systems with a collaboration layer and a physical layer, which interact within themselves, but also with each other. Synergies and vulnerabilities of bilateral collaborations and the functionality of physical transport should not only be considered on an isolated basis, but implications of changes or disruptions needed to be assessed from a system perspective as well.

The research objective has been approached by developing a new model employing the science of complex multi-layer networks to map the complex constellations at the physical transport and at the collaborative level. The model is inspired by existing multi-layer network models used to study cyber-physical systems, but has been adjusted for the transportation-specific interdependence between network layers. Compared to existing models for transportation analysis, the model enables an integrated analysis of synergies and vulnerabilities at large scale. A useful tool has emerged for the analysis of networks with decentral control of flow on edges,

which can be used for various problems in the field of collaborative transport with little adjustment. We used it to show that market structure represented by carrier size disparity has a non-trivial impact on the vulnerability of a transport network to targeted disruption at the collaborative level, see Figure 3.6. Networks are most vulnerable if they have intermediate disparity in carrier sizes, i.e. carriers are overall similarly sized, but there is some heterogeneity with a moderate gap between few larger and many smaller carriers. As a result, the robustness curve is not monotone, but has a minimum at intermediate disparity levels. Networks with perfectly homogeneous carrier sizes exhibit medium to high levels of robustness and highly disparate networks exhibit the highest robustness.

The study sets the ground for future interesting research exploring the interdependence between collaboration and transport networks as well as determinants influencing the vulnerability induced by it. This can include a refinement of the model, for instance by incorporating transshipment operations at the physical level as well as transshipment operators at the collaborative level. On the evaluation side, different structures of the collaboration layer can be tested to analyze the effect of limitations regarding the establishing of collaborations or to test the role of different competitive setups. This would enhance the understanding of the interplay between physical and collaboration layer, which is currently only analyzed by varying the physical layer. Moreover, the disruption mechanism could be enhanced incorporating the risk of spreading and cascading disruption, which would be a step towards a better understanding of the impact of cyber attacks, such as the 2017 (Not)Petya hack. All these changes are relatively easy to implement with a simulation-based network class, whereas the applicability to probabilistic networks is less trivial. A methodological contribution can further be provided by extending the applicability of the analytical model variant (probabilistic network class) to networks with arbitrary degree distributions as well as different disruption types and layer mappings.

Our findings will become increasingly relevant in a world of transportation that is becoming evermore interconnected through information technology. New visions of transportation such as synchromodal transport or the Physical Internet are heavily dependent on close collaboration between carriers in order to be realized. Moreover, these visions require strong technological integration, including the sharing of large amounts of data and the usage of sophisticated technologies such as sensor technology or smart contracts. It is crucial to understand the vulnerabilities that come with these developments.

3.6 Acknowledgements

This research has been developed as part of the Trans-Sonic project (project no. 439.16.119, https://transsonic.nl/), which is funded by the Dutch Organisation for Scientific Research (NWO) and supported by a number of academic and industry partners in the field of hinterland shipping.

Appendix

3.A Analytical network model formulation - Details

The model is capable of handling non-uniform distributions of collaboration probabilities. For instance, two large carriers could be more likely to set up a collaboration link since they tend to have more adjacent services in the physical network, hence $p^{\kappa}_{c_1c_2}$ would correlate with the two carrier sizes, i.e. $p^{\kappa}_{c_1c_2} = f(c1, b, 0)f(c2, b, 0)$. However, the structure of the collaboration network is not a variable tested in this research, thus p^{κ} is chosen to be a constant parameter.

Derivation of transshipment probability p^{θ}

Using p^{ξ} and p^{κ}, the transshipment probability p^{θ} can be derived. Let $T_{e_1e_2}$ be a binary random variable, which is 1 if a transshipment between e_1 and e_2 is feasible, and 0 otherwise. A transshipment is feasible, if there is at least one feasible (collaborating or same carrier) pair of carriers operating on the two edges. Let $T_{e_1e_2c_1c_2}$ be a binary random variable indicating if a transshipment from e_1 to e_2 is feasible and it is enabled specifically by c_1 operating on e_1, c_2 operating on e_2, and c_1 collaborating with c_2. The probability of $T_{e_1e_2}$ writes as

$$P(T_{e_1e_2} = 1) = P(\sum_{c_1,c_2 \in V^C} T_{e_1e_2c_1c_2} > 0) \tag{3.A.1}$$

$$= 1 - P(\sum_{c_1,c_2 \in V^C} T_{e_1e_2c_1c_2} = 0) \tag{3.A.2}$$

$$= 1 - \prod_{c_1,c_2 \in V^C} (1 - p^{\kappa}_{c_1c_2} p^{\xi}_{e_1c_1} p^{\xi}_{e_2c_2}). \tag{3.A.3}$$

Since all edges are independent, all pairs of edges are equal and we can write $P(T_{e_1e_2} = 1) =: p^{\theta}$. Plugging in the assumption that all p^{κ} except $p^{\kappa}_{c_ic_i} = 1$ are equal, and using Zipf's law $p^{s}_{c_i} = \frac{\frac{1}{i^b}}{\sum_{j=1}^{N^C} \frac{1}{j^b}}$ to generate a distribution of services per carrier for a set of carriers $V^C = \{c_1, ..., c_{N^C}\}$ ordered by size, we get

$$p^{\theta} = 1 - \prod_{\substack{c_q, c_r \in V^C \\ q \neq r}} \left(1 - p^{\kappa} p_{c_q}^{\xi} p_{c_r}^{\xi}\right) \prod_{\substack{c_q, c_r \in V^C \\ q = r}} \left(1 - (p_{c_q}^{\xi})^2\right) \tag{3.A.4}$$

$$\overset{\text{Zipf law}}{=} 1 - \prod_{\substack{c_q, c_r \in V^C \\ q \neq r}} \left(1 - p^{\kappa} \frac{\frac{1}{(qr)^b}}{(\sum_{j=1}^{N^C} \frac{1}{j^b})^2}\right) \prod_{\substack{c_q, c_r \in V^C \\ q = r}} \left(1 - \frac{\frac{1}{q^{2b}}}{(\sum_{j=1}^{N^C} \frac{1}{j^b})^2}\right). \tag{3.A.5}$$

Parameter b of the Zipf law indicates how concentrated services are (market structure).

3.B Simulation network generation - Details

Simulations allow for the analysis of more realistic representations of collaborative transport networks as they are less constrained by the boundaries of tractability and networks can be generated with the desired characteristics of CTNs. The biggest difference to the networks in the analytical part is that carriers' individual service networks are connected and exhibit a scale-free structure.

First, the size of carriers is determined in the same way as for the analytical part using Zipf's law $f(i, b, N^C) = \frac{\frac{1}{i^b}}{\sum_{j=1}^{N^C} \frac{1}{j^b}}$. Then for each of the N^C carrier's an individual service network is generated using the Barabasi-Albert model (Barabasi and Albert, 1999) for scale-free networks with parameters for the size given by the carrier's allocated share of the predefined total number of services in the network

The full transportation network is then assembled by assigning a weight to each of the N nodes, and randomly mapping the nodes of the individual networks on the full network according to the assigned weights. The weights are useful to induce a specific degree distribution for the overall service network. The desired distribution will only be achieved approximately as the degree of nodes in the individual network is not taken into account when making the allocation to the full network. Node weights are drawn from a power law distribution to also give the full network an approximately scale-free structure and generate a network that resembles real-world transportation networks.

The collaboration networks are generated by establishing a collaboration link between all pairs of carriers that have at least one transshipment point (adjacent service) in the transport layer. This results in all theoretically possible transshipments being

actually feasible as long as there is no disruption, i.e. all paths can be formed as if there were no transshipment restrictions of carriers. This is a neat way to enable an analysis of the full magnitude of vulnerability, while ensuring that the collaboration layer has a meaningful structure resulting from plausible collaboration links.

There are numerous alternative choices for collaboration network generation. For instance, setup constraints could be introduced by turning the presented mechanism into a threshold rule, placing a link between carriers if the number of touch points (adjacent services) between the two carriers in the transport network is larger than a threshold k. The larger k becomes, the more sparse is the information network. Moreover, a budget of collaboration links (total or per carrier) could be introduced, aiming at finding system-optimal or emerging constellations under different levels of carrier rationality and information availability. All these mechanisms have in common that they do not provide full physical functionality at the initial stage before disruption, making the question of vulnerability mainly one of the initial functionality and thereby obfuscating the general role of market structure under disruption. Other alternative mechanisms such as random selection of collaboration links or a fully connected collaboration layer are not really plausible since they contain many links that do not add any value to the transportation links. In practice, such links could exist for instance if have establish collaboration that are not directly transport related, e.g. for knowledge sharing. Even though such collaborations are also subject to a risk of disruption and can indirectly hamper physical transportation, they are out of scope. Nevertheless, the choice of collaboration network mechanism does have an impact on the results, but it is not critical to show the dependence between the layers and the role of market structure, as discussed in Section 4.4.

3.C Efficiency in ER networks with transshipment constraints

Derivation of shortest paths and efficiency

The analysis of distances or shortest paths and their distribution in different types of random network models has received considerable attention in literature (Albert and Barabási, 2002; Blondel et al., 2007; Chung and Lu, 2001; Fronczak et al., 2004; Katzav et al., 2018; Katzav et al., 2015). The models by Fronczak et al. (2004), Blondel et al. (2007), and Katzav et al. (2015) provide analytical approaches to approximate the distribution of distances in Erdos-Renyi graphs $G(N, p)$. Fronczak

et al. (2004) provide a closed form equation for the average shortest path length $l = \frac{ln(N)-\gamma}{ln(pN)} + 0.5$, which is though quite inaccurate for small ($c < 2$) and very large (c close to N) values of the parameter $c = pN$, as shown by Blondel et al. (2007). The definition of c is exclusive to this section of the Appendix. c has a different meaning in the rest of the paper. Blondel et al. (2007) and Katzav et al. (2015) developed a recursive equation for the derivation of the shortest path distribution of $G(N, p)$, which is robust to a much wider range of c. Robustness to parameter variation is crucial since we want to assess vulnerability through the impact of failure on average distances, which is expressed by a change of parameters.

All of these approaches can be adjusted such that routing constraints expressed by a constant p^θ can be captured with moderate additional complexity. We will show this on the example of the Recursive Shell Approach (RSA) by Katzav et al. (2015), which is almost equivalent to the approach by Blondel et al. (2007), except that the case of a random node pair being the same node twice with distance 0 is excluded. The definition of average shortest paths usually requires origin and destination to be different. The RSA approach considers an arbitrary but fixed source node $s \in V$ and analyzes the shell structure around it. Let $\overline{N}_d$ describe the number of nodes that are at distance larger than d from the source s, and N_d the number of nodes with exact distance d from s with $N_0 = 1$ and $N_d = \overline{N}_{d-1} - \overline{N}_d$. For an arbitrary d, N_d can be described by the share of the remaining nodes $\overline{N}_{d-1}$ (nodes that are not within distance $d-1$), which is connected to at least one node in N_{d-1}, hence

$$N_d = \overline{N}_{d-1}\left(1 - (1-p)^{N_{d-1}}\right). \tag{3.C.1}$$

This can be reformulated as

$$\overline{N}_d = \overline{N}_{d-1}(1-p)^{\overline{N}_{d-2}-\overline{N}_{d-1}}. \tag{3.C.2}$$

At $d = 0$, all nodes but s are in $\overline{N}_0 = N - 1$, and at $d = 1$, all nodes that are not s or neighbours of s are in $\overline{N}_1 = (N-1)(1-p)$. In order to transfer eq. (3.C.2) into a probability distribution, we define the probability F_d that a randomly selected node is at a distance greater than d from the source, and $f_d = F_{d-1} - Fd$ the probability that the distance is exactly d. $F_0 = 1$ since distances between same nodes are excluded, and $F_1 = 1 - p$ representing the share of nodes that are not directly connected to the source. The relation between $\overline{N}_d$ (absolute number of nodes) and F_d (probability)

is expressed by $\overline{N}_d = (N-1)F_d$. $N-1$ is chosen as factor instead of N in order to exclude the source s. Plugging this in eq. (3.C.2) yields

$$F_d = F_{d-1}(1-p)^{(N-1)(F_{d-2}-F_{d-1})} \tag{3.C.3}$$

With routing constraints, an edge on a path can only be taken with probability p^θ unless it is the first edge in the path. Therefore, $F'_0 = 1$ and $F'_1 = 1-p$ remain unchanged in the adjusted recursion formula F'_d. For $d > 1$ routing constraints apply and the possibility that the random node is connected by a path to the source, but the connection is infeasible needs to be accounted for. The probability of being connected by a direct feasible link to at least one node in N_{d-1} becomes $1-(1-pp^\theta)^{N_{d-1}}$, which affects equation (3.C.1), and as a result thereof also equations (3.C.2) and (3.C.3). The recursion formula (3.C.3) becomes

$$F_d = F_{d-1}(1-pp^\theta)^{(N-1)(F_{d-2}-F_{d-1})}. \tag{3.C.4}$$

In theory, p^θ also depends on d, as with growing d, a random node in N_d could be connected to more than one node in N_{d-1}. Multiple incoming links that are part of a shortest path increase the chance of a feasible transshipment to an adjacent link to a node in N_{d+1}. We analyzed the evolution of p^θ with d and found that the impact on the result is negligible even for small networks, therefore it is omitted. The recursive equations with (3.C.4) and without (3.C.3) routing constraints allow the calculation of all f_d as well as the average shortest path length between arbitrary pairs of nodes $\phi^{sp}(N,p,p^\theta)$:

$$\phi^{sp}(N,p,p^\theta) = \frac{\sum_{d=1}^{\infty} df_d}{\sum_{d=1}^{\infty} f_d} \tag{3.C.5}$$

The shortest path with unconstrained routing is obtained by setting $p^\theta = 1$. The denominator is needed because $\sum_{d=1}^{\infty} f_d < 1$ if c is below the threshold $ln(N)$ at which the random network is almost surely connected (Bollobás, 2001). In this case, the asymptotic value $F_\infty < 1$, $1-F_\infty$ describes the probability that a node pair is not connected, and eq. (3.C.5) describes the average shortest path for an arbitrary node pair given it is in the same connected component. In finite networks paths cannot be longer than $N-1$ edges in a network with N nodes, therefore $F_\infty = F_{N-1}$ and the sum in (3.C.5) stops at $d = N-1$. If routing constraints are in place, shortest

paths could theoretically be longer than $N-1$ edges if nodes are revisited in order to enable transshipment to a constrained edge. Practically this is a very hypothetical scenario and can be neglected.

As mentioned before, the average shortest path $\phi^{sp}(N,p,p^{\theta})$ is not a very suitable measure for the functionality of disconnected networks. If $c < ln(N)$, the network is not expected to be connected and if $c < 1$, the random network even consists of small fragmented components (Bollobás, 2001), resulting in $d(i,j) = \infty$ for most node pairs. The transition of ϕ^{sp} into ϕ^{eff} is made as follows:

$$\phi^{eff}(N,p,p^{\theta}) = \frac{1}{N(N-1)} \sum_{i,j|d(i,j)<\infty} \frac{1}{\phi^{sp}(N,p,p^{\theta})} \tag{3.C.6}$$

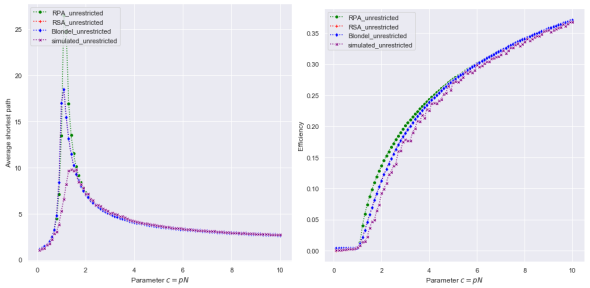
$$= \frac{1}{N(N-1)} \frac{(1-F_{\infty})N(N-1)}{\phi^{sp}(N,p,p^{\theta})} \tag{3.C.7}$$

$$= \frac{(1-F_{\infty})}{\phi^{sp}(N,p,p^{\theta})} \tag{3.C.8}$$

With this measure, networks have their average shortest path devalued by the level of their connectivity $(1-F_{\infty})$, which is very low for networks with $c < 1$.

