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Risk and Resilience Assessment of Inland Waterway Transport Networks

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Inland waterway transport constitutes a vital component of the logistics network, connecting suppliers, producers, and end consumers. The identification and assessment of the risks affecting these transport operations is not merely an optional process, but rather a critical condition for the sustainability of the entire supply chain. Disruptions in inland transport processes can trigger cascading effects impacting all subsequent stages of the supply chain. Ensuring the safety, security, and resilience of autonomous inland waterway transport systems is a central objective in advancing sustainable logistics in Europe. Inland waterways represent a key element within multimodal transport chains, yet their operation remains exposed to disruptions arising from various aspects, such as infrastructure failures, congestion, and the increasing complexity introduced by incorporated autonomous technologies. Addressing these vulnerabilities requires analytical methods capable of representing systemic interdependencies and assessing how localised disturbances can compromise overall network performance. Within the framework of the EC-funded Horizon Europe project AUTOFLEX, this study employs network analysis as a quantitative framework to assess the structural robustness and resilience of inland waterway transport operated by autonomous vessels. It investigates how system connectivity evolves as nodes or edges are progressively removed. By modelling ports and AUTOFLEX operational interfaces and locations, the approach enables a systematic exploration of connectivity degradation under both random and targeted disruption scenarios. The results aim to identify critical components, the loss of which could cause fragmentation or reduce network efficiency, thus providing quantitative indicators of vulnerability and resilience. These outcomes will inform risk control and mitigation strategies and guide the prioritisation of redundancy and protection measures, while also supporting the design of resilient operational frameworks for autonomous inland waterway transport. The approach adapts established percolation-based reliability analyses and methods to the context of autonomous and digitally integrated logistics, contributing to a deeper understanding of resilience in future European transport systems.

Keywords: Inland Waterways Transport, autonomous shipping, risk assessment, network analysis, percolation theory.

1. Introduction

The transportation of cargo through inland waterways serves as a fundamental link in the European supply chain, facilitating the efficient exchange of goods and having the potential to decongest road traffic. At the same time, the field's accelerating adoption of automation and digitalization is introducing new operational and cybersecurity risks that should be accounted for. The systematic identification, management and evaluation of potential risks within Inland Waterway Transport (IWT) operations is therefore essential for ensuring and maintaining supply chain continuity and long-term viability (Gast et al. 2019). Disturbances or disruptions affecting IWT operations have the potential to propagate across interconnected supply chain networks, adversely affecting the efficiency, robustness and reliability of successive logistics activities (Wehrle et al. 2022). Existing empirical studies indicate that insights from purely topological network analysis frequently diverge from those obtained through dynamic simulation methods. Consequently, the two above mentioned approaches may identify different nodes or edges as critical, highlighting the need for improved graph-based indicators that more accurately reflect and approximate functional performance and system behavior (Eusgeld et al. 2009). In this context, the combination of network theory with percolation theory provides a unified and coherent framework for analyzing vulnerabilities within transportation networks. This combined approach captures systemic interdependencies and assesses how localized disruptions may degrade overall network performance. It also examines how connectivity evolves as nodes or edges are progressively removed, identifying critical thresholds beyond which the network experiences fragmentation (Liu et al. 2018).

The objective of this paper is to evaluate the characteristics of an innovative Inland Waterway (IWW) transport system, which is designed within the context of the EC-funded Horizon Europe project AUTOFLEX. AUTOFLEX focuses on supporting the shift to climate-friendly, flexible, and resilient transport by reactivating small and constrained waterways in IWT. The approach proposed in this paper involves implementing network analysis and percolation theory on a graph of the transport system where the weights of the nodes and edges are calculated on the basis of the risk levels assessed from scenarios identified through a Hazard Identification (HAZID) process. The method is applied to a case study of the AUTOFLEX transport system in the Netherlands and Belgium.

The remainder of the paper is structured as follows: Section 2 summarizes prior work on methods for risk and resilience assessment of inland waterway transport networks. Section 3 describes the methodological framework underpinning the proposed approach. Section 4 presents the case study of the AUTOFLEX Transport System and its innovations. Section 5 applies the methodology to each percolation scenario (both random and targeted disruption scenarios are examined) and discusses the results of the proposed contribution. Finally, the paper concludes by delineating the forthcoming research directions and planned methodological advancements.

