Simulation of Road Network Recovery after Disasters

A Data-Driven Approach to Prioritizing Road Repairs

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by

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Cover: An image showing autumn road hazards, sourced from Surovell Firm (Surovell, n.d.)

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Preface

In front of you lies my master thesis, the final part of my studies in Complex Systems Engineering and Management. Since September I have worked on it with great dedication, and although the process took a bit longer than originally planned, I am proud of the end result.

In my research I analysed the impact of disaster on a road network and looked at recovery strategies. By studying which road sections should be restored first and how different recovery strategies lead to different outcomes, I was able to gain valuable insights. Based on this, I was able to formulate recommendations on which strategies are preferable, depending on the chosen focus. Given the societal relevance of this topic, I hope that this thesis contributes to a better understanding of effective recovery strategies for disasters.

Writing this thesis was an educational, but certainly not always easy process. Programming in particular was a challenge, as this was not my strong point when I started this research. Analysing complex networks and developing models required skills that I had to develop along the way. This sometimes meant struggling with code, tracking down bugs and endless testing before I got the right results. However, this challenge has made me broaden my technical knowledge and gain a deeper insight into data analysis and modelling. Looking back, I am proud of the growth I have made and the skills I have acquired during this process.

This thesis would not have been possible without the support and guidance of a number of people. First of all, I would like to thank my supervisors Nazli Aydin, Patrick Stokkink and Srijith Balakrishnan, whose valuable feedback, critical perspective and expert guidance played an essential role in the course of my research. Their advice not only helped me to sharpen my research questions and methodology, but also provided new insights that lifted my thesis to a higher level. In particular, I would like to thank Patrick and Srijith for the (bi)weekly meetings and their guidance during this process. These conversations offered structure and direction and gave me the confidence and motivation to continue, especially in moments of doubt or getting stuck. I greatly appreciated their willingness to answer questions, think along about problems and provide constructive feedback.

Finally, I would like to thank my friends, family, rowing team, and the fellow members of the bar committee for their support throughout the process of writing this thesis. Balancing an intense rowing schedule, with graduating and helping run the bar committee at the rowing club wasn't always the easiest combination. In those busy months, your support really made a difference. Whether it was lending me a laptop, taking a quick coffee break together, sitting down to study side by side, or simply giving me the space to share some frustration, it all helped more than you might think. Without their support, this process would have been a lot harder, and I am incredibly grateful that I could always count on them.

Thura van der Schans
Delft, April 2025

Summary

Several (natural) disasters have occurred in recent years, and with the expected increase in extreme weather events, such events are likely to increase. Warmer weather increases the risk of forest fires, and the frequency and severity of other disasters will also increase. These disasters cause various structural damage to road networks, but the functional consequences often show striking similarities, such as reduced accessibility, delays and disruptions of vital services. In some cases, roads can become completely or partially impassable, leading to serious disruptions to transport and logistics.

This research aims to analyse the impact of disasters on road networks and to develop recovery strategies utilising multi-objective graph metric recovery. The primary research question is:

How do disruptions affect road networks, and which recovery strategies are most effective under varying conditions based on different network metrics?

To address this question, a literature review was conducted to explore existing recovery strategies. This review identified five distinct recovery strategies, each employing a different approach:

- Recovery based on proximity to centre.
- Recovery based on proximity and road hierarchy.
- Recovery based on proximity and recovery time.
- Recovery based on recovery time and proximity.
- Dynamic simulation of the recovery process based on time-dependent variables.

To evaluate the effectiveness of these strategies, six network metrics were employed: accessibility, betweenness, connected components, efficiency, resilience, and robustness.

The analysis was performed on four networks: Sioux Falls, Eastern Massachusetts, Anaheim, and Munich, which differ in size and topology (United States and Germany). The Sioux Falls network served as a test network for the model code, which was later applied to the other networks. Each network was tested with four different percentages of edge removal (25%, 50%, 75%, and 100%) to simulate different disaster scenarios. Instead of analysing only one set of removed roads per percentage, 100 simulations were performed per network. This approach was necessary because of the unpredictability of which specific roads would be affected. This increased the reliability of the results and provided a broader overview of possible combinations of removed connections, which better reflected the variability and uncertainty of disasters.

The results showed that the effectiveness of recovery strategies seems to be highly dependent on network structure. In networks with a central or radial structure, such as Sioux Falls and eastern Massachusetts, strategies based on *proximity and hierarchy*, *recovery time and proximity* and *dynamic recovery* perform well under limited disturbance. As disturbance increases, effectiveness shifts to strategies that focus on *proximity and hierarchy* for the Sioux Falls network, or on *proximity to the centre*, *proximity and hierarchy* and *proximity and recovery time* for the Eastern Massachusetts network. In networks such as Anaheim (decentralised) and Munich (ring-radial), strategies focusing on *proximity to centre* and *proximity and recovery time* perform better under larger disturbances. It is important to recognise that these effects were derived from four networks. There was no opportunity to include multiple networks of the same structure in the analysis, making it impossible to assert with certainty that the observed effects apply to all networks of a similar structure.