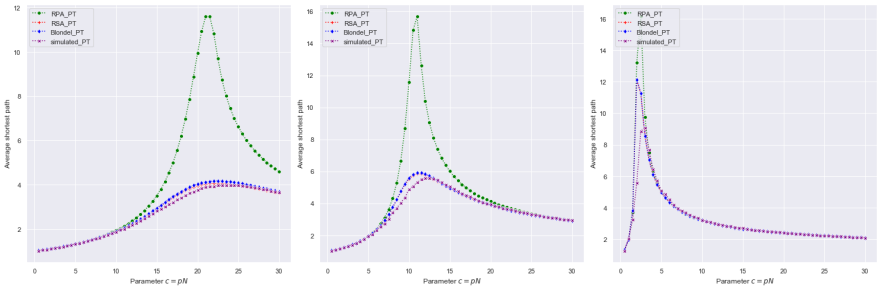
Accuracy

We test the accuracies of the two approaches by Katzav et al. (2015) RSA, RPA, and the approach by Blondel et al. (2007) by comparing them to simulation results. See figures (3.C.1), (3.C.2), (3.C.3), (3.C.4), and (3.C.5) for the results. In the unconstrained case, the biggest deviations from the results are found at $c = 1$, which is the threshold for the formation of a giant component. Much of the deviation can be traced back to the use of the expected value for calculating N_{d+1} from N_d and $\overline{N}_d$, instead of using the actual distribution. For very small c, the distribution is centered at close to 0, since most nodes are not connected. The expected value is close to 0 as well. For large c, almost all nodes are connected, hence the distribution of N_{d+1} is centered around its expected value. Around $c = 1$, there are large components, but many node pairs are still not connected. The distribution of N_{d+1} has a peak at 0 for the disconnected share and a second peak at the expected number of nodes if only connected pairs were considered. The expected value is therefore not very representative for the distribution.



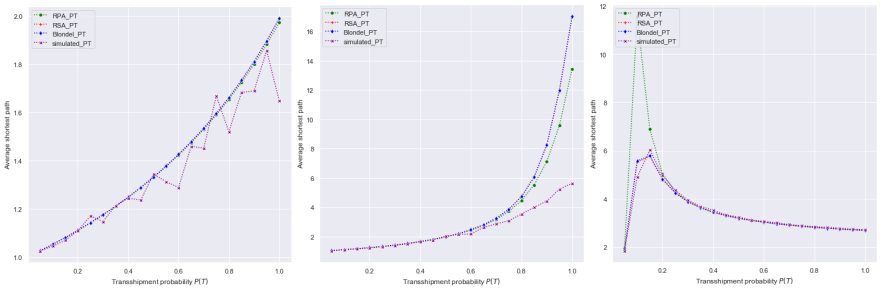
(a) Average shortest path - **(b)** Efficiency - unrestricted unrestricted

Figure 3.C.1: The Figures shows average shortest path $\phi^{sp}(N, p, 1)$ and efficiency $\phi^{eff}(N, p, 1)$ for parameters $c \in [0, 10]$ and $N = 300$. Calculations are made using three different analytical methods (RPA, RSA, Blondel) as well as simulations. The approaches are quite inaccurate in the range $c \in [1, 2]$ as pointed out by the authors, with RPA being the farthest off simulations results. The values for efficiency (b) are more accurately than those for average shortest path (a).



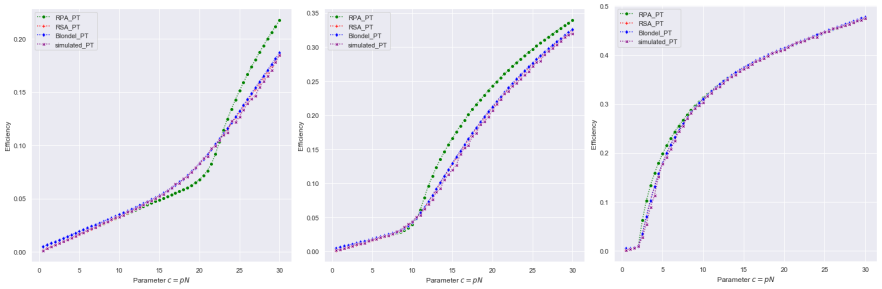
(a) $p^{\theta} = 0.05$ **(b)** $p^{\theta} = 0.1$ **(c)** $p^{\theta} = 0.5$

Figure 3.C.2: The Figures shows average shortest path $\phi^{sp}(N, p, p^{\theta})$ for parameters $c \in [0, 10]$ and $N = 300$ with constrained routing for different values of p^{θ}. All methods show solid accuracy for most c except there is one transition point corresponding with $c = 1$ in the unrestricted case where the analytical approaches deviate from the simulations. RSA and Blondel can cope with this transition much better than RPA.



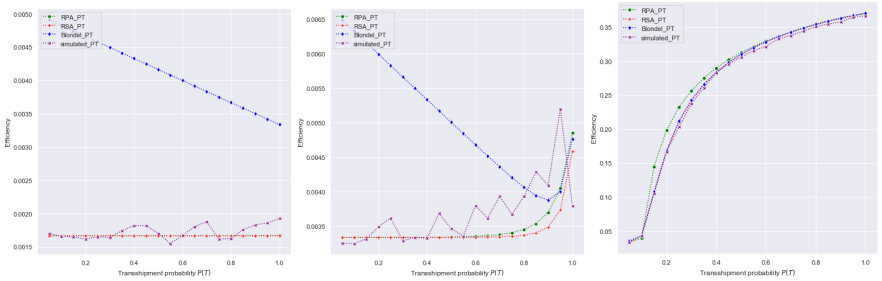
(a) $c = 0.5$ **(b)** $c = 1$ **(c)** $c = 10$

Figure 3.C.3: The Figures shows average shortest path $\phi^{sp}(N, p, p^{\theta})$ for transshipment probability $p^{\theta} \in [0, 1]$ and $N = 300$ with constrained routing for different values of c. For small (a) and large c (c), the variation of p^{θ} seems not to have a large impact on the accuracy of the model. At $c = 1$ (b), which is the transition point in the unrestricted model, accuracy is only good for small and medium p^{θ}. As p^{θ} approaches 1, the model converges to the unrestricted case.



(a) $p^{\theta} = 0.05$ **(b)** $p^{\theta} = 0.1$ **(c)** $p^{\theta} = 0.5$

Figure 3.C.4: The Figures shows efficiency $\phi^{eff}(N, p, p^{\theta})$ for parameters $c \in [0, 10]$ and $N = 300$ with constrained routing for different values of p^{θ}. All methods show high accuracy for all c, especially RSA and Blondel.



(a) $c = 0.5$ **(b)** $c = 1$ **(c)** $c = 10$

Figure 3.C.5: The Figures shows efficiency $\phi^{eff}(N, p, p^\theta)$ for transshipment probability $p^\theta \in [0, 1]$ and $N = 300$ with constrained routing for different values of c. RPA seems to show the best accuracy for efficiency. Blondel deviates before and RPA after the transition point.

Surprisingly, the modified approaches incorporating routing constraints are more accurate than the original versions. An explanation is found in the fact that a network with routing constraint p^θ can be compared to a network with expected degree c for the source node and cp^θ for all other nodes. At $d = 0$ the expected value for N_{d+1} is very accurate since N_0 and $\overline{N}_0$ are exactly known. For $d > 1$, the real c is much closer to zero and therefore well represented by the expected value for N_{d+1} as explained above. The modified RSA approach provides the most accurate results for almost all parameters and is therefore used for subsequent analysis.

3.D Detailed definition of 'Almost shortest path' measure

Let Π_h be the set of paths between all OD pairs that are at most h units longer than the shortest path in a non-constrained setup. We denote the basic asp measure by $\phi^{asp} = |\Pi'|$, where $\Pi' \subseteq \Pi_h$ is the subset of almost shortest paths that are feasible under the given collaboration network.

The asp measure is further refined in order to account for cases, in which it can be misleading. First, the score can be biased if there is a disproportionately high number of almost shortest paths for a small number of OD pairs while many OD pairs are not even connected. An even distribution of almost shortest paths across OD pairs is preferred. Therefore, the marginal contribution to the asp score diminishes with increasing number of paths for a certain OD pair. Second, not every path is equally

relevant for a dynamic transport system. Paths that use largely the same services to serve an OD pair add less value than a completely disjoint path, since in case of failure of services, multiple overlapping paths can be eliminated at once, while disjoint paths have no correlated impact. This is dealt with by weighting the value of a path by its level of disjointness from other paths serving the same OD pair. The decreasing marginal contribution of additional paths on the same OD pair is accounted for by the calculation $\phi_{od}^{asp} = \sum_{h=1,\dots,|\Pi'_{od}|} x^{h-1}$, where Π'_{od} is the set of feasible almost shortest paths connecting o and d and $x \in (0,1]$ is a parameter describing how quick the additional value of more paths is diminishing. We set $x = 0.8$, which means that an OD pair with only 1 path will have a score of $0.8^0 = 1$, an OD pair with 2 paths will have a score of $0.8^0 + 0.8^1 = 1.8$, and so on. Since paths are weighted by their relevance, i.e. each path π has a relevance r_π, the calculation needs to be slightly adjusted. Let $W_{od} = \sum_{\pi \in \Pi'_{od}} r_\pi$, then

$$\phi_{od}^{asp'} = \sum_{h=1,\dots,\lfloor W_{od} \rfloor} x^{h-1} + (W_{od} - \lfloor W_{od} \rfloor) x^{\lceil W_{od} \rceil}. \tag{3.D.1}$$

The full score adjusted for diminishing additional path value and path relevance is calculated as

$$\phi^{asp'} = \sum_{o,d \in V^T} A'_{od}. \tag{3.D.2}$$

The relevance of a path r_π is determined by how disjoint the services of the path are from those used for other paths on the same OD pair. Let $EP(\Pi_h, e)$ be the number of times the service $e = (v_1, v_2, c)$ occurs over all paths $\pi \in \Pi_h$. A path π is described by the set of services e_π that jointly form the path. We define the relevance of a path $\pi \in \Pi'_{od}$ as

$$r_\pi = \frac{|e_\pi|}{\sum_{e \in e_\pi} EP(\Pi'_{od}, e)}. \tag{3.D.3}$$

A path that uses exclusively services that are not used for other paths serving the same OD pair will have relevance $r_\pi = 1$. A path, whose services are all used for exactly one other path on the same OD connection exhibits $r_\pi = 0.5$.

Chapter 4

The impact of collaborative connectivity on the risk of failure cascades in collaborative transport systems

4.1 Introduction

4.1.1 Motivation

Collaboration and information integration between actors in decentrally operated transportation systems is a key enabler to create synergies through more efficient use of existing service infrastructure. Intermodal container transport, for instance, aims at providing a competitive and more sustainable alternative to truck transport by using barge and rail services. However, the presence of many small and medium sized carriers restrains the set of destinations reachable through rail and barge services and leads to unfavorable transport routes when carriers provide their services in isolation. Carriers can cope with this by combining their individual transport offerings through collaborative provision of services. This includes facilitating integrated booking, transshipment between consecutive transport services, and joint planning of transport services to avoid unnecessary waiting times between arrivals and departures of consecutive transport services. When such collaborative arrangements are made, the performance of intermodal transport improves. Indeed, when more (joint) transport routes are offered, there are more options to transport freight efficiently, frequently and timely between origins and destinations. As a result, intermodal transport becomes more competitive as compared to direct truck transport. Other decentrally operated transportation systems, e.g. in air passenger or public transport, experience similar benefits through collaboration and information integration between carriers. The more carriers are getting engaged in collaboration, the more synergies of integration emerge. Ultimately, transport systems become more efficient with flexible routing and shorter average transport times (Cardillo et al., 2013b).

Despite these benefits, collaboration comes with new and often disregarded threats. Collaborations are fueled by the exchange of data, since collaborative provision of services requires close coordination between parties on the arrangement of transshipments, synchronization of capacities for integrated booking, and service disruption handling amongst others (Buijs and Wortmann, 2014). For instance, while coordinating intermodal transport chains, intermodal carriers depend on each other for the quality of exchanged information on service schedules, bookings, available capacities, transshipment plannings, and so on. If carriers fail to provide their partners and involved terminals with the required data or if the data is of poor quality, e.g. resulting from a cybersecurity breach or poor data management, transport chains performance deteriorates or even collapses. As a consequence, collaborations are at risk of failure,

e.g. through technical disruption, cyber attacks, or even inter-organizational issues (Kumar and van Dissel, 1996; Tonn et al., 2019).

More importantly, however, disruption in a carrier's information system can lead to subsequent disruption at its partners and partners of partners. For instance, false data injected by a malicious attack or unintended errors, or missing data resulting from an information system failure does not only hamper the operations of the attacked carrier, but also that of its partners if the false/missing data is shared and needed to maintain collaborative operations (Wang et al., 2019). Even an organizational conflict causing the failure of a collaboration for strategic or commercial reasons can have implications for the carriers' other collaborations as there can be second order interdependencies, i.e. a carrier could only see the benefits in a partnership as long as that partner has a partnership with another strategically important carrier. The risk of propagation indicates that carriers are not only exposed to their own risk of disruption, but also to that of their partners. Research in the field of epidemiology even suggests that the magnitude of the latter increases with the number of partners, i.e. a higher number of connections increases the risk of infectious disruption turning into a cascade disrupting large parts of a population (Newman, 2002). Disruption at a single carrier can then be a serious threat to an entire cyber-physical systems (Bagula et al., 2019; Wang et al., 2019).

The vulnerability to cascades of disruption at the collaborative level stands in contrast to the supposed benefits of collaboration, and raises the question whether more collaboration is indeed purely positive as suggested by the potential synergies, or whether there is a trade-off between synergies and vulnerability. As emerging concepts in transportation such as synchromodal transport or the Physical Internet are heavily dependent on close collaboration between carriers and lead to transportation systems being increasingly interconnected by information technology, it is crucial to understand the trade-offs between synergies and vulnerabilities that come with these developments.

4.1.2 Aim of research

This research aims to identify a trade-off between synergies and vulnerabilities through collaboration between carriers in transportation systems. This trade-off shall be quantified depending on the collaborative connectivity, i.e. the relative quantity (density) of collaborations.

The provision of an appropriate model for such an analysis is a challenge. First, the model needs to capture the complex interdependence between physical transportation and collaboration from a system perspective. The performance of physical transport services is not only a result of the network of available transport services, but also of the collaborative arrangements between the operating carriers. Moreover, the model needs to capture the impact of changes in the collaborative arrangements, e.g. caused by disruption. In Chapter 3 we propose a model based on the science of complex networks that is capable to accomplish that. In particular, they develop a new multi-layer network model of transportation systems with vertical collaboration between carriers, who each operate their own proprietary network of transport services. In this system, carriers have the possibility to establish dyadic collaborations, enabling them to provide shared sequential transportation chains including transshipments. Transportation services and collaborations between carriers are represented in a network with two separate network layers. The collaboration layer comprises carriers as nodes and their dyadic collaborations as edges. The physical layer is defined by attributed edges representing transportation services associated with the operating carrier, and nodes representing transshipment points, e.g. ports or inland terminals.

Second, the dynamics of disruption at the collaborative level need to be captured, i.e. the mechanism of disruption propagation following an initial disruption in the collaboration layer. While the impact of disruption on transportation performance is derived from the multi-layer network model, the mechanism how disruption can propagate between collaborating carriers requires an additional modelling step. We model this propagation using methods from the field of epidemiology, which provides a wide range of models for spreading dynamics in networks. Specifically, we use an SIR (susceptible-infected-recovered) model (Newman, 2002), which is the most general epidemic model applicable to a wide range of epidemic dynamics including disruption propagation in collaboration and data exchange networks. For instance, Bagula et al. (2019) use an SIR model to model propagation of hazards, faults, and disturbances at the cyber level in IoT enabled networks.

Integrating the two modelling components, the multi-layer network model for collaborative transport and the SIR failure propagation model, we are able to conduct the desired analysis for arbitrary collaborative transport systems under variation of collaborative connectivity. Both models as well as the coupling between outcome of failure propagation and network performance are solved analytically for a class of probabilistic networks. Moreover, a mix of analytical and simulation-based methods

is used to derive results for collaborative transport network instances that better represent real-world systems as well as an actual real-world instance generated from data on intermodal transport services in Europe.

4.1.3 Contribution

Integrating the transportation-collaboration model introduced in Chapter 3 and an SIR model for failure propagation (Newman, 2002), we provide a model that allows for analysing the impact of collaboration in transportation systems with respect to both synergies and vulnerabilities. It is sophisticated enough to capture the complex performance outcome under a given transportation-collaboration scenario and adjusted for the risk of disruption propagation at the collaborative level. At the same time, it is simple enough to be applied to a large set of random network instances and allow for the systematic assessment of varying transportation and collaboration scenarios. Our model constitutes a useful tool to support decisions for potential partners to comprehensively evaluate the impact of their partnership, but also for policy makers to propose an optimal level of collaborative connectivity balancing synergies and vulnerability, or to identify preventive measures. The tool can easily be adjusted to solve related problems and will therefore be useful in future research.