2. State of the Art & Related Work

Risk analysis of networked logistics systems is challenging because risk can propagate through interdependent nodes and channels, an effect well captured by diffusion-based approaches, such as epidemic models (Feng et al. 2024), (Chen et al. 2019). Entropy-based models (Wen et al. 2019) or approaches that focus exclusively on identifying network risks through graph theory (Ongkowijoyo et al. 2018) may offer valuable insights in identifying structurally fragile modules in complex networks; however, they only account for network structure and topology, and do not consider heterogeneous hazards associated with individual nodes and edges of the transport system under consideration. With respect to network resilience, some approaches attempt to quantify it by modelling post-disruption recovery dynamics, as in the work of Zahng et al. (2018). Moreover, conventional methodologies, such as FMEA, often lack the granularity required to adequately predict the risks introduced by these solutions, particularly when both their technical features and operational environment attributes should be simultaneously considered (X. Li et al. 2023). Analyses based on cascading-impact frameworks are often conditioned on a specific event footprint (e.g., grounding), with direct and indirect effects propagated through explicit dependency relations (Brunner et al. 2024). In the present framework, hazards are evaluated collectively rather than modelled separately.

3. Methodology

Figure 1 illustrates a methodology that integrates risk assessment with network analysis to evaluate the characteristics of transport networks. The process begins with identifying risks related to the system's key elements that may affect cargo flow throughout the network in terms of delay or disruption (Step 1) (Tao et al. 2024). For the systematic documentation of potential hazardous scenarios, as well as their causes and consequences, a HAZID (Hazard Identification) approach is applied. Each scenario is ranked according to its likelihood of occurrence and the consequences related to cargo flow, using a risk matrix approach. The resulting risk levels are then used as weights assigned to the network elements. The transport system is subsequently constructed as a weighted graph, in which nodes represent operational locations and system elements and edges represent vessel routes.

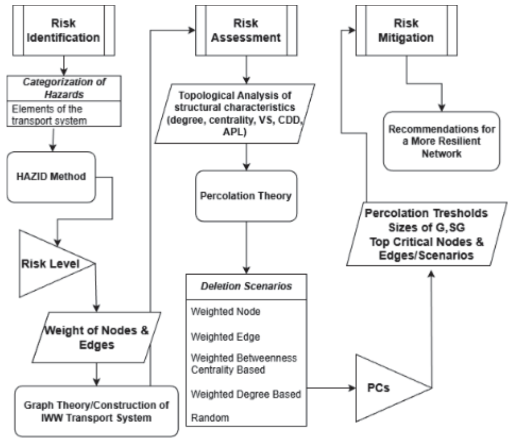

Fig. 1. Risk and Resilience Assessment Method of Inland Waterway Transport Networks.

Using this weighted graph, Step 2: Risk Assessment, is conducted through graph-theoretic analysis. A topological analysis of structural characteristics is performed using the metrics Node Degree, Centrality, and Average Path Length (APL) (Wen et al. 2019), as well as additional indicators (Vertex Strength, Cumulative Degree Distribution, Clustering Coefficient) (Han et al. 2024), with the aim of identifying structurally critical elements and examine how network topology influences functional resilience (Dunant et al. 2021). Network density is defined as the ratio of a network's total link length to the area it spans (Żochowska et al. 2018), while the diameter is defined as the maximum distance over all pairs of nodes in a graph (Mukwembi et al. 2012).

Next, Percolation Theory is applied to evaluate the network given disruptions in terms of cohesion and connectivity as nodes or edges are progressively removed (Saxena et al. 2014). These include removal of nodes or edges based on their weight, weighted Betweenness Centrality (BC x Weight Node) where elements acting as "bridges" for many paths are removed first, Weighted Degree (Degree x Weight Node) where highly connected nodes are removed first, and random removal (LaRocca et al. 2011). The results are represented as diagrams showing how network connectivity degrades as node and/or edges are removed. For each scenario, the Percolation Threshold (PC) is determined as the point at which the network loses global connectivity (Han et al. 2024). As the network elements are progressively removed, the occupancy rate (p), which represents the fraction of nodes or edges that remain connected, varies and the network may shift from a fragmented state to a state where a large, connected subnetwork spans most of the system. In transport networks, the presence of a giant cluster implies that cargo can reach most locations through connected routes (M. Li et al. 2021). The network is evaluated at successive values of p by computing the size of the largest connected cluster G and the second-largest cluster SG. The value of p at which SG peaks and G rapidly declines is defined as the percolation threshold, marking the critical point where the network transitions between global connectivity and fragmentation (Wang et al. 2015). The most critical nodes and edges requiring risk mitigation are identified, and the most disruptive failure scenarios are evaluated by assessing which loss mechanisms lead to faster or more severe fragmentation.