We use our model to study the trade-off between synergies and vulnerabilities in transportation systems depending on collaborative connectivity. We show that an increase in the number of collaborations does not have a monotone positive effect on system performance any more, if performance is adjusted for the risk of disruption cascades. Instead, there is a connectivity threshold at which performance peaks. At very low connectivity, the number of neighbours susceptible to disruption propagation through an infected carrier is very low, leading to little risk of disruption turning into a cascade. Thus, increasing collaborative connectivity has a strongly positive effect through synergies. Around the connectivity threshold, system performance reaches a maximum, as most of the potential synergies are reaped, while the network is still sufficiently sparse to prevent cascades from disruption propagation. Beyond the threshold, failure cascades become larger and more likely while the marginal added synergies are diminishing, leading to a very quick decay back to the performance that is achieved without any collaboration. The more collaborations are centred among the largest carriers, the more synergies are realized already at low connectivity, but also propagation between them is facilitated, leading to a lower connectivity threshold.

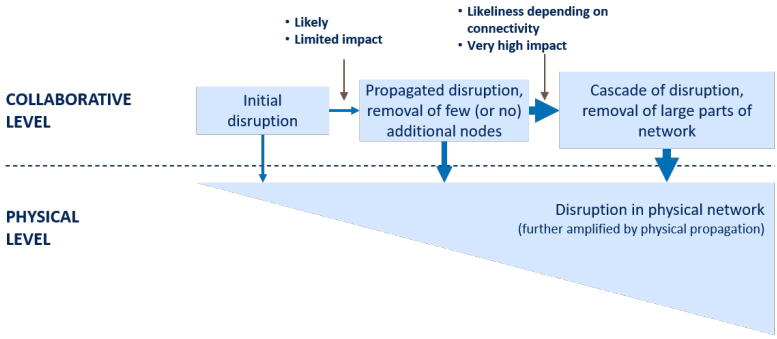


Figure 4.1: The figure shows the potential consequences of disruption at the collaborative level. Each disruption in the collaboration layer directly reduces the functionality of the physical layer. Moreover, disruption propagation in the collaboration layer can lead to further failures, impacting the physical layer additionally. With a certain probability, disruption propagation turns into a cascade disrupting large parts of the collaboration network, thereby annihilating all synergies of collaboration for the transportation network. Disruption in the physical network can further be amplified by propagation on the physical level such as congestion or delay propagation (not considered in this work).

Our findings support the claim that disruption in collaborative transport networks at the collaborative level is not necessarily an isolated event reducing the transportation functionality, but collaborations form a network, in which disruption can propagate and amplify the disruption at the physical level, see Figure 4.1. Given the 'infectiousness' of disruption at the collaborative level, the decision for establishing a collaboration cannot solely be based on the synergies, but the effect on the cascade risk through propagation needs to be carefully considered, especially in networks where large players tend to connect among themselves first.

4.1.4 Outline

The remainder of this paper is organized as follows. The subsequent section comprises a review of relevant literature on synergies and vulnerabilities of collaborative transportation as well as the role of cyber/data failure in cyber-physical systems. Section 4.3 is dedicated to the methodology. Section 4.4 comprises the results of the analysis, serving as a basis for the discussion in Section 4.5. Section 4.6 concludes and provides an outlook for future research.

4.2 Theoretical background

4.2.1 Collaborative transport

Research on collaborative transport is facing increasing popularity in recent years. The potential of vertical and horizontal collaborations between carriers to enable a more efficient use of existing transport resources and thereby contribute to more sustainable transport (Cruijssen et al., 2007b) is well understood (Pan et al., 2019). A large number of papers address the creation of synergies through collaborative planning, e.g. by maximizing fill rates (Cruijssen et al., 2007a), reducing empty runs (Adenso-Díaz et al., 2014; Ergun et al., 2007; Lin and Ng, 2012), finding optimal locations to foster participation of carriers Hernández et al. (2011), and optimize supply network pooling Pan et al. (2013). Potential synergies of collaborative planning in general are substantial, for instance w.r. to cost synergies (Adenso-Díaz et al., 2014; Cruijssen et al., 2007a), or carbon footprint reduction (Lin and Ng, 2012). These results generally describe the potential synergies of collaborative transport, whereas threats emerging from the increasing integration of players are less in focus. In fact, these collaborations do not come without complications. Besides the potential synergies, researchers have also studied conditions for establishing stable collaborations, e.g. the alignment of side payments in liner shipping (Agarwal and Ergun, 2010) or truck transportation (Özener et al., 2011), incentivisation schemes (Houghtalen et al., 2011), organizational readiness (Verstrepen et al., 2009; Zacharia et al., 2011), or the creation of trust (Pomponi et al., 2015). If collaborations are not set up the right way, they can be unstable and therefore prone to failure, e.g. in the case of overcapacity (Giudici et al., 2021). In general, stability depends on a trade-off between fostering carriers' participation in collaboration and making them take system-optimal decisions (Houghtalen et al., 2011)

4.2.2 Data and cyber threats

Data and cyber threats are an important issue in collaborative transport since collaborations usually come with agreements on exchanging information or even the integration of information systems. Technical failure or cyber attacks can lead to disruption of these interfaces and impact the system functionality (Kumar and van Dissel, 1996). Insufficient information infrastructure can greatly hamper collaboration, especially in systems with many SMEs, where information infrastructure investments are generally lower and the need for communication is disproportionately high (Cruijssen et al., 2007b). However, literature addressing the impact of cyber

disruption on transport systems is limited, despite cyber incidents affecting transportation infrastructure increasing in quantity and monetary impact (Tonn et al., 2019). Laszka et al. (2016) and Ezell et al. (2013) find that small attacks to critical traffic lights can cause heavy disruption across an entire road network. Moreover, Tam and Jones (2019) provide a framework to classify cyber threats and physical threats based on the presence of operational technology, information technology, and human factors.

A larger body of knowledge on cyber disruption is available for general cyber-physical systems. The general interdependency between cyber and physical level is reviewed in Rinaldi et al. (2001), Ouyang (2014), and Mohebbi et al. (2020), concluding that the state of one infrastructure system depends on information transmitted through the communication infrastructure. Axon et al. (2019) analyze cyber insurance claims to trace back the propagation of disruption at the physical level induced by cyber disruption, finding that disruption at the information level in cyber-physical systems does not only have a direct impact on the physical functionality, but cyber and data attacks can as well spread at the information level amplifying the overall impact. Wang et al. (2019) study the interplay between fault propagation in a physical (power) network and virus propagation in a communication network using an SIR model for virus propagation (Newman, 2002). They find that communication networks with scale-free structure are more vulnerable to virus propagation in cyber-physical systems. Bagula et al. (2019) also use SIR to model propagation of hazards, faults, and disturbances at the cyber level in IoT enabled networks and propose a surveillance approach to reconfigure the network after faults are observed. Liu et al. (2021) provide a measure related to closeness centrality to identify critical nodes in a cyber-physical system under spreading cyber attacks.

4.2.3 Synthesis

While research on vulnerability at the collaborative level in cyber-physical systems has gained traction in recent years, there is still a lack of knowledge in the context of collaborative transport, especially considering the risk of propagation and the consequences at collaborative and physical level. Not considering the propagation potential could lead to the illusion that more collaboration is always better, while missing the fact that higher collaborative connectivity facilitates failure propagation. In fact there can be an epidemic threshold describing the level of connectivity (or

transmission probability) at which initial failure leads to a cascade disrupting the entire network (Moore and Newman, 2000).

It seems reasonable to use similar methods from the science of complex networks used for general cyber-physical systems to study the issue. However, the interdependency between collaboration and transport layer is different from the typical power-communication setup, and therefore results from general cyber-physical systems do not directly apply (cf. Chapter 3). Propagation models need to be combined with transport-collaboration models to assess the impact of connectivity on synergies and vulnerabilities of collaborative integration, which is done by the present study.

4.3 Methodology

4.3.1 Modelling overview and assumptions

Our model to study the effect of collaboration on probability and impact of failure cascades at the collaborative level is based on the science of complex networks. This allows us to capture the interdependence between transportation and collaboration while allowing for the analysis of large sets of network populations to systematically derive the trade-off between synergies and vulnerability. Using more conventional optimization or agent-based methods, the multi-layer mapping between transportation and collaboration would be difficult to capture and computational effort to analyze large-scale networks would be large. A qualitative approach could be useful to understand the dynamics of collaborations and disruption better, but does not allows for a system-wide comparison of synergies and vulnerabilities.

We take a rather general and high-level perspective on collaborative transport. Operational details are omitted and performance is observed at system-level. The purpose is not to derive explicit action points for decision makers to reduce vulnerability, but to provide a general understanding of the trade-off between synergies and vulnerabilities that arise with increasing collaborative connectivity in transportation. Findings apply to a wide range of different decentrally operated transport networks, in which carriers can engage in collaboration. Our domain of application is intermodal transport in the seaport hinterland. Intermodal transport involves the flexible use of alternative transport modes train and barge, possibly resulting in transport chains involving multiple transport modes and carriers. Enabling such transport chains requires vertical collaboration between carriers. The aim of intermodal transport is to provide more flexible, resilient, and sustainable transport systems with little

need for truck transport. The core modelling step taken in our work comprises the integration of two existing network models; the multi-layer network model to map transport network and collaboration network introduced in Chapter 3, and a model for propagation of cyber/data disruption in a collaboration network (Newman, 2002).

4.3.1.1 Transportation-collaboration model

The transportation-collaboration model from Chapter 3 combines physical level and collaborative level of transportation systems in a multi-layer network model with a transport and a collaboration layer. See their paper for a detailed description of modeling collaborative transport and the associated assumptions. The physical level describes the network of physical transportation and transshipment services, and the carriers that operate these transportation services. The operators involved in the physical transshipment processes between consecutive transportation services in a transport chain are not included in the current model set-up. Disruption at the physical level comprises the unavailability of physical transport services, as a result of for instance low or high water levels, or (un)planned rail maintenance.

The collaborative level addresses activities beyond the physical movement of goods, which include non-physical coordination efforts and information exchanges between involved parties required to enable collaboration. Coordination efforts include, for instance, sharing of booking and planning information, redistribution of costs and benefits, tracking of deliveries, and error handling. In intermodal transport, coordination is necessary between a number of parties, especially truck, train, and barge carriers, as well as terminal operators. We define a collaboration between two carriers as a dyadic agreement between two carriers to provide a joint portfolio of transport routes built from shared transport services on consecutive network legs. Collaborations come at least with basic coordination efforts and information exchanges to ensure feasibility of transshipment, but can be more advanced. A basic collaboration could entail sharing of data on schedules and availability capacity on manual request as well as manual coordination of bookings and compensations between carriers. More advanced collaborations come with an interface enabling integrated booking of transportation services involving both carriers at either carrier's platform or even a shared interorganizational information system (van Baalen et al., 2008). These systems can include automated compensation schemes for service sharing and automated coordination of transshipment with terminal operators.

In the transportation-collaboration model, the physical level is formalized by a network of transport services (edges) and transshipment points (nodes). Each edge additionally contains information about the operating carrier of the associated transport service. The collaborative level and the concomitant coordination efforts are formalized through bilateral carrier collaborations mapped in a separate network layer consisting of carriers as nodes and collaborations as edges. By default, carriers can only offer routes using their own services, which limits the total available routes to those operated by a single carrier. However, if two carriers establish a collaboration, i.e. there is a link between them in the collaboration layer, paths formed in the transport network can include successive services operated by the two carriers connected through transshipments. Therefore, the set of bilateral collaborative arrangements determines the set of feasible routes in the transportation network. The more carriers are getting engaged in collaboration, the more synergies of integration emerge. Ultimately, the transport system becomes more efficient with flexible routing and shorter average transport times (Cardillo et al., 2013b). The multi-layer network model including the interdependence between transportation and collaboration layer is visualized in Figure 3.1. A technical description of the transportation-collaboration model and how it is evaluated with respect to the purposes of this study is provided in Subsection 4.3.2.1.

4.3.1.2 SIR model for propagation of disruption

The second component of our integrated model is the representation of vulnerability at the collaborative level. Vulnerabilities in the transportation-collaboration model are inevitably linked to the synergies that are created through collaboration, as these synergies are at risk. For instance, while coordinating intermodal transport chains, intermodal carriers depend on each other for the quality of exchanged information on service schedules, bookings, available capacities, transshipment plannings, and so on. If carriers fail to provide their partners and involved terminals with the required data or if the data is of poor quality, e.g. resulting from a cyber security breach or poor data management, transport chains performance deteriorates or even collapses. We formalize disruption by disruption event and disruption propagation. A disruption event describes an event happening to a carrier at the collaborative level, that leads to the loss of that carrier's ability to perform collaborative transportation. Disruption events are for instance cyber attacks. In the network model, a disruption event corresponds with the loss of all edges in the collaboration layer attached to the node associated with the disrupted carrier. According to the transportation-collaboration

interdependence, this leads to the set of feasible routes at the physical level being curtailed by routes that involve transshipment between the disrupted carrier and its collaboration partners. The disrupted carrier can however still offer routes that do not involve transshipment with other carriers. For the continuation of their own transport services, carriers are not fully dependent on their information systems or may have backup procedures for internal communication.

The analysis in Chapter 3 is considering isolated disruption events, whereas in this work we additionally take into account the probability of disruption propagation. Disruption propagation describes the case when a disruption event at one carrier triggers further disruption events at the carrier's collaboration partners, which is likely to happen in the case of cyber disruption such as ransomware attacks or false data injections (Wang et al., 2019). We model disruption propagation dynamics applying a discrete networked SIR (susceptible-infected-recovered) model (Newman, 2002), which features an initial infection size (share of nodes with disruption event) and a fixed probability that a disruption event propagates along a link in the collaboration network. SIR is commonly used to model the epidemic spread of infectious diseases, but it is also used for the modeling of other types of spreading entities such as failure in cyber-physical systems (Bagula et al., 2019; Wang et al., 2019) or delay propagation in transportation networks (Baspinar and Koyuncu, 2016). An assessment of the suitability of SIR in our context is provided in Appendix 4.A.

The original discrete SIR model additionally features a period of infection, which is a number of discrete time steps during which an infected node can transmit disruption to its neighbours before recovery. Since we are not considering a specific time frame, parameters of the SIR model are chosen such that disrupted nodes immediately recover after they are 'infectious' for a single time step. As a result, time steps in the original SIR correspond with stages of disruption in our context and recovery corresponds with the removal of disrupted nodes from the collaboration network. Instead of the spreading dynamics over time, our focus of interest is the total magnitude of disruption at the collaborative level and the resulting impact on performance at the physical level. Therefore, a marginal initial disruption event at the collaborative level, which represents a cyber incident at a single carrier, is simulated and the propagation process is observed until it ceases and the network is in a steady state. We assume that a random disruption will almost certainly happen at some point over a long time span and the impacts can be long-lasting. Decision makers should additionally assess how realistic a disruption at the collaborative level is in the first

place, before assessing the impact of it. If the risk of initial disruption is negligible, one could opt for higher connectivity than suggested by our model. Vulnerability of the given transportation-collaboration instance is obtained by measuring the damage made to the collaboration layer.

The propagation process can have two diametrically opposed outcomes. Depending on the transportation instance and the propagation parameters, the initial disruption event can either propagate very little or not at all, or it can cause a cascade disrupting large parts of the network. If there is no cascade, transportation performance after disruption is almost at the pre-disruption level. If there is a cascade, transportation performance drops massively, in the worst case down to a system without any collaboration and isolated provision of services by each carrier. The probability of a disruption turning into a cascade is crucial to the assessment of vulnerability at the collaborative level. Besides creating synergies in the form of shared transportation services, increased collaborative connectivity drives the cascade risk of disruption. By testing the vulnerability of a set of transportation-collaboration instances under variation of collaborative connectivity, we can identify the threshold connectivity at which transportation performance is maximized given the trade-off between synergies and vulnerability.

SIR can be evaluated in various ways, analytically and through simulation (Kiss et al., 2017). The appropriate approach to evaluate SIR is dependent on the selected instance of the transportation-collaboration model. In Section 4.3.2.2 we show the suitable combinations of SIR solver and transportation-collaboration instance for analyzing the synergy-vulnerability trade-off. Under certain conditions, the threshold connectivity can be derived analytically (see Section 4.3.3).