Having identified critical nodes, actions and recommendations for enhancing network resilience are determined in Step 3. Although risk mitigation is outside the scope of this paper, indicative types of measures could include reducing the risk level of specific scenarios associated with nodes and edges, increasing network redundancy by adding alternative routes, redesigning connections at central points of the network, and implementing organizational and operational continuity measures, so that the IWW network maintains its functionality even under severe disruption conditions.

4. Case Study: The AUTOFLEX Transport System

AUTOFLEX designs and introduces new distribution hubs that connect waterborne transport with road logistics operations, enabling efficient cargo transshipment while supplying both vessels and trucks with zero-emission energy. These concepts will be tested and validated through two demonstration use cases between Rotterdam and Amsterdam and in the Ghent region. The AUTOFLEX innovations are briefly outlined below.

Temporary Port Terminals (TPTs) are rapidly deployable and modular logistics hubs designed to enable efficient cargo handling in constrained, underutilised, or non-permanent locations where building a conventional terminal is impossible. They integrate three core functions: cargo handling, short-term storage, and controlled access. TPTs aim to improve the flexibility, resilience, and overall performance of the transport and logistics network.

Stow & Charge (S&C) hubs are dedicated energy and logistics nodes located at ports and TPTs that supply clean energy. Using battery containers, AUTOFLEX vessels can be powered with renewable electricity through a rapid and flexible battery-swapping process without reliance on fixed charging infrastructure or prolonged downtime.

Mobile Distribution Centres (MDCs) are ISO-standard 20- or 40-foot containers adapted into mobile, modular micro-distribution units for industrial (B2B) customers. They are capable of carrying heterogeneous load units, including pallets, roll cages, crates, mini-containers, and cargo-bike boxes. MDCs are intended to be positioned at waterside locations across an urban area, within TPTS and ports and remain at predefined pickup points from where customers can collect and deliver cargo directly after transshipment from a vessel, or have it moved a short distance by road to a nearby location (Kloch et al. 2025).

In Table 1 and Table 2, some indicative places and vessel routes of the AUTOFLEX Transport system examined in this study are presented, together with the corresponding calculated node weight, weighted degree and weighted betweenness centrality, as computed in accordance with the methodology described in Section 3. It is noted that showing the hazardous scenarios (e.g., collisions, groundings, cyberattacks) and the corresponding risk levels that were used as weights in the graph is outside the scope of this paper.

Table 1. Metrics for the nodes of IWW system.

Port/TPT	Node Weight	Weighted Degree	Weighted BC
Rotterdam	166.5	1665	101.5
Amsterdam	246.5	1972	51.0
Moerdijk	279.5	1677	111.5
Delft	199.5	798	16.1
Utrecht	246.5	1972	88.5
‘s-Herto/sch	279.5	1118	21.6
Nijmegen	279.5	559	0.0
Eindhoven	199.5	798	74.6
Roosendaal	199.5	798	2.5
Den Hague	199.5	798	6.2

Table 2. Weight for Vessel Route of IWW system.

Vessel Route	Edge Weight
Rotterdam⟶ Utrecht	199
Rotterdam ⟶ Moerdijk	199
s-Hertogenbosch ⟶ Utrecht	199
Delft⟶ Den Hague	199
Tiel⟶ Dordrecht	199
Dintelmond ⟶ Roosendaal	199

The graph illustrated in Figure 2 presents a specific use case of this transport system, assuming that Rotterdam and Amsterdam are the main ports (blue) and that all other nodes are TPTs (yellow). Moreover, the deployment of Stow & Charge hubs (green) in locations such as Amsterdam, Moerdijk, ’s-Hertogenbosch, Utrecht, and Nijmegen is associated with higher localized risk levels, owing to an additional operational and technological complexity introduced by this innovation. All routes are represented by bidirectional, equally weighted edges with different colours denoting the five distinct alternative IWW routes in the network, while the grey colour indicates those routes that are common across multiple paths. The graph consists of 25 nodes and 58 edges.