4.3.2 Model evaluation

4.3.2.1 Transportation-collaboration model: Instance generation and measurement

The generation of instances for the transportation-collaboration model is driven by two objectives. On the one hand, instances should be simple in order to be computationally tractable and ideally allow for an analytical evaluation approach. On the other hand, instances should be plausible and representative of real-world systems. In order to cope with these objectives, we present three different network classes for physical layers and three different network classes for collaboration layers. The different network classes come with different levels of analytical tractability and real-world

proximity. They are a mix of probabilistic network classes, which are not explicitly generated but only expressed by parameters, and simulation-based network classes, which are generated following a random graph process inducing the desired characteristics. In addition, a real-world network class generated from data on intermodal hinterland transport services by rail and barge in Europe is used. Using different combinations of transport and collaboration network classes, we are able to analytically establish general insights on the impact of collaborative connectivity on the risk of failure cascades while verifying the model and ensuring consistency of results in real-world systems. Populations of the probabilistic network class are referred to as probabilistic networks and populations of the simulation-based and real-world network class are referred to as realized networks.

We define a multi-layer network $G = (G^T, G^C)$ with a transportation layer $G^T = (V^T, E^T)$, a collaboration layer $G^C = (V^C, E^C)$, and a mapping of the interdependence between the layers, which allocates carriers (nodes) $c \in V^C$ in the collaboration network to the services $e = (v_1, v_2, c) \in E^T$ they operate in the transportation network. The size of the sets is denoted by $N^T = |V^T|$, $M^T = |E^T|$, $N^C = |V^C|$, and $M^C = |E^C|$.

The first definition (ER) of the physical layer is a probabilistic network class. The physical layer $G^T(N^T, p)$ is defined as an Erdos-Renyi network $G(N, p)$ with N nodes and a probability of p that an arbitrary edge exists. The activity of carriers in the physical network is described by a probability p_c^ξ for a carrier $c \in V^C$ to operate a service on an arbitrary transport edge.

The second definition (RGP) covers realized networks generated from a random graph process that induces the desired network characteristics. It is based on the simulation of scale-free random network instances using the Barabasi-Albert model (Barabasi and Albert, 1999). Scale-freeness is a general characteristic found across different types of real-world transport networks including air transport (Guimera et al., 2005) or public transport networks (Ferber et al., 2009). In the context of freight transport, the notion of scale-free networks is rather novel. The transport layer is defined as a composition of scale-free carrier networks with power-law degree distribution $P(k) \sim k^{-\delta}$. The $N^c \leq N^T$ nodes of these carrier networks are randomly matched with the N nodes of the full transportation layer such that it follows a power-law distribution $P(k^c)$ in terms of the number of times k^c a node from a carrier network is matched with a certain node in the full network, i.e. the number of distinct carriers that operate a service adjacent to that node. Under the assumption that the

degree distribution of the individual carrier networks is independent of $P(k^c)$, i.e. the carrier network degree of a node is not correlating with the number of distinct carriers operating from that node k^c, the actual degree distribution $P(k)$ of the full network is also approximately power-law distributed (Sun and Zhuge, 2011). See Figure 3.2 in Chapter 3 for a visualization.

For the two random network definitions we introduce the additional parameter b of the Zipf law $f(i,b,N^C) = \frac{\frac{1}{i^b}}{\sum_{j=1}^{N^C}\frac{1}{j^b}}$ describing the market structure in terms of disparity in carrier sizes, i.e. the distribution of services per carrier p_c^ξ. $f(i,b,N^C)$ describes the share of total services of the i-th largest carrier. $b = 0$ corresponds with a fully balanced carrier market structure, i.e. each carrier operates a share of $1/N^C$ of total services. Under $b = 1$, the largest carrier operates around 20% of all services and the largest 7 operate 50%. The third definition (IML) is based on a real-world network. We use the intermodal links data set[1] (IML) containing all intermodal services by rail and barge in the European hinterland for container transport in 2019.

The first definition (ER) of the collaboration layer again follows a probabilistic network class. Each possible collaboration link between the N^C carriers exists with probability p^κ, which corresponds with an Erdos-Renyi network $G^C(N^C, p^\kappa)$. With this definition, the structure of physical and collaboration layer are uncorrelated and therefore only the share of disrupted carriers is relevant, but not which carriers are disrupted. The second collaboration network class (PInd) is derived from the physical network. The first $M^C = p^\kappa \frac{N^C(N^C-1)}{2}$ edges are selected from the list of carrier pairs (potential edges) sorted by the number of adjacent services they have in the physical network. This leads to carriers' positioning in both layers being correlated, since large carriers with many transport services tend to have many touch points with other carriers, so they will exhibit a large degree in the collaboration layer. This mechanism follows the rationale that collaborations will first be established where they can generate the most synergies for the carriers and the system. A collaboration between carriers that have many adjacent services tends to be particularly useful.

The third collaboration layer definition (PIndDB) is also physical-induced, prioritizing collaborations between carriers with many adjacent services, but employs a degree balancing principle. It follows a process of allocating collaborations one-by-one by the number of adjacent services until the desired connectivity $M^C = p^\kappa \frac{N^C(N^C-1)}{2}$ is reached. Along this process, collaborations can only be established between carriers,

[1] Source: https://www.ecorys.com/netherlands/our-work/intermodal-links-disclose-your-own-hinterland-data (Date accessed: February 21, 2022)

whose current number of collaborations (degree) is smaller than the current maximum number of collaborations per carrier in the network. When at some point all carriers have equal degree, i.e. no more collaboration can be established given the degree restriction, the allowed maximum number of collaborations is increased by 1. Thereby, all carriers have about the same amount of collaborations at each level of connectivity, representing a scenario, in which collaborations are more exclusive between partners, i.e. complex to establish and subject to the carriers' other collaborations. The level of connectivity at the collaborative level can be manipulated by varying the main parameter p^{κ} describing the expected share of existing connections in the collaboration layer.

Performance of the system is measured using the 'Efficiency' measure $\phi^{eff}(G) = \frac{1}{N(N-1)} \frac{|\{i,j \in V^T, d(i,j) < \infty\}|}{\phi^{sp}(G)}$ defined in Chapter 3, which is inspired by the efficiency measure of Latora and Marchiori (2001). 'Efficiency' does not only capture average transport time between arbitrary node pairs, it also captures network coverage. Compared to the average shortest path measure $\phi^{sp}(G)$, which is not providing realistic results if a network has disconnected components, the efficiency score is discounted by the share of disconnected node pairs in order to capture the performance impact of disconnected network components. It is a good proxy to measure the level of achievement of collaborative transport goals, which are the creation of more feasible transport routes in order to connect more origins and destinations and to connect them through faster and more flexible services while achieving a higher utilization of existing transport infrastructure. Computing 'Efficiency' is not straightforward due to the multi-layer nature of the system. The links in the collaboration layer constrain the feasibility of transshipments in the transportation layer, which curtails the number of feasible transport routes and therefore needs to be taken into account when calculating shortest paths.

For realized networks of the simulation-based and real-world network class, a minor adjustment needs to be made to breadth first search (BFS) to compute $\phi^{eff}_{real}(G^T, G^C)$. Not only the nodes are stored per level, but also the carriers operating a feasible service to these nodes. In each step of BFS, transshipment feasibility needs to be assessed between the stored carriers and carriers operating on outgoing edges leading to not visited nodes. In probabilistic networks, however, 'Efficiency' cannot be computed in a deterministic manner as transport services, collaborations, and transshipment feasibility are probabilistic. Instead, we compute expected 'Efficiency' ϕ^{eff}_{prob}, which requires the adjustment of existing average shortest path approximations due

to paths being probabilistic. This is achieved by introducing a transshipment probability p^θ describing the feasibility of transshipment between two arbitrary adjacent edges. Efficiency is then calculated by

$$\phi^{eff}_{prob}(N^T, p, p^\theta) = \frac{(1 - F_\infty)}{\phi^{sp}_{prob}(N^T, p, p^\theta)}, \tag{4.1}$$

where $\phi^{sp}_{prob}(N^T, p, p^\theta) = \frac{\sum_{d=1}^{\infty} df_d}{\sum_{d=1}^{\infty} f_d}$. $f_d = F_{d-1} - F_d$ describes the probability that two arbitrary nodes are at distance exactly d from each other and is derived from the recursive equation $F_d = F_{d-1}(1 - pp^\theta)^{(N-1)(F_{d-2}-F_{d-1})}$ with $F_0 = 1$ and $F_1 = 1 - p$. F_∞ describes the probability that an arbitrary node pair is not connected by a transshipment-feasible path. The transshipment probability can be computed using the collaboration probability p^κ and the probability p^ξ_c that a carrier $c \in V^C$ operates a service on an arbitrary edge:

$$p^\theta = 1 - \prod_{\substack{c_q, c_r \in V^C \\ q \neq r}} \left(1 - p^\kappa p^\xi_{c_q} p^\xi_{c_r}\right) \prod_{\substack{c_q, c_r \in V^C \\ q = r}} \left(1 - (p^\xi_{c_q})^2\right). \tag{4.2}$$

See Chapter 3 for a full derivation.

4.3.2.2 Integration transportation-collaboration model with disruption propagation

In order to capture the impact of propagating disruption at the collaborative level, the transportation-collaboration network model needs to be coupled with a failure propagation model. We use a standard discrete networked SIR model (Newman, 2002) with initial infection probability $\rho = 1/N^C$ corresponding with an expected initial removal of a single random node, a fixed propagation rate τ, and a recovery rate $\gamma = 1$.

We use the notation Γ_i to describe the state of the collaboration layer after the i-th stage of disruption propagation (in literature mostly referred to as the i-th discrete time step) under a given collaborative connectivity p^κ. The corresponding 'Efficiency' is denoted by $\phi^{eff}(\Gamma_i, p^\kappa)$. More parameters are relevant to describe the input transportation-collaboration system $G = (G^T, G^C)$, but except from p^κ they are constant within each experiment and therefore omitted. The relevant stages of disruption are 'no disruption' $\phi^{eff}(\Gamma_0, p^\kappa)$ and 'final state after propagation ceases' $\phi^{eff}(\Gamma_\infty, p^\kappa)$.

$\phi^{eff}(\Gamma_0, p^\kappa)$ can be simply computed using BFS (realized networks) or equation (4.1) (probabilistic networks), since Γ_0 describes the undisrupted collaboration layer. Computing $\phi^{eff}(\Gamma_\infty, p^\kappa)$, however, requires the evaluation of SIR. Many variations of the SIR model can be solved analytically or numerically using differential equations (Kiss et al., 2017; Newman, 2002). In the present context, the choice of SIR model variant depends on the suitability with the transportation-collaboration setup.

The setups with probabilistic (ER) collaboration network $G^C(N^C, p^\kappa)$ can best be treated with the discrete EBCM approach (edge-based compartment model, see system (6.10) in (Kiss et al., 2017)). EBCM employs a Markovian modelling approach to analytically approximate the expected final epidemic size of an outbreak for configuration model networks, i.e. networks with arbitrary degree distributions but no degree correlation (Newman, 2010). Exploiting the approximate independence between the statuses of neighbouring nodes in large networks, the share of eventually disrupted nodes can be approximated by the probability that a randomly selected node v gets disrupted by an initially disrupted node u following a disruption chain $u - v$ of length d. The aggregated expected share of disrupted nodes $\Gamma_\infty \in [0, 1]$ provided by EBCM is sufficient to calculate the resulting 'Efficiency' score ϕ^{eff}. If the transport layer is (ER), $\phi^{eff}_{prob}(N^T, p, p^\theta)$ is computed by incorporating failed collaborations into the transshipment probability p^θ and plugging it into Equation (4.1). Therefore, collaboration probability p^κ in Equation (4.2) needs to be adjusted by the probability $(1 - \Gamma_\infty)^2$ that none of the two carriers has faced disruption, i.e. their collaboration is still in place.

$$p^\theta = 1 - \prod_{\substack{c_q, c_r \in V^C \\ q \neq r}} \left(1 - (p^\kappa (1 - \Gamma_\infty)^2) p^\xi_{c_q} p^\xi_{c_r}\right) \prod_{\substack{c_q, c_r \in V^C \\ q = r}} \left(1 - (p^\xi_{c_q})^2\right). \tag{4.3}$$

If the transport layer is realized (IML, RGP), random realizations of disrupted carriers in the collaboration layer G^C are generated using Γ_∞ and the resulting 'Efficiency' $\phi^{eff}_{real}(G^T, G^C)$ is computed. EBCM is simple and accurate, but more importantly, the coupling between failure propagation at the collaborative level and physical impact is feasible.

If the transport network is realized from a random graph process or data (RGP, IML), and the collaboration network is physical-induced (PInd, PIndDB), feasible coupling between the models is a bit more difficult. Due to the correlation between carriers'

	Physical network	Collaboration network	Performance measurement (computation of 'Efficiency')	SIR model	Integration of transportation-collaboration instance and SIR model
ER-ER	Probabilistic (Erdos-Renyi)	Probabilistic (Erdos-Renyi)	Expected 'Efficiency' based on Equations (4.3) and (4.1)	EBCM	Fully analytical: EBCM output (probability of disruption for arbitrary node) can directly be plugged in Eq. (4.3)
RGP-ER	Random graph process (composed scale-free)	Probabilistic (Erdos-Renyi)	Breadth-first search with transshipment feasibility check (backtracing of operating carriers)	EBCM	Mixed analytical-simulation: EBCM output is used to generate random realizations of failed nodes, 'Efficiency' is computed for each realization, and average of results is taken
RGP-PInd/ PIndDB	Random graph process (composed scale-free)	Induced from physical network (adjacent services/ degree balancing)	BFS with transshipment feasibility check	Individual-based	Mixed analytical-simulation: Same as RGP-ER, but random realizations of failed nodes are generated using the weights per node provided by individual-based output.
IML-ER	From data (Intermodal Links)	Probabilistic (Erdos-Renyi)	BFS with transshipment feasibility check	EBCM	Mixed analytical-simulation: Same as RGP-ER
IML-PInd	From data (Intermodal Links)	Induced from physical network (adjacent services)	BFS with transshipment feasibility check	Individual-based	Mixed analytical-simulation: Same as RGP-PInd

Table 4.1: Overview of the different transportation-collaboration instances considered in this work and how they are analyzed regarding the impact of disruption at the collaborative level. Each row describes a transportation-collaboration instance including the two network layers, the corresponding performance measurement approach, the appropriate SIR disruption propagation model, and a description of how the outcome of the SIR model serves as an input for performance measurement. For details regarding physical network instances and performance measurement, see Chapter 3. For details regarding SIR see Kiss et al. (2017)

positioning in the physical and in the collaboration layer, carriers differ in their criticality for the system and it matters which carriers are affected by the propagation, which means that the outcome of the propagation model cannot be an aggregate failure rate, but needs to be reported per carrier. The individual-based approach in (Kiss et al., 2017), system (3.30), satisfies this requirement. It describes the propagation dynamics in the system at each stage of disruption through a set of differential equations with the initially disrupted nodes as initial condition. We apply closure at the level of pairs, i.e. propagation dynamics in triples, quadruples and beyond are only approximated in order to get an analytically tractable system. Solving this system yields an array of disruption probabilities $\Gamma_\infty(c)$ with $\Gamma_\infty = \frac{1}{N^C}\sum_{c\in V^C}\Gamma_\infty(c)$, which can be used to compute disrupted instances of the collaboration layer G^C and the resulting 'Efficiency' $\phi^{eff}_{real}(G^T, G^C)$.

The explanations above are summarized in Table 4.1. It shows the different combinations of transportation (ER, RGP, IML) and collaboration (ER, PInd, PIndDB) layer definitions as well as the corresponding SIR model and performance evaluation. Implementations of the SIR model variants used are provided by the Python package (EoN) accompanying (Kiss et al., 2017).

It is important to mention that the SIR models we use provide the expected outcome (share of disrupted nodes) conditional to the marginal initial disruption turning into a cascade. However, in case of a sufficiently small initial attack, low transmission rate, or low network connectivity, there is a significant chance that (almost) no propagation

takes place. Ignoring the no-cascade scenario could lead to an overestimation of vulnerability. Therefore, we want to compute a synthesized expected outcome taking into account the binary random variable describing the risk of a cascade happening. The parameter of this binary variable is called epidemic probability p^{ϵ} and can be determined depending on the propagation probability τ and the degree distribution using system (6.2) in (Kiss et al., 2017). In an Erdos-Renyi collaboration network, the degree distribution is purely defined by the average degree $(N^C-1)p^{\kappa}$. The aggregate outcome is a convex combination of 'no disruption' and 'disruption including cascade' system performance with parameter ϵ.

$$\phi_{agg}^{eff}(\Gamma_{\infty}, p^{\kappa}, p^{\epsilon}) = (1-p^{\epsilon})\phi^{eff}(\Gamma_0, p^{\kappa}) + p^{\epsilon}\phi^{eff}(\Gamma_{\infty}, p^{\kappa}) \tag{4.4}$$

and serves as an additional indicator of vulnerability in addition to the outcome with assumed cascade $\phi^{eff}(\Gamma_{\infty}, p^{\kappa})$.