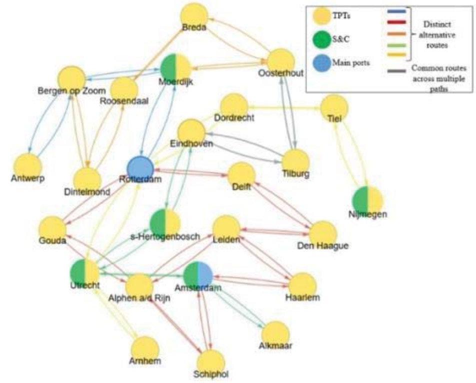

Fig. 2. Graph of the AUTOFLEX Transport System.

Figure 2 presents a centralized and therefore vulnerable hub-and-spoke architecture, with Rotterdam accounting for 61% of the total betweenness centrality, which highlights its criticality in terms of cargo flow. Notably, the network contains isolated nodes, indicated by low density (0.097) that shows a sparse network topology with limited connectivity, while the diameter of 7 for a network comprising 25 nodes indicates a relatively elongated structure without shortcuts between remote areas. The average in and out strength of 2.32 reveals that most nodes possess a small number of connections, which, combined with the complete absence of clustering (CC=0) and the APL=3.14, characterizes the network as functionally efficient, yet highly vulnerable. Overall, the network exhibits a tree-like structure, in which most paths depend on a limited number of central nodes.

This study evaluated 5 scenarios for network element removal. In the first, 30 repetitions of random removal were performed, with each node having an equal probability of being removed. The other scenarios applied targeted removals in descending order, focusing on nodes or edges ranked by weight, weighted betweenness centrality and weighted degree. This approach can capture the fragmentation of the network not only topologically but also based on the weights which are the risk levels that represent how vulnerable the network is related to its structural and functional characteristics, The results analysed in Section 5.

5. Results & Discussion

As illustrated in Figure 3, random deletion results in a threshold of PC = 0.320, indicating that the network maintains its connectivity even when 32% of its nodes are randomly removed. The smooth decline of the giant cluster (G) and the gradual growth of the secondary cluster (SG) suggest that for random, untargeted breakdowns, the system has sufficient resilience.

Fig. 3. The percolation process under Random scenario.

Subsequently, as illustrated in Figure 4, the Edge Weight strategy removal shows the highest percolation threshold (PC = 0.466). This implies that the network remains stable until approximately 46.6% of the edges (i.e., 27 edges) are removed, after which an abrupt fragmentation occurs. The results indicate significant redundancy among network edges, implying that the most important connections can be replaced by alternative paths, which would however delay cargo flows.

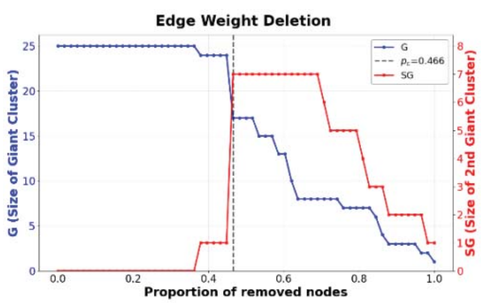

Fig. 4. The percolation process under Edge Weight scenario.

As shown in Figure 5 and Figure 6, the Weighted Degree (Degree × node weight) and Weighted Betweenness Centrality (BC × node weight) strategies yield a low threshold, PC = 0.120. This means that removing 12% of the nodes (i.e., 3 nodes) is sufficient to fragment the network. The steep collapse of the giant cluster and the rapid emergence of a sizeable second cluster point a strong reliance on nodes that combine high connectivity with high-risk weight. The fact that both approaches produce the same PC suggests that high-degree nodes also function as key flow bottlenecks. However, the plots indicate that the patterns of fragmentation differ across the two strategies. Notably, the weighted-degree removal order is Amsterdam→ Utrecht → Moerdijk, contrary to the expectation that Rotterdam would appear first, whereas the weighted-betweenness removal order is Moerdijk → Rotterdam → Utrecht. This highlights that understanding the network's topology alone is insufficient; and that the risk profile of each node must also be explicitly taken into account.