4.3.3 Analytical derivation of threshold connectivity in ER collaboration networks

The threshold connectivity $p^{\kappa *}$, which maximizes the expected outcome $\phi_{agg}^{eff}(\Gamma_{\infty}, p^{\kappa}, p^{\epsilon})$ under disruption to a random marginal fraction of the collaborative network, can be derived analytically for instances with ER collaboration network using the reproduction number $\mathcal{R}_0$. $\mathcal{R}_0$, a well known indicator for the spread of epidemic diseases, describes the infection behaviour of a typical infected node early in the epidemic with most of the population still susceptible, i.e. how many new infections are expected to be caused by that node. If $\mathcal{R}_0 > 1$, it is likely that initial infections turn into an epidemic (Kiss et al., 2017). See Appendix 4.B for a derivation of $\mathcal{R}_0$ in probabilistic network classes that are based on the configuration model. In ER collaboration networks, every node has the same expected degree, and $\mathcal{R}_0$ can simply be calculated from the expected transmissions: $\mathcal{R}_0 = (N^C - 1)p^{\kappa}\tau$.

The expected performance of a collaborative transport system under a marginal random attack is maximized, if collaborative connectivity is as high as possible to create maximum synergies, but sufficiently low in order to have very little risk of a disruption cascade. This condition is satisfied if the reproduction number $\mathcal{R}_0 = 1$, which is the case if

$$p^{\kappa *} = \frac{1}{(N^C - 1)\tau}. \tag{4.5}$$

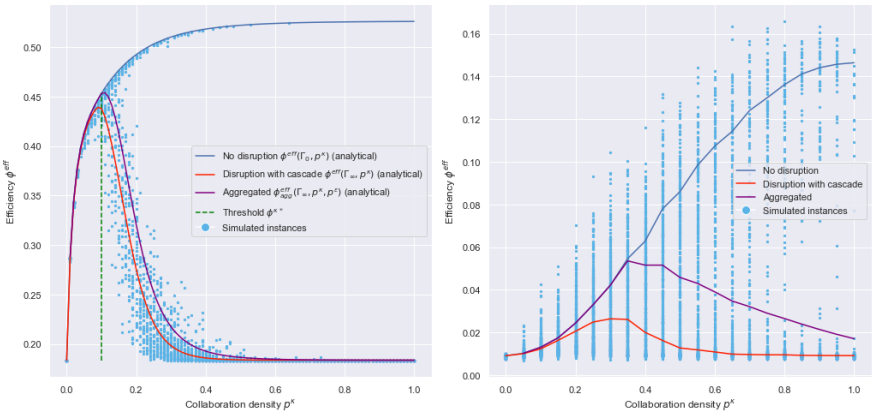
The threshold $p^{\kappa *}$ is purely defined by the number of edges and the transmission rate. Thus, if the collaboration network is ER, the structure of the physical layer only has an impact on the actual performance level, but not on the threshold itself. However, if the collaboration network is induced from the physical layer (PInd), the degrees are correlated and the physical layer can indeed have an impact on the threshold $p^{\kappa *}$.

4.4 Results

The results section is divided in three parts. First, the general trade-off between synergies and vulnerability as well as the existence of a connectivity threshold is analyzed using the analytical (ER-ER) network instances and verified by the (RGP-ER) instance with more realistic transportation networks. Second, the impact of certain network characteristics and model parameters on the threshold level and the overall trade-off are analyzed. Isolated variation of single characteristics is achieved by analytical means, whereas combined variation of multiple characteristics is done using network simulations (RGP). Third, the trade-off is tested on a real-life collaborative transport system. In each instance, the impact of a disruption and potential cascade of failure in the collaboration network on the system performance ϕ^{eff} are observed under varying collaborative connectivity p^{κ}, which is the realized share of all potential collaborations between all carriers.

4.4.1 Synergy-vulnerability trade-off and connectivity threshold

The (ER-ER) instance is analytically tractable and therefore does not require any simulations. The analytical computation produces the expected 'Efficiency' for a realization from a fully probabilistic transportation-collaboration instance. Figure 4.2 (a) visualizes the results for (ER-ER) for a system with an ER physical network $G^T(1000, 0.1)$, an ER collaboration network $G^C(100, p^{\kappa})$, and a somewhat disparate market structure of carriers ($b = 0.5$), i.e. there are a few larger and many intermediate and small carriers in terms of expected services operated. Propagation is computed by solving the discrete SIR model (EBCM) for an initial infection probability



(a) (ER-ER) **(b)** (RGP-ER)

Figure 4.2: The figures show efficiency of two different collaborative transport systems (carrier size distribution $b = 0.5$) under disruption at the collaborative level for varying collaboration network density p^{κ}. The blue line shows efficiency without disruption, the red line shows efficiency with disruption ($\tau = 0.1$) given that a cascade is triggered, and the purple line shows the aggregated outcome weighted by the epidemic probability p^{ϵ}. The vertical green line indicates the threshold connectivity $p^{\kappa *}$. Blue dots show the results of a Monte Carlo simulation with the same parameters. The average of simulation instances corresponds with the purple line. (a) Probabilistic networks: System with probabilistic Erdos-Renyi physical $G^{T}(1000, 0.1)$ and collaboration $G^{C}(100, p^{\kappa})$ layers. (b) Simulated networks: Average of 15 realized (composed scale-free) physical network instances. The collaboration layer with 30 carriers is described by an Erdos-Renyi network $G^{C}(30, p^{\kappa})$.

$\rho = 1/N^C$ and fixed propagation rate $\tau = 0.1$. The analytical result is complemented by a Monte-Carlo simulation with the same parameters (blue dots). Instances of the Monte-Carlo simulation reveal the binary nature of the cascade threat by either corresponding with the no cascade line (blue) or the cascade line (red), whereas the average of instances at each level of p^κ corresponds with the aggregated result ϕ_{agg}^{eff} (purple line).

The results show the hypothesized trade-off between system performance and vulnerability for varying collaboration connectivity. Increasing the number of collaborations initially leads to a steep increase of system functionality as low connectivity hinders propagation and consequently disruption at the collaborative level has very little impact. If carriers only have few partners, they are less likely to be affected by disruption caused by a partner. If no disruption takes place (blue line), increasing collaboration connectivity has only a positive effect on performance, since more collaborations lead to more transshipments and more paths being feasible in the physical network, which ultimately lowers the average distance between destinations. The disruption-affected performance lines (red and purple line), however, do not increase monotonously. The aggregated performance (purple line) reaches a maximum at a density of $p^\kappa = 0.101$, then falls steeply to its lowest level beyond $p^\kappa > 0.4$, indicating that all collaborations will be lost if such highly connected networks experience disruption.

The range with intermediate connectivity $p^\kappa \in [0.05, 0.3]$ is particularly interesting since there is a trade-off between additional benefits in the physical network and higher risk of failure in the collaboration network. At $p^{\kappa *} = 0.101$, sufficient collaborations are in place to reap most of the potential synergies given by the physical network, while the collaboration network is sparse enough that cascades are unlikely or only disrupt a small part of the collaboration network. In epidemic terms, this means that the reproduction rate $\mathcal{R}_0 = 1$, indicating that a typical node infected early in the propagation process infects exactly one other node on average. Under normal circumstances, this is not sufficient for a cascade. The more p^κ is increased from there, the lower the marginal added synergies and the higher the reproduction rate $\mathcal{R}_0 > 1$. Both the chance that a cascade happens as well as the impact are rapidly increasing at $p^\kappa > p^{\kappa *}$. Nevertheless, up until $p^\kappa = 0.3$, which corresponds with a reproduction rate of $\mathcal{R}_0 = 2.97$, there is still a significant chance ($p^\epsilon = 0.06$ at $p^\kappa = 0.3$) that an initial disruption ceases quickly and does not trigger a cascade, which is confirmed by the Monte-Carlo simulation. Collaboration connectivity higher

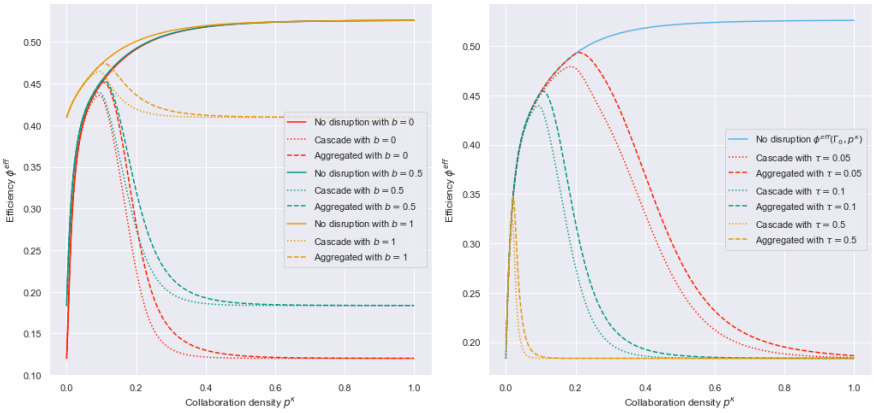
than the maximum shown here can be optimal for systems, in which disruption at the collaborative level is very unlikely in the first place.

Results with realized network instances verify the finding that increasing collaboration density comes with a trade-off between synergies and vulnerabilities, as Figure 4.2 (b) shows efficiency curves similar to those found in the probabilistic instance. The connectivity threshold in the (b) panel ($p^{\kappa *} = 0.34$) is much higher than in the (a) panel ($p^{\kappa *} = 0.101$) due to the lower number of carriers (cf. Eq. (4.5)). The main difference lies in the creation of synergies. In contrast to the probabilistic setup (ER-ER), which has the highest marginal efficiency increase at $p^{\kappa} = 0$ and exhibits declining increase from there on, efficiency for realized networks and ER collaboration layer (RGP-ER) grows in a logistic fashion with slow increase at low p^{κ}, high increase at intermediate p^{κ}, and ultimately converging against an upper bound at $p^{\kappa} = 1$. The difference in synergy creation lies in the random allocation of collaborations (ER). Random allocation is a solid strategy in case the physical network is also fully random (ER-ER), since every collaboration is useful. If the physical network resembles a real-world network (RGP-ER), the first few randomly allocated collaborations are unlikely to be useful since carriers might be operating in different regions of the network.

4.4.2 Influence of network characteristics and model parameters on trade-off

After showing the existence of a general synergy-vulnerability trade-off as well as a connectivity threshold, we are now assessing how structural network features can lead to a deviation from the baseline outcome in the previous subsection. Therefore, the role of market structure b, propagation probability τ, and collaboration layer structure are analyzed.

The former two can be analyzed by analytical means in the (ER-ER) setup. Changing the collaboration layer structure, however, is more complicated since non-ER collaboration layer structures introduce layer correlation, which cannot be captured analytically. Therefore, we first conduct a sensitivity analysis of market structure and propagation probability in the (ER-ER) setup followed by a simulation-based analysis including PInd and PIndDB collaboration layers as well as combinations of the three characteristics.



(a) Variation of b **(b)** Variation of τ

Figure 4.3: The figures show the efficiency ϕ^{eff} for the same network setup as in Fig. 4.2, but with (a) different market structures $b \in \{0, 0.5, 1\}$ and (b) different failure propagation probabilities $\tau \in \{0.05, 0.1, 0.5\}$. The permanent lines shows efficiency without disruption, the dotted lines show efficiency with disruption given that a cascade is triggered, and the dashed lines show the aggregated outcome weighted by the epidemic probability p^{ϵ}.

4.4.2.1 Carrier market structure and propagation probability

Carrier market structure (choice of b) and propagation probability (choice of τ) can be evaluated in an isolated fashion using the fully analytical (ER-ER) instance. Having an ER collaboration layer leads to a decoupling between physical and collaboration layer in the sense that the probability of existence of a collaboration link is in no way influenced by the physical layer structure. As a result, the impact of variation of model parameters can directly be traced back to the originating layer.

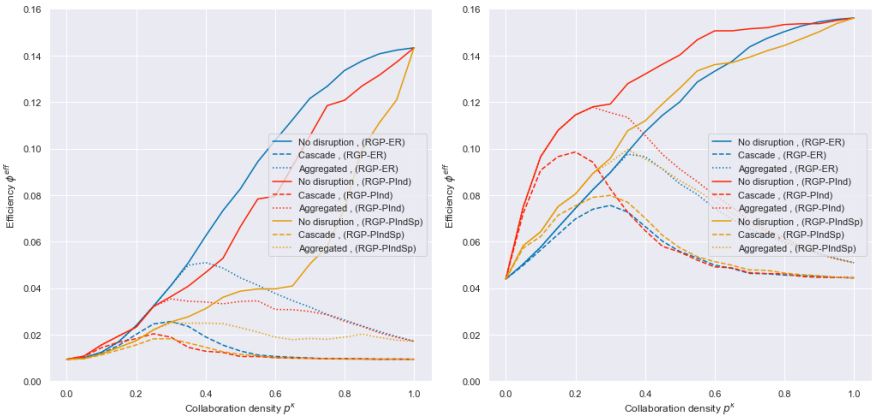
Market structure (choice of b) has a large impact on the functionality of the system in general, as shown by the difference in performance between balanced (b = 0, red line) and disparate (b = 1, yellow line) market structure at p^{κ} = 0 in Fig. 4.3 (a). It influences the criticality of carriers and a system's overall synergy potential through collaboration. The more balanced, the more synergies can be created through collaboration (Cruijssen et al., 2007a; Harter et al., 2022), leading to a higher overall performance increase as collaborations are established. However, since these criticalities do not correlate with the collaboration constellation in this instance, the reproduction rate $\mathcal{R}_0$ is not affected and therefore market structure has no impact on the connectivity threshold and the performance-vulnerability trade-off. In contrast, variation of propagation probability τ only has an impact in the collaboration

layer, influencing the cascade risk and thereby leading to a shift of threshold $p^{\kappa *}$, but is not influenced by the physical network structure. Figure 4.3 (b) shows the synergy-vulnerability trade-off for different propagation probabilities τ, revealing the expected outcome. The higher τ, the lower the connectivity level p^{κ} at which the reproduction rate $\mathcal{R}_0 = 1$ (cf. Eq. (4.B.4)) and cascade vulnerability outweighs the synergies gained through collaboration.

4.4.2.2 Correlation layer structure and combined effects

It is reasonable to assume that in most collaborative transport systems, carriers will establish their partnerships based on their potential benefit given the positioning of services in the physical layer, creating a non-random collaboration layer structure that correlates with the positioning of carriers' services in the physical layer. This can not only have an impact on the trade-off by itself, but can also moderate the effect of market structure and propagation probability. Changes to these variables now indirectly affect both layers, making it more difficult to predict the outcome. Layer correlation cannot be captured by our analytical approach, hence we resort to simulation-based analysis with networks realized from a random graph process. We show systematically the role of collaboration layer structure induced by layer correlation on the trade-off including the combined effects with market structure and propagation probability.

Figures 4.4 and 4.5 show the impact of the three alternative collaboration layer structures ER, PInd, and PIndDB under different market structure and propagation probability setups. We expect that prioritization of collaboration links between carriers with many adjacent services (PInd) will lead to a steeper synergy increase at low p^{κ} compared to random allocation, i.e. more synergies can be realized with the same amount of collaboration links. Moreover, the number of adjacent services is expected to be strongly correlated with the size of the two carriers in terms of number of services operated. As a result, the PInd mechanism tends to connect large carriers first, leading to a high concentration of collaboration links among these carriers, whereas the rest of the collaboration network is sparser compared to a random network. High connectivity within this 'rich-club' causes a higher reproduction rate $\mathcal{R}_0$ in the respective subnetwork, which facilitates failure cascades and leads to a shift of the connectivity threshold to the left, $p^{\kappa *}_{PInd} < p^{\kappa *}_{ER}$. The physical-induced collaboration layer with degree balancing PIndDB is based on the rationale to establish correlations in a synergy-creating way while avoiding the creation of highly connected clusters, i.e. combine the synergy creation from PInd and the cascade

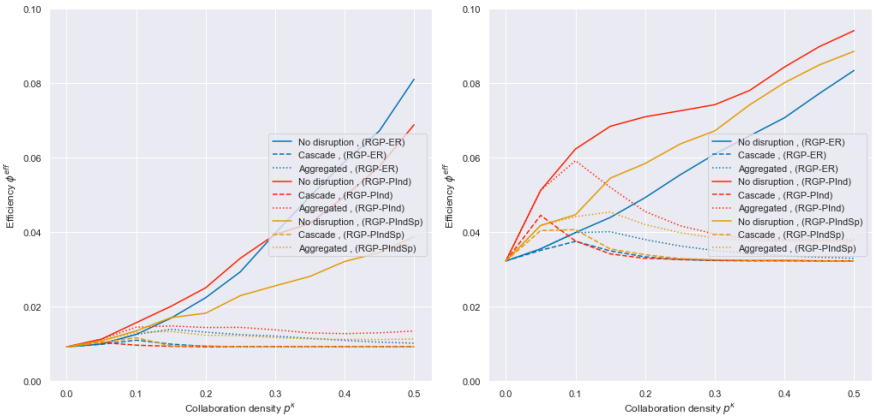


(a) $\tau = 0.1$, $b = 0.0$ **(b)** $\tau = 0.1$, $b = 1.0$

Figure 4.4: The figure shows the average efficiency ϕ^{eff} of 15 realized (composed scale-free) physical network instances under disruption at the collaborative level for varying collaboration network density p^{κ} and propagation probability $\tau = 0.1$. Market structure comes in a fully balanced setup with $b = 0$ (a), and a disparate setup with $b = 1$ (b). Different collaboration layer structures with 30 carriers are compared: an uncorrelated Erdos-Renyi network $G^{C}(30, p^{\kappa})$ (ER, blue), collaborations derived from the physical network based on the number of transshipments (PInd, red), and the same transshipment based structure with degree balancing (PIndDB, yellow). The permanent lines show efficiency without disruption, the dashed lines show efficiency with disruption ($\tau = 0.1$) given that a cascade is triggered, and the dotted lines show the aggregated outcome weighted by the epidemic probability p^{ϵ}. Blue dots show the results of simulations. The average of simulation instances corresponds with the purple line.

resilience from the random allocation. This should lead to an intermediate result with synergy realization slightly below PInd, but connectivity threshold at the level of ER.

These hypothesized outcomes are confirmed in the instance with disparate market structure ($b = 1$) and low propagation probability ($\tau = 0.1$), see 4.4 (b). Under balanced market structure, however, neither can PInd realize significantly more synergies nor is PIndDB resilient against cascades. In fact, random allocation of collaborations exhibits better performance at almost every level of connectivity and both with and without disruption. If all carriers are the same size, there is little potential to strategically select collaboration links, which eliminates the benefits of PInd. At the same time, PInd still leads to concentration of collaboration links, resulting in a sort of cannibalization of synergies. Random selection of collaboration links leads to a balanced



(a) $\tau = 0.3$, $b = 0.0$ **(b)** $\tau = 0.3$, $b = 1.0$

Figure 4.5: The figure shows the same as Figure 4.4. but with a propagation probability $\tau = 0.3$

constellation of correlation links such that synergies are realized in a complementary way.

Results with high propagation probability ($\tau = 0.3$) are shown in Figure 4.5 (p^{κ} only in range $[0, 0.5]$ for better visibility). Higher propagation probability leads to a lower connectivity threshold and lower peak performance under disruption as shown in the isolated analysis. Especially under balanced market structure, synergies through collaboration are vitiated through a high cascade risk before they are even really noticeable. Otherwise, interaction effects with collaboration layer and market structure are limited. See Fig. 4.6 for an overview of the interaction between the effects of collaboration layer structure on vulnerability to failure cascades under varying market structure and propagation probability.

4.4.3 Application to intermodal links data set

Using a real-world data set of intermodal transport services by rail and barge in Europe yields the same trade-off as in the analytical and simulation-based approaches, see Figure 4.7 and 4.8. The main difference is that the randomly generated collaboration network (IML-ER) is now less efficient in every aspect, facing high risk of cascades already at very low connectivity. (IML-PInd) in turn creates high synergies already at a low level and is relatively robust to variation of connectivity in the range of $p^{\kappa} = [0.05, 0.25]$. The reason lies in the specific characteristics of the intermodal

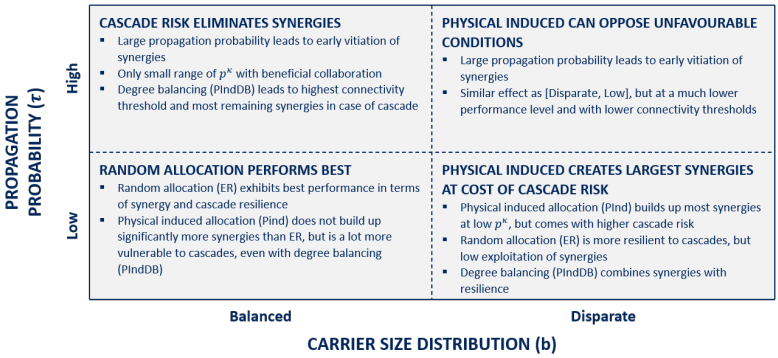
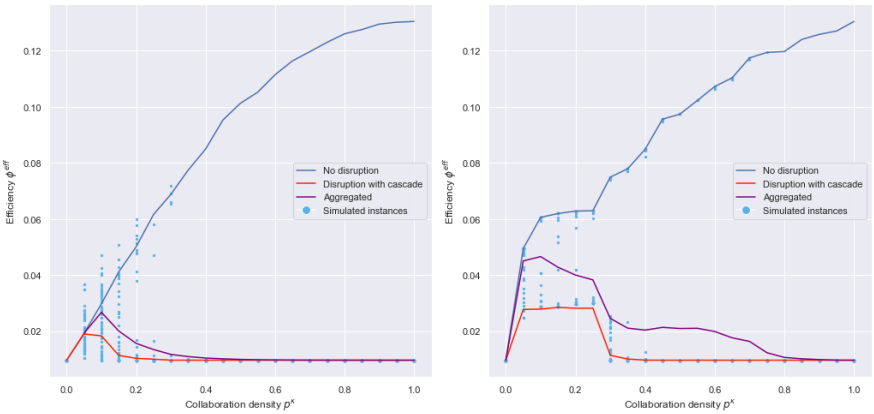


Figure 4.6: Overview of effect of collaboration layer structure on vulnerability to failure cascades under varying model parameters market structure (b) and propagation probability (τ)

links network. The network has a heterogeneous market structure with a small number of large carriers and many small ones, which leads to a steep synergy increase at low p^{κ} similar to the previous instances. At the same time, many carriers have a different regional focus, covering the network regions in a complementary way, and avoiding the creation of a highly connected subnetwork of collaborations. The second group of carriers getting collaboration links at medium p^{κ} are connectors between the large carriers, not contributing much to shorter average transport times, but providing alternative services in case the collaboration between the largest carriers fails. Thereby, performance under disruption can be uphold at the threshold peak level despite increasing cascade risk. Beyond $p^{\kappa} = 0.3$, the difference to a random collaboration network converges to 0. The IML network seems to have favourable conditions over the random and simulation based network classes, which could for instance be the outcome of a Darwinistic process, in which resilient features emerge over time as they are able to respond better to disruption.

4.5 Discussion

While the potential synergies of collaboration between carriers in transport networks are extensively studied (Cruijssen et al., 2007b; Pan et al., 2019), this research puts synergies into perspective with the threat of adverse impact through disruption cascades at the collaborative level. A decent number of papers look at conditions for establishing collaborations and their stability, e.g. commercial arrangements (Agarwal and Ergun, 2010; Houghtalen et al., 2011; Özener et al., 2011), organizational



(a) (IML-ER) **(b)** (IML-PInd)

Figure 4.7: The figure shows the average efficiency ϕ^{eff} of the European network of intermodal hinterland transport services under disruption at the collaborative level for varying collaboration network density p^{κ}. The collaboration layer with 117 carriers is described by (a) an Erdos-Renyi network $G^{C}(117, p^{\kappa})$ and (b) a network derived from the number of adjacent services in the physical network (physical-induced). The blue line shows efficiency without disruption, the red line shows efficiency with disruption ($\tau = 0.1$) given that a cascade is triggered, and the purple line shows the aggregated outcome weighted by the epidemic probability p^{ϵ}. Blue dots show the results of simulations. The average of simulation instances corresponds with the purple line

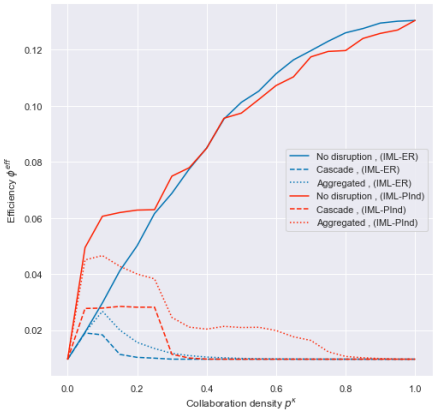


Figure 4.8: For the same network setup as in Fig. 4.7, the present figure shows a comparison of efficiency ϕ^{eff} under disruption at the collaborative level for an Erdos-Renyi collaboration layer (blue lines) and a physical-induced collaboration layer (red lines). The solid lines shows efficiency without disruption, the dashed lines show efficiency with disruption given that a cascade is triggered, and the dotted lines show the aggregated outcome weighted by the epidemic probability p^{ϵ}.

issues (Audy et al., 2012; Verstrepen et al., 2009; Zacharia et al., 2011), the creation of trust (Pomponi et al., 2015), or instability through overcapacity (Giudici et al., 2021), but only in Chapter 3 of this work we made a first attempt at studying the system impact of disruption at the collaborative level under varying carrier market structure. Nevertheless, knowledge on the dynamics of disruption at the collaborative level and the concomitant amplification of the system impact as shown in Figure 4.1 is limited. Disruption at the collaborative level is not necessarily an isolated event reducing the transportation functionality, but collaborations form a network, in which disruption can propagate and amplify the disruption at the physical level. Only in the related field of cyber-physical systems, the relationship between connectivity and vulnerability is studied at the non-collaborative example of power-communication coupled systems (Korkali et al., 2017; Schneider et al., 2013). Following the hypothesis that high levels of collaboration facilitate the emergence of disruption cascades at the collaborative level, which beyond a certain level can outweigh the synergies of collaboration, this research constitutes a crucial step towards filling this gap.

The attempt to reach the research objective is made through coupling two existing models for collaborative transport (Chapter 3) and epidemic spreading in networks (Newman, 2002) in order to capture the system impact of disruption propagation at the collaborative level under varying connectivity. The coupled model can handle a

probabilistic network class suitable to derive analytical results and establish a general relationship, but it is also capable of handling arbitrary realized network instances generated through a random graph process or from data. Moreover, with moderate adjustment it can be used for related problems in the field of cyber-physical systems with propagation risk at the cyber level and decentrally managed flow at the physical level.

Our research finds that the level of collaborative connectivity creates a trade-off between synergies of collaboration and vulnerabilities through disruption cascades. Maximum system functionality under disruption is reached at a connectivity threshold, when a large share of potential synergies is reaped while cascade risk is still low. Very low connectivity and very high connectivity lead to poor outcomes due to low synergies in the former case and high cascade risk combined with decreasing marginal added synergies in the latter. If large carriers are more likely to establish a collaboration among themselves, cascades are facilitated and the connectivity threshold is lower. Despite connectivity being a key driver, the disruption propagation following a random disruption at the collaborative level is still a random outcome, i.e. there is a chance that no or almost no propagation takes place. With increasing connectivity, this chance becomes negligible. However, since synergies through collaborations are realized in any case while disruption cascades are subject to an initial disruption, systems in which initial disruption is unlikely to happen in the first place can afford higher connectivity for the sake of more synergies.

The findings of this research are an important complement to the existing knowledge on the synergies and vulnerabilities induced by collaborative integration in collaborative transport networks, but also in cyber-physical systems in general. Our findings on the impact of the density of collaboration networks on their vulnerability to disruption spreading complement Wang et al. (2019) and Liu et al. (2021), who focus on the impact of network structure and the criticality of single nodes on epidemic spreading, respectively. For a full assessment of vulnerability at the collaborative level, both structure and connectivity need to be assessed. Being a multi-layer system, only looking at the collaboration layer is not sufficient. Exploring the moderating role of carrier market structure in the physical network represented by the distribution of carrier sizes, Chapter 3 contributes to an even more comprehensive understanding. Cardillo et al. (2013b) find that increasing collaborative transport contributes to the robustness of transportation at the physical level due to more flexibility in case of disruption of services. While this is undisputed and also captured by the synergies

in our model, collaborative connectivity also leads to a higher vulnerability at the collaborative level, which in turn creates vulnerability against physical disruption, and therefore needs to be considered for decisions on the collaborative constellation.

The stability of collaborations is addressed by Giudici et al. (2021) and Houghtalen et al. (2011), who find that instability can result from overcapacity and commercial misalignment, respectively. In fact, our work shows that stability is not only a bilateral thing, but also subject to the stability of adjacent collaborations, which should be taken into account to enrich the assessment of collaboration stability. Last but not least, Cruijssen et al. (2007b) find that collaboration can be compromised by insufficient information infrastructure, which is particularly often the case in systems with many SMEs. On the one hand, systems with many small actors usually have a relatively sparse collaboration network, which relieves the high risk of disruption and propagation due to poor information infrastructure to some extent. On the other hand, the need for communication and the potential synergies in such systems is very high (Harter et al., 2022), which will lead to the establishment of more collaborations. If infrastructure investments are not increased accordingly, high connectivity and high propagation rate can lead to exceptionally high vulnerability. In fact, even if an individual node is well protected, a single disrupted carrier somewhere else in the network can lead to the disruption of the entire collaborative system. Carriers therefore have a mutual responsibility to ensure cyber security.

Due to the increasing relevance of the results and the general applicability of the developed model, promising directions for future research building up on this work are plenty. A very important step would be to gather empirical backup for the calibration of the model, in particular the disruption propagation, and to do real-world case-studies in order to substantiate the results. Moreover, this research aims at using minimum complexity sufficient to show a general trade-off. The knowledge about this trade-off is only at its starting point and can be enriched in various ways. Follow-up studies on the role of and interplay between physical network structure (e.g. scale-freeness, assortativity, rich-club), collaboration network structure (e.g. correlation with physical layer, competitive aspects), carrier market structure (e.g. regional vs. interregional), coupling mechanism, as well as size and type of initial attack (random or targeted), regarding the vulnerability at the collaborative level will contribute to the results of this study. Some of these aspects and their combinations might have an impact on the connectivity threshold or the trade-off in general. Finally, the integration of disruption propagation at the physical level, e.g. through congestion

or delay propagation (Baspinar and Koyuncu, 2016), would be instrumental to get a complete understanding of the dynamics of disruption in collaborative transport as visualized in Figure 4.1.

The awareness of vulnerability at the collaborative level and the threat of disruption propagation inevitably triggers the discussion on how to protect a system from such disruption. In Chapters 3 and 4 we showed that structural aspects such as market structure and collaborative connectivity are influencing the level of vulnerability. The structure of a system, however, can only be influenced to a limited extent. A seemingly more feasible solution is constituted by dedicated investments in cyber security in order to protect selected carriers/nodes in the collaboration layer from failure. Given that the largest carriers tend to possess the largest financial backing, they are most likely to be able to protect themselves through such investments. This seems reasonable not only from an individual perspective, but also from a system perspective as the largest carriers have the biggest system impact in case of disruption. However, if propagation is prone to spread, protection is not only about protecting the largest assets, but also about effectively mitigating the spread. Cohen et al. (2003) showed that breaking down a network into as many roughly equally-sized subnetworks as possible by immunizing the set of vertices that separates them, is a more efficient strategy than immunization by largest degree. In transportation-collaboration systems, it will be a delicate question to answer under which circumstances it is better to protect the system against spreading rather than protecting the most important carriers.

4.6 Conclusion

The research goal of this study has been accomplished. Its results confirm the hypothesis that collaborative integration in transportation systems does not only create synergies, but also increases the risk of failure cascades at the collaborative level in case of disruption, impacting the system performance heavily. The level of collaborative connectivity is a key indicator for vulnerability at the collaborative level and plays an important role in explaining this trade-off. A coupled model for failure propagation in collaborative transport has been developed and turned into a tool to understand the role of collaborative connectivity for a probabilistic network class in an analytical fashion, and for real-world networks using simulations. This provides the foundation to conduct further intriguing research on the trade-off between synergies and vulnerabilities, the optimal level of collaboration in transportation, and

protection strategies through investments in cyber security. In an industry that is increasingly becoming more connected through the rise of new technologies, our results should raise awareness that the investment in cyber security needs to be ramped up accordingly, and that investments need to be federated as a single failure can disrupt an entire collaborative system. In this respect, this work constitutes an important decision support for policy decisions on the collaborative integration of transport systems.