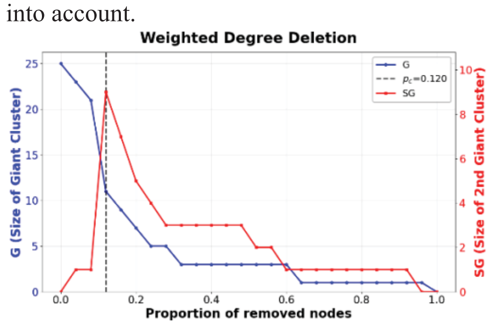

Fig. 5. The percolation process under Weighted Degree scenario.

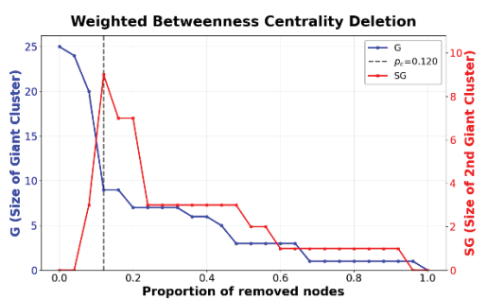

Fig. 6. The percolation process under Weighted Betweenness Centrality scenario.

Finally, when the Node Weight removal strategy is applied, an even more pronounced effect is observed, as network collapse occurs at PC = 0.080, the lowest threshold among all strategies, as depicted in Figure 7. This result implies that removal of only 8% of the highest-weight nodes (i.e., 2 nodes) is sufficient to induce an immediate disconnection of the network. It is thereby indicated that, when node importance is evaluated solely based on weight (i.e., the associated risk level), the nodes with the greatest weights must be treated as the top-priority elements for protection and mitigation measures.

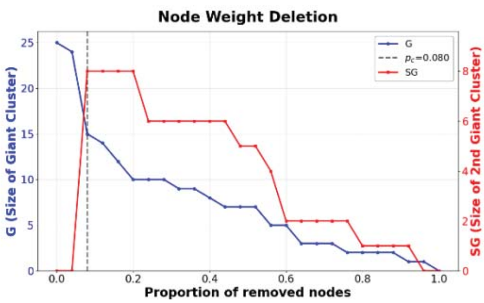

Fig. 7. The percolation process under Node Weight scenario.

Based on the finding that high-risk nodes can trigger rapid fragmentation of the network, it is also essential to examine how the loss of a single critical node reshapes the network. The results indicate that Moerdijk can be considered as a critical node as it has the highest weighted betweenness centrality (BC), weight, and weighted degree, and its removal from the network is associated with relatively low percolation thresholds. To assess the impact of removing the most critical node, the change in betweenness centrality (BC) of the remaining nodes before and after the removal is calculated. The removal of Moerdijk, causes a substantial reconfiguration of flow patterns within the network. Paths that previously passed through Moerdijk are forced to reroute through alternative routes, thereby increasing BC of specific nodes that take on additional load and role. The analysis indicates that 's-Hertogenbosch experiences the largest absolute change in node-weighted BC, with Δ(NW×BC) = 110.97, meaning that 's-Hertogenbosch emerges as the primary alternative mediation node. It is worth noting that other nodes, such as Roosendaal and Eindhoven, exhibit higher percentage increases (1770.1% and 1082.4%, respectively) compared to 's-Hertogenbosch (513.6%). However, these values reflect the low initial BC of those nodes and do not necessarily indicate a higher absolute burden. Therefore, risk mitigation efforts should also consider how the network changes dynamically given the order with which disruptions occur at the nodes.

6. Conclusions

The methodology applied in this study combined network analysis and percolation theory with hazard identification to assess the characteristics of the AUTOFLEX transport system. By simulating progressive node and edge removal, both randomly and with specific orders, the analysis systematically identified the thresholds where network connectivity is degraded and fragmentation is accelerated. The results indicate that reliance only on the network's topological structure is not sufficient for robust detection of vulnerabilities. Node and edge specific risks should also be considered for mitigation strategies. The proposed approach can provide the basis for risk-informed prioritization of mitigation strategies (e.g. strategic introduction of redundancy) by using the quantitative indicators that characterize the network and how it changes when nodes and edges are progressively removed. Future research will explore how the weights of the vessel routes can be differentiated with respect to identified risks, thereby enabling more granular assessments of operational exposure and resilience at the route level. The goal is to effectively support the design of resilient, safer, more reliable and sustainable autonomous IWT systems.

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