4.7 Acknowledgements

This research has been developed as part of the Trans-Sonic project (project no. 439.16.119, https://transsonic.nl/), which is funded by the Dutch Organisation for Scientific Research (NWO) and supported by a number of academic and industry partners in the field of hinterland shipping. Special thanks goes to Ecorys B.V. for providing the intermodal links data set to the Trans-Sonic project.

Appendix

4.A Justification of SIR model

SIR is the most general epidemic model applicable to a wide range of epidemic dynamics including disruption propagation in collaboration and data exchange networks. However, all results are subject to the parameters of SIR, particularly the propagation rate τ. Our choice of τ is not sufficiently backed up with data, but a sensitivity analysis showed that the nature of the results is independent of τ. A connectivity threshold $p^{\kappa*} \in (0, 1]$ exists for any $\tau > 1/(N^C - 1)$ in instances with ER collaboration network according to Equation (4.5). If τ is smaller, even full collaborative connectivity is not sufficient to create a significant cascade risk. Deriving an empirical value for τ would require in-depth knowledge about the technical details of collaborative integration, which can be vastly different for every system, in particular since collaborations between real-world companies are most likely heterogeneous, i.e. the level of integration and synergy potential varies as well as the security and transmission potential of such links. There are other disruption propagation models that are more sophisticated and more tailored to a cyber-physical setup than SIR, e.g. featuring reinfection (SIS) or a more fine-grained transmission mechanism distinguished by radiation, transmission, and reception (Vermeer et al., 2018). Such propagation models could be considered in future research, but the calibration with limited data would be even more difficult and the added value in our context needed careful assessment. Overall, SIR provides a sufficiently realistic depiction of propagation, while keeping parametric complexity manageable.

4.B Computation of collaborative connectivity threshold

The computation of the threshold connectivity $p^{\kappa*}$, which maximizes the expected outcome under disruption to a random marginal fraction of the collaborative network, is closely linked to the reproduction number $\mathcal{R}_0$. $\mathcal{R}_0$, a well known indicator for the spread of epidemic diseases, describes the infection behaviour of a typical infected individual early in the epidemic with most of the population still susceptible, in particular how many new infections are expected to be caused by that individual. If $\mathcal{R}_0 > 1$, it is likely that initial infections turn into an epidemic (Kiss et al., 2017). For probabilistic network classes that are based on the configuration model, i.e. networks

with arbitrary degree distributions but no degree correlation (Newman, 2010), $\mathcal{R}_0$ can be derived analytically following (Kiss et al., 2017). Being the neighbour of the node that infected them, newly infected node follow the neighbour degree distribution $P_n(k) = kP(k)/\langle K\rangle$ with $\langle K\rangle$ being the average degree. A newly infected node with transmission rate τ is expected to cause $(k-1)\tau$ new infections. The expected number of transmissions of an early infected node can then be calculated as follows:

$$\mathcal{R}_0 = \sum_k P_n(k)(k-1)\tau \tag{4.B.1}$$

$$= \tau \sum_k \frac{kP(k)}{\langle K\rangle}(k-1) \tag{4.B.2}$$

$$= \tau \frac{\langle K^2 - K\rangle}{\langle K\rangle} \tag{4.B.3}$$

Erdos-Renyi networks, which have a degree distribution $P(k) = \frac{\lambda^{k-1}e^{-\lambda}}{k!}$ and no degree correlations, are the simplest application. Since average degree in our ER collaboration network class is described by $\langle K\rangle = (N^C - 1)p^\kappa = \lambda$, we get

$$\mathcal{R}_0 = \tau\lambda = (N^C - 1)p^\kappa\tau. \tag{4.B.4}$$

The expected performance of a collaborative transport system under a marginal random attack is maximized, if collaborative connectivity is as high as possible to create maximum synergies, but sufficiently low in order to have very little risk of a disruption cascade. This condition is satisfied if the reproduction number $\mathcal{R}_0 = 1$, which we can calculate using Equation (4.B.4):

$$p^{\kappa *} = \frac{1}{(N^C - 1)\tau}. \tag{4.B.5}$$

The threshold $p^{\kappa *}$ is purely defined by the number of edges and the transmission rate. Thus, if the collaboration network is an Erdos-Renyi network, the structure of the physical layer only has an impact on the actual performance level (Harter et al., 2022), but not on the threshold itself. However, equation (4.B.5) only holds if the

collaboration network is an Erdos-Renyi network. If the collaboration network is induced from the physical layer (PInd), the degrees are correlated and the physical layer can indeed have an impact on the threshold $p^{\kappa *}$.

Chapter 5

Conclusion and future outlook

In this dissertation, the impact of vertical collaboration in transportation systems with multiple transport modes and carriers has been studied from a complexity angle. Vertical collaboration allows the provision of multi-mode and multi-carrier transport chains, creating a better connected and more flexible transport network compared to the isolated mode and carrier service networks. It is well established in the airline industry through code sharing and alliances, and is strongly promoted by European policies to become a central element of the cargo transportation of the future. However, vertical collaboration comes with a strong intervention into a transportation system on many levels, e.g. the operational, technical, or commercial levels. In fact, the integration of multiple individual networks into a multi-mode and/or multi-carrier network creates a new system complexity, at which the system impact of changes at the individual level cannot be predicted easily.

Since it is crucial to understand the implications of vertical collaboration at the system level in order to derive meaningful policies for network development, we identified the need for a network model that is able to capture the emergence of structural characteristics of the integrated network from the inherent structure of the individual networks. Using existing and self-developed methods from the science of complex networks, we developed a novel multi-layer network model, which maps the interdependencies between the different transport modes and carriers under vertical collaboration along with the physical transport services. Moreover, we presented ways to define, generate, and analyze realistic random transportation networks without the need for actual data. We used our model to describe structural changes induced by vertical collaboration and analyzed their impact on the transportation system with a particular focus on the trade-off between synergies and vulnerability.

This final chapter of my dissertation comprises a summary of the main research results as well as a discussion of promising directions for future research.

5.1 Main findings and implications

In the introduction chapter, the benefits of vertical collaboration in transportation systems were put into relation with sources of interdependence and vulnerability and explained in the context of hinterland container transport. Thereby, the need for a complexity perspective on vertical collaboration efforts in transportation systems was motivated. Moreover, the science of complex networks was identified as a suitable method to approach such an analysis. Network science provides the right tools to

analyze large-scale natural and engineered system and exhibits a history of impactful research on complexity in cyber-physical systems related to transportation.

The second chapter addressed the notion of connectivity in hinterland transportation. Since hinterland transportation chains in the past usually consisted of 1 intermodal leg only and transshipment across multiple transport modes was rarely an option, hinterland connectivity of ports and inland terminals was mainly defined by the quantity of direct services offered. We showed that under increasing popularity of intermodal transport, which is in fact fostered by European policy makers, this notion is not sufficient any more. The system undergoes substantial structural changes and relevant aspects of intermodal transport cannot be captured. First, the presence of transport chains with multiple legs indicates that not only the directly connected ports and terminals should be taken into account for the assessment of connectivity, but also the ones connected through a transfer connection, i.e. the neighbours of neighbours. Second, the offering of intermodal transport chains is facilitated by (inland) ports that offer transshipment across transport modes. Therefore, the modal split of hinterland services offered by an (inland) port plays an important role for its connectivity (RQ 2.1). We presented a new non-local and multimodal notion of connectivity that captures these aspects and showed that the role of (inland) ports can change under vertical collaboration. Smaller (inland) ports that are well connected to the largest hubs increase their connectivity significantly and more importantly, ports that provide intermodal transshipment are assigned a new role as multimodal 'Connector' nodes (RQ2.2).

In purely structural terms, the chapter highlighted the increase in complexity that comes with vertical collaboration as well as the need to review the measurement of connectivity. Port authorities as well as policy makers will have to understand this additional complexity for their strategic decision making, which is a challenge, but we showed that a lot of information can be gathered with comparably simple structural measures.

In Chapter 3 and 4, the focus shifted from transport modes to carriers. The purely service structure based analysis of Chapter 2 was complemented by a functional component describing the bilateral interaction and information exchange between carriers to enable transshipment along sequential transport chains. Besides the potential synergies through vertical collaboration, Chapter 3 and 4 addressed the increased interdependency and subsequent vulnerability at the collaborative level that result from collaboration. A major contribution of Chapter 3 and 4 is our multi-

layer network model, which captures both the physical transport services and the collaborations as separate layers, and maps the interdependency between these layers based on plausible assumptions derived from real-world collaborative transport systems. These features allowed us to simulate disruptions in the functional network of collaborations and assess their impact on the transport performance with structural measures only. In addition to the model itself, an approach for the generation of realistic random networks with adjustable characteristics was developed. Using this approach, populations of networks with arbitrary characteristics were generated and the role and impact of specific characteristics could be compared. Beyond the analysis in this dissertation, the model combined with the realistic random network generation approach can serve as a valuable tool for decision support in transport policy making. For instance, specific policies or investments can be evaluated regarding their impact on vulnerability. The changes associated with the policy can be mapped in the collaboration layer and the impact can be derived through the coupling. Moreover, favourable structural conditions of a transportation system can be identified in order to guide the policy making or investment allocation.

In Chapter 3 we showed that vulnerability at the collaborative level is driven by the market structure of carriers, i.e. the underlying service structure composition. As opposed to synergy potential, which is higher the more evenly distributed the number of services per carrier, vulnerability is highest at intermediate disparity of carrier sizes, whereas balances service distributions and highly disparate distributions exhibit low vulnerability (RQ 3.1). We identified two contrary effects leading towards this counterintuitive result. On the one hand, the dependence on collaboration decreases with higher carrier size disparity as few carriers can cover large parts of the network with little need for collaboration. On the other hand, these large carriers are obvious targets for attacks, making the system more susceptible compared to a system with evenly distributed carrier sizes, in which market structure cannot be exploited for targeted attacks. In aggregate, the two effects cause a U-shaped vulnerability curve under varying market structure. This research did not aim to provide recommendations for optimal market structures of a transportation systems, since this is not something that can easily be influenced without major political intervention. Instead, it can serve as a decision support for determining necessity and allocation of protective measures against attacks to carriers' at the collaborative level.

Chapter 4 constituted another crucial step towards the understanding of complexity through vertical collaboration. Having identified structural conditions for vul-

nerability at the collaborative level in Chapter 3, Chapter 4 connected vulnerability with the synergies created through vertical collaboration. We explored how collaborative integration can facilitate the propagation of cyber/false data disruption and potentially lead to a cascade largely disrupting the collaborative network and consequently the capability to operate sequential transport chains. Coupling a generic SIR propagation model with our collaborative transport network model, we explored a synergy-vulnerability trade-off of collaborative connectivity and quantified the performance-maximizing threshold (RQ 4.2). Establishing an increasing number of collaborations is expectedly very beneficial as more transshipment options results in shorter paths and more routing flexibility. However, the marginal benefits of collaborations are decreasing, whereas at the same time disruption cascades following a small initial disruption are becoming more likely and at some point almost certain. The performance-maximizing connectivity threshold is reached when connectivity is as high as possible to create maximum synergies, but sufficiently low in order to have very little risk of a disruption cascade. Systems with disproportionately many collaborations among large carriers tend to create more synergies with fewer collaborations, but the dense 'rich-club' subnetwork facilitates disruption propagation, leading to a lower connectivity threshold (RQ 4.1). From a managerial perspective, these results showed that level and quantity of collaboration should not only be assessed by its synergy potential, but also by its contribution to failure cascade risk. This applies to individual companies, who should carefully select the number and disruption risks of their partners, but also to policy makers, who have the power to steer a system towards a healthy level of collaboration. If the collaboration threshold is too low to create sufficient synergies, investments in the security of collaboration links should be considered, leading to lower disruption and transmission risk, and thus allowing for more collaboration and an overall higher transport performance.

Using networks to map complex constellations in vertically integrated transportation systems, this dissertation provided a tractable interface to study the impact of disruptive changes to transportation systems. While each chapter comprises a number of findings relevant for managerial practice, it is the attempt to describe complex issues with a tractable framework that prevails across all chapters. It allowed us to analyze and understand the consequences of vertical collaboration in transportation from new angles.

5.2 Future outlook

In this dissertation, we explored the complexity of vertical collaboration in multi-mode and multi-carrier transportation systems with a focus on describing complex system outcomes based on the underlying network structure. The conducted research generated a number of interesting insights, but also opened up new directions for future research. The final section comprises a discussion of potential extensions of the work done in this dissertation as well as a number of more general future research opportunities. Last but not least, we present a vision for collaborative transport research.

The approach we took was overall quite generic, which proved very useful for the scope of this dissertation, but might not answer all questions for specific collaborative transport systems. Vertical collaboration in hinterland transport is for instance only in a nascent stage and comes with significant operational complexity for transshipment, which has not been addressed in this work. The customization to specific contexts is an important step to strengthen the results of this dissertation and get more hands-on insights. A key requirement is the availability of data. Customization and refinement of the model can happen at the physical level, at the collaboration level, and especially at the interface between the two. At the physical level, operational details of transshipments depending on the terminal infrastructure would allow for more accurate results of the outcome in the transportation layer. Transshipment operations are also subject to the collaboration between the involved parties. Distinguishing between different levels of collaboration, representing different levels of information integration with different impact on the transshipment capability, would strengthen the validity of the coupling between the layers. Variation in collaboration types might also affect the disruption and propagation behaviour, which leaves potential for a more accurate vulnerability analysis. Moreover, there can be multiple carriers forming an alliance, as is happening in the airline and maritime shipping industry. Multi-lateral collaborations might change the statics of the collaboration network, but cannot explicitly be mapped in the current model.

Another interesting aspect of collaborative transport is decentrality. Not just with the rise of Blockchain technology, decentral approaches are becoming more popular, be it in Tech, Finance, or Transportation. Collaborative transport is a parade example of a decentrally managed system due to carriers being independent companies. The complications and interdependencies imposed by collaborations in a decentral system on the commercial, competitive, and political level would have a

significant impact on the conditions under which collaborations are formed, which could be worthwhile exploring. Last but not least, future research should look into ways to protect collaborative transport systems against vulnerability at the collaborative level. In this dissertation we showed how structure influences vulnerability, but vulnerability can also be reduced through investments in cyber security of carriers. The specific transportation-collaboration setup requires decision makers to balance the protection of most important carriers with the mitigation of spreading when allocating such investments.

The research directions outlined above contribute to our vision for collaborative transport modelling, which comprise the development of a flexible model for accurate prediction of synergies and vulnerability on both system and individual level under changes to the system. The vision embraces the potentially competitive positioning of players in the system and is easily customizable to different collaborative transport context. It allows carriers to evaluate decisions on collaborations, collaboration intensity, or adoption of information systems. Cities, ports, or terminals can use it to evaluate investments in transshipment capability towards an integrated transshipment hub. Moreover, policy makers can use it to evaluate the impact of policies related to an integrated decentral transportation system. Our vision aims at providing a tool that leads to good decisions and enables efficient transportation with low vulnerability, and ultimately low environmental footprint.

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Summary

Vertical collaboration in transportation involves the sequential execution of transportation services from origin to destination. A sequence of services can involve different carriers and different transport modes providing an integrated service. Through vertical collaboration, a decentrally operated transportation system can reach a higher level in terms of transport times, flexibility, resilience, and environmental footprint due to a more efficient use of existing resources and better responsiveness under disruption to the service network. For instance, rail and barge services for intermodal container transport in the seaport hinterland can be combined through vertical collaboration in a complementary way to increase the coverage of destinations, reduce transport times, and thereby provide a competitive alternative to unimodal trucking.

However, the benefits of vertical collaboration do not come for free. First, deploying successful collaborative transport requires close coordination and exchange of data between the parties involved. For instance, collaborating carriers have to rely on each other that information is provided on services, bookings, capacities, transshipments, and that this information is correct. Collaboration therefore always comes with interdependency, which creates a new risk of disruption at the collaborative level that comes on top of the existing physical disruption risks (disruption of physical services, e.g. through low water levels). If carriers fail to provide their partners and involved terminals with the required data or the data is falsified, e.g. resulting from a ransomware attack, transport chains become infeasible. Moreover, disruption at the collaborative level can be caused by strategic misalignment in collaborations, e.g. from a commercial, competitive, legislative, or trust perspective.

Second, vertical collaboration creates a new level of complexity emerging from the network integration, the transshipments between transport modes and carriers along a path with sequential services, as well as the collaboration and information exchange

between autonomous carriers required to provide such services. This complexity is difficult to capture at large scale with conventional notions and models used in transportation research. Operational, technical, commercial, and organizational aspects of collaborative transport systems are well researched at the individual and local level. At scale, however, individual and local decisions lead to the emergence of a complex adaptive system with non-trivial features. These features are difficult to trace back to the individual level, which leads to low predictability of the impact of changes to the system.

Expanding the knowledge on vulnerability induced by vertical collaboration is crucial given the potentially severe impact of disruption, but complexity of the system complicates such an analysis. Growing transport demand, constrained infrastructure expansion, technological innovation, and increasing need for sustainable solutions will further drive the relevance of collaboration and lead to even higher complexity. This dissertation focused on presenting innovative modeling approaches based on the science of complex networks that are able to capture the complexity of transportation systems with vertical collaboration, and to use these to answer two core questions:

Complexity
: How do changes in the characteristic of a transportation system emerge under the adoption of vertical collaboration?

Vulnerability
: Which system characteristics influence vulnerability at the collaborative level?

We presented a novel multi-layer network model and analysed it with a combination of well-known metrics from network science and new methods developed ourselves. Moreover, a mix of analytical computations and simulation-based methods is applied to be able to establish general findings derived from random network classes, verify them through simulation, and generate insights for real-world transportation systems with data.

In Chapter 2, we analyzed changes in network structure under vertical integration of multiple transport modes in the European network for hinterland container transport. Hinterland connectivity of a port is mostly treated as a local indicator, describing the number of different hinterland locations served from a port via a direct service. However, with multimodality being on the rise and transfer connections becoming more feasible and common, the existing local notion of connectivity was not sufficient anymore. This chapter extended the notion of hinterland connectiv-

ity by non-local (network) and multimodal aspects, and used this notion to analyze hinterland connectivity for the European hinterland transport network of scheduled rail and barge services. The results showed that overall structural capability to perform hinterland transport assignments increases strongly as transfer connections and multimodal routes are established. Moreover, non-local measures showed that ports with poor local connectivity can still be well positioned within a vertically integrated network if they have a connector role between the different network layers. Last but not least, all ports benefit individually from multimodal integration, but some do more than others.

In Chapter 3, we analyzed how the market structure of carriers and their positioning in the transport network drive vulnerability at the collaborative level of vertical carrier collaboration. Therefore, the transportation network in our model is complemented by a collaboration network representing the collaboration links between carriers and the system impact of disruption to this new network layer is assessed. Instead of demonstrating our results on particular instances of such multi-layer networks, we described a population of networks by its structural properties, capturing the constraints imposed by collaborations in an analytically tractable way. The analysis was complemented by a simulation study on less tractable, but more realistic networks to validate the analytical findings. The results indicate that market structure, represented by disparity in carrier sizes, has a non-trivial impact on the vulnerability of a collaborative transport network to targeted disruption at the collaborative level. Networks are most vulnerable if they have intermediate disparity in carrier sizes, i.e. carriers are overall similarly sized, but there is some heterogeneity with a moderate gap between few larger and many smaller carriers.

In Chapter 4, we studied the trade-off between synergies and vulnerability through vertical collaboration. Since offering shared routes requires close alignment between parties, collaborations are fueled by the exchange of data and the integration of information systems, which creates dependencies through the risk of disruption in the form of technical failure, cyber attacks, or organizational conflicts. Research has shown that failure in interdependent networks can propagate and lead to a cascade of failures, which casts doubt on the claim that more collaboration has a solely positive impact on system performance. To answer this question, the network model from the previous chapter is coupled with a model for propagation of cyber/false data disruption, and the impact on network performance under varying levels of collaborative connectivity is observed. Results show that increasing collaborative

connectivity does not have a monotone effect on performance, but there is a maximum at intermediate connectivity levels. Below this threshold level, more collaborations have a mostly positive impact on performance, since unused synergy potential is high while the risk of disruption causing a cascade is low. Above it, failure cascades become larger and more likely while the marginal added synergies are diminishing.

In conclusion, we explored the complexity of vertical collaboration in multi-mode and multi-carrier transportation systems. A particular focus was set on describing complex system outcomes such as vulnerability based on the underlying network structure. First, we developed novel models that serve as useful support tools for decision making on the adoption of vertical collaboration in decentrally operated transport networks. Second, we presented interesting results on the vulnerability of transportation systems in general and the European hinterland transport network in specific. Last but not least, the conducted research opens up new directions for the analysis of multi-layered transportation systems using methods from the science of complex networks.

Samenvatting

Bij verticale samenwerking in de transportsector draait het om de sequentiële uitvoering van vervoersdiensten van herkomst naar bestemming. Een sequentie van diensten kan verschillende vervoerders en verschillende vervoerswijzen omvatten die een geïntegreerde dienst leveren. Via verticale samenwerking kan een decentraal opererend transportsysteem een hoger niveau bereiken voor wat betreft transporttijden, flexibiliteit, veerkracht en milieuvoetafdruk dankzij efficiënter gebruik van bestaande middelen en een beter reactievermogen bij verstoring van het dienstennetwerk. Zo kunnen bijvoorbeeld spoor- en binnenvaartdiensten voor intermodaal containertransport in het achterland van een zeehaven op aanvullende wijze worden gecombineerd via verticale samenwerking om de dekking van bestemmingen uit te breiden, transporttijden te verkorten en zodoende een concurrerend alternatief te bieden voor unimodaal vrachtvervoer.

Aan de voordelen van verticale samenwerking zijn echter wel voorwaarden verbonden. Ten eerste is voor succesvol coöperatief transport nauwe coördinatie en uitwisseling van gegevens tussen de betrokken partijen nodig. Zo moeten samenwerkende vervoerders onderling erop kunnen rekenen dat informatie over diensten, boekingen, capaciteiten en overladingen wordt verschaft, en dat deze informatie correct is. Samenwerking gaat dus altijd gepaard met onderlinge afhankelijkheid, wat een nieuw risico op verstoring op coöperatief niveau met zich meebrengt, naast de bestaande risico's van fysieke verstoring (verstoring van fysieke diensten, bijvoorbeeld door lage waterstanden). Als vervoerders verzuimen hun partners en betrokken terminals de vereiste gegevens te verstrekken of de gegevens vervalst zijn, bijvoorbeeld als gevolg van een ransomwareaanval, worden transportketens onuitvoerbaar. Bovendien kan verstoring op coöperatief niveau worden veroorzaakt door onjuiste strategische afstemming bij de samenwerking, bijvoorbeeld vanuit commercieel, concurrentie-, wetgevings- of contractueel oogpunt.

Ten tweede creëert verticale samenwerking een nieuw complexiteitsniveau dat voortkomt uit netwerkintegratie, de overladingen tussen vervoerswijzen en vervoerders langs een route met sequentiële diensten, alsook de samenwerking en informatie-uitwisseling tussen onafhankelijke vervoerders die vereist zijn om dergelijke diensten te verlenen. Het is moeilijk om deze complexiteit op grote schaal in goede banen te leiden met conventionele noties en modellen die in het onderzoek op transportgebied worden gebruikt. Operationele, technische, commerciële en organisatorische aspecten van coöperatieve transportsystemen zijn goed onderzocht op individueel en lokaal niveau. Op schaal leiden individuele en lokale besluiten echter tot het ontstaan van een complex adaptief systeem met niet-triviale kenmerken. Deze kenmerken zijn moeilijk te herleiden tot het individuele niveau, wat leidt tot slechte voorspelbaarheid van het effect van veranderingen in het systeem.

Een betere kennis van de kwetsbaarheid die gepaard gaat met verticale samenwerking is cruciaal, gezien het potentieel ernstige effect van verstoring, maar de complexiteit van het systeem bemoeilijkt deze analyse. Toenemende vervoersvraag, beperkingen aan uitbreiding van infrastructuur, technologische innovatie en de toenemende noodzaak van duurzame oplossingen zullen samenwerking nog relevanter maken en tot nog meer complexiteit leiden. Dit proefschrift is erop gericht innovatieve modelleringsbenaderingen te presenteren op basis van de wetenschappelijke kennis over complexe netwerken die in staat zijn met behulp van verticale samenwerking de complexiteit van transportsystemen op te vangen, en deze te gebruiken om twee kernvragen te beantwoorden:

Complexiteit

Hoe ontstaan veranderingen in de kenmerken van een transportsysteem bij inzet van verticale samenwerking?

Kwetsbaarheid

Welke systeemkenmerken zijn van invloed op de kwetsbaarheid op coöperatief niveau?

We hebben een nieuw meerlaags netwerkmodel gepresenteerd en geanalyseerd met een combinatie van bekende meetgegevens uit de netwerkwetenschap en nieuwe, door onszelf ontwikkelde methoden. Bovendien wordt een mix van analytische berekeningen en op simulatie gebaseerde methoden toegepast om algemene conclusies te kunnen trekken die afkomstig zijn van willekeurige netwerkklassen, deze door middel van simulatie te verifiëren en met gegevens inzichten te genereren voor transportsystemen in de echte wereld.

In hoofdstuk 2 analyseren we veranderingen in de netwerkstructuur bij verticale integratie van meerdere vervoerswijzen in het Europese netwerk voor containertransport in het achterland. De verbondenheid van een haven met het achterland wordt meestal behandeld als een lokale indicator die aangeeft hoeveel verschillende locaties in het achterland via een directe verbinding vanuit een haven worden bediend. Nu multimodaliteit in opkomst is en overslagverbindingen beter uitvoerbaar en gangbaarder worden, is de bestaande notie van verbondenheid niet langer voldoende. In dit hoofdstuk wordt de notie van verbondenheid met het achterland verruimd met niet-lokale (netwerk-) en multimodale aspecten, en wordt deze notie gebruikt om verbondenheid met het achterland voor het Europese achterlandvervoersnetwerk van geplande spoor- en binnenvaartdiensten te analyseren. De resultaten laten zien dat de totale structurele capaciteit om achterlandtransportopdrachten uit te voeren sterk toeneemt naarmate overslagverbindingen en multimodale routes tot stand worden gebracht. Niet-lokale maatregelen tonen bovendien dat havens met slechte lokale verbindingen toch goed gepositioneerd kunnen zijn binnen een verticaal geïntegreerd netwerk als ze een verbindende rol hebben tussen de verschillende netwerklagen. Tot slot blijkt dat alle havens individueel profiteren van multimodale integratie, maar niet in gelijke mate.

In hoofdstuk 3 analyseren we hoe de marktstructuur van vervoerders en hun positionering in het transportnetwerk van invloed zijn op de kwetsbaarheid op het coöperatieve niveau van verticale samenwerking tussen vervoerders. Daarom wordt het transportnetwerk in ons model aangevuld met een coöperatief netwerk dat de samenwerkingsverbanden tussen vervoerders vertegenwoordigt en wordt het systeemeffect van verstoring van deze nieuwe netwerklaag onderzocht. In plaats van onze resultaten te tonen voor specifieke gevallen van dergelijke meerlaagse netwerken, beschrijven we een populatie van netwerken aan de hand van hun structurele eigenschappen, door de beperkingen die door samenwerkingen worden opgelegd, op een analytische traceerbare wijze in kaart te brengen. De analyse wordt aangevuld door een simulatiestudie over minder goed traceerbare, maar meer realistische netwerken om de analytische bevindingen te valideren. De resultaten wijzen erop dat marktstructuur, gevormd door ongelijkheid in de omvang van vervoerders, een niet-triviaal effect heeft op de gevoeligheid van een coöperatief transportnetwerk voor gerichte verstoring op coöperatief niveau. Netwerken zijn het meest kwetsbaar als de ongelijkheid in de omvang van vervoerders gemiddeld is, d.w.z. als de vervoerders ongeveer even groot zijn, maar sprake is van enige heterogeniteit, met een beperkt onderscheid tussen enkele grotere en talrijke kleinere vervoerders.

In hoofdstuk 4 onderzoeken we de wisselwerking tussen synergieën en kwetsbaarheid door verticale integratie. Aangezien het aanbieden van gedeelde routes nauwe afstemming tussen partijen vereist, worden samenwerkingen aangedreven door de uitwisseling van gegevens en de integratie van informatiesystemen. Dit creëert afhankelijkheden vanwege het risico op verstoring in de vorm van technische gebreken, cyberaanvallen of organisatorische conflicten. Uit onderzoek blijkt dat een verstoring in netwerken met onderlinge afhankelijkheid zich kan verspreiden en een cascade-effect teweeg kan brengen, wat twijfel zaait over de bewering dat meer samenwerking een louter positief effect heeft op de systeemprestatie. Om deze vraag te beantwoorden wordt het netwerkmodel van het vorige hoofdstuk gekoppeld aan een model voor verspreiding van een verstoring door een cyberaanval of valse gegevens, en wordt het effect op de netwerkprestatie bij verschillende niveaus van coöperatieve verbondenheid bekeken. De resultaten laten zien dat een toename van coöperatieve verbondenheid geen eenduidig effect op de prestatie heeft, maar dat er een maximum wordt bereikt bij een gemiddeld niveau van verbondenheid. Onder dit drempelniveau heeft toenemende samenwerking meestal een positief effect op de prestatie, aangezien het onbenutte synergiepotentieel hoog is en het risico op verstoring met een cascade-effect laag is. Boven dit niveau worden verstoringen met een cascade-effect groter en waarschijnlijker, terwijl de marginale toegevoegde synergieën verminderen.

Kortom, we hebben de complexiteit van verticale samenwerking in multimodale transportsystemen met meerdere vervoerders onderzocht. De focus lag op het beschrijven van resultaten van complexe systemen, zoals kwetsbaarheid op basis van de onderliggende netwerkstructuur. Eerst hebben we nieuwe modellen ontwikkeld die dienen als nuttige hulpmiddelen voor besluitvorming over de invoering van verticale samenwerking in decentraal opererende transportnetwerken. Vervolgens hebben we interessante resultaten gepresenteerd met betrekking tot de kwetsbaarheid van transportsystemen in het algemeen en het Europese achterlandtransportnetwerk in het bijzonder. Tot besluit opent het uitgevoerde onderzoek nieuwe richtingen voor de analyse van meerlaagse transportsystemen door gebruik te maken van wetenschapsmethoden op het gebied van complexe netwerken.

About the author

Camill was born in Gengenbach (Germany) in 1991. He studied Business Mathematics at the University of Mannheim and obtained his M.Sc. degree from there in 2014 with a thesis on the mathematical modeling of criminal movements in urban areas. During his master studies, Camill visited the UPC BarcelonaTech (Spain) as a visiting student in the master programme Advanced Mathematics and Mathematical Engineering. After his studies, Camill worked as a consultant at Roland Berger in their Operations Strategy Competence Center for two years. In 2017, Camill started as a PhD candidate at the Technology and Operations Management Department at Rotterdam School of Management, Erasmus University under the supervision of Prof. Rob Zuidwijk and Dr. Otto Koppius.

Camill's research focuses on the modelling of transportation systems with the aim to establish general relationships between changes at the micro-level and their impact at the macro-level. Among the wide range of quantitative methods he is using for his research, the science of complex networks plays a central role. His particular interests include the impact of novel technologies and increased technological integration on the vulnerability of transportation systems. His work has been presented at several international conferences, including INFORMS, LOGMS, NetSci, and CNA.

Portfolio

Publications

Publications in journals:

S. Göttlich and C. Harter (2016). "A weakly coupled model of differential equations for thief tracking". *Networks and Heterogeneous Media* 11.3, pp. 447–469. URL: http://www.aimsciences.org/journals/displayArticlesnew.jsp?paperID=12769

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Vertical collaboration describes the integration of transportation service networks to enable the provision of multi-mode and multi-carrier transportation services in sequence. It comes with many benefits such as efficiency, utilization of infrastructure & carbon footprint reduction. However, a higher level of collaboration creates new dependencies, for instance induced by the need for coordination, information exchange, and interconnected information systems, which can ultimately turn into disruption threats. While the benefits of vertical collaboration are extensively covered in existing research, knowledge on the concomitant vulnerabilities has been rather limited.

This dissertation addresses the vulnerabilities that emerge from vertical collaboration in complex transportation networks with multiple carriers and transport modes and provides decision support tools for policy making in collaborative transportation. A novel multi-layer network model is developed to capture both the physical and collaborative aspects of transportation networks in an integrated fashion, and analysed with a combination of well-known metrics from network science and new self-developed methods.

We find that vulnerability is strongly influenced by the market structure of carriers. Systems with mainly similar-sized carriers are robust to targeted disruption, whereas the total magnitude of potential failure is very large. Systems with a few dominating carriers have a lower magnitude of failure but are highly susceptible to targeted disruption. Moreover, there is an optimal level of collaboration where the increasing risk of disruption cascades outweighs the decreasing marginal added benefits of additional collaboration.

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