In addition, the analysis shows that the specific recovery goal also plays an important role in the choice of an appropriate strategy. If the goal is to improve the accessibility, or the number of nodes that can be reached from a certain centre node, strategies based on *proximity to the centre*, *proximity and hierarchy*, and *proximity and recovery time* appear to be beneficial. When the goal is to restore nodes that are on a lot of shortest paths (betweenness) or reduce network fragmentation, also known as the connected

components, strategies focusing on *recovery time and proximity* or *dynamic recovery* seem to be more appropriate. When the focus is on reducing the shortest distances between nodes as quickly as possible, i.e. improving efficiency, or on restoring links with the most traffic first, aimed at increasing robustness, strategies such as *recovery time and proximity* and *dynamic recovery* can be considered.

These findings underline that there is no universal recovery strategy that is optimal in all situations. The study, therefore provides valuable insights into how recovery strategies can be tailored to both network topology and functional purpose. This is particularly relevant for policymakers and emergency planners when drawing up recovery plans. They can first determine the specific goal of the recovery and then choose a strategy that fits that. In addition, they can analyse the type of network and determine whether the strategy resulting from the metric analysis performs well within their network structure as expected. However, it is important to emphasise that the results were analysed per network type. This means that the findings cannot be directly applied to other networks with a similar structure.

By understanding how different networks respond to different levels of disasters, this study provides valuable tools for optimising recovery strategies. This helps to improve network connectivity and reduce recovery time after extreme disasters, which is essential for infrastructure recovery and minimising damage. Furthermore, this study contributes to the existing literature by analysing recovery strategies across multiple networks with different structures, instead of just one type of network as in previous studies. This shows that there is no universal strategy and that the effectiveness strongly depends on the network structure and the type of disruption. While previous studies indicated the dynamic strategy as the best, this study shows that alternative strategies, such as proximity and hierarchy, perform better in some cases. The study uses multiple performance indicators and systematically varies the degree of network disruption, which allows for a more realistic and broadly applicable analysis. This provides valuable insights for policymakers and emphasises the importance of context-specific choices in network recovery.

In summary, this study provides detailed insights into the effectiveness of different recovery strategies in relation to different network topologies and different levels of disasters. It emphasizes that there is no universal "best" strategy, but that the choice of a specific strategy should be tailored to the structure of the network and the level of disruption. These findings contribute to a better understanding of how we can increase the resilience of road networks and reduce the impact of disasters by implementing efficient recovery strategies.

Contents

1

Introduction

In 2021, Limburg was hit by a severe flood, which was the result of 160 to 180 millimetres of rain that fell in two days (Kok et al., 2023). The consequences were significant: highways were flooded, campsites had to be evacuated and soldiers were deployed to provide assistance (NOS, 2021). In addition to the consequences of floods, the impact of natural disasters is also visible on a larger scale. For example, in 2023, Europe, the Middle East and Africa experienced one of the most severe wildfire seasons in recent decades (Directorate-General for European Civil Protection and Humanitarian Aid Operations (ECHO), 2024). More than 500,000 hectares of nature reserve were affected by forest fires, which is equivalent to about half the surface area of the island of Cyprus (San-Miguel-Ayanz et al., 2024). Furthermore, in 2024, a staggering 1,374 earthquakes of magnitude five or greater were recorded worldwide, causing not only tragic loss of life, but also enormous economic damage, costing billions of dollars in damage to infrastructure and private property (Statista, 2024).

These examples show that natural hazards can occur anywhere in the world and have far-reaching consequences. They not only affect people and the environment, but also damage essential infrastructure. Roads can be damaged or become impassable, severely limiting the accessibility of affected areas. Restoring road networks after a disaster requires careful consideration of which routes should be restored first. Such decisions are made based on strategies and trade-off criteria such as resilience, robustness, efficiency and accessibility of the network. These aspects are essential for effectively dealing with the aftermath of natural disasters and provide tools for determining priorities during the recovery process.

This study focuses on applying previous research on recovery strategies of road networks after natural disasters to four specific cases: the Sioux Falls, Eastern Massachusetts, Anaheim and Munich networks. The recovery will be analysed using different strategies and measured with various metrics. The central research question that motivates this research is as follows:

How do disruptions affect road networks, and which recovery strategies are most effective under varying conditions based on different network metrics?

To answer this main question, the following sub-questions are examined:

1. What are the structural and functional consequences of different types of natural hazards for road networks?
2. What recovery strategies exist to make damaged road networks functional again?
3. How can different recovery strategies for a disrupted road network be modelled, optimized, and evaluated using multi-objective graph metric recovery?
4. How do different road network structures influence the performance of recovery strategies under varying levels of disruption?
5. What recommendations can be made for choosing the most appropriate recovery strategy for a disrupted network?

This research focuses on road network restoration after disruptions, evaluating the effectiveness of different restoration strategies using six metrics: accessibility, betweenness centrality, connected components, efficiency, resilience, and robustness. Using simulations and network models, the four cities, Sioux Falls, Eastern Massachusetts, Anaheim, Munich, are analysed. These cities represent diverse network structures and geographic contexts, providing a broad insight into different impacts of disasters and subsequent restoration strategies. In the simulations, roads are randomly removed at four different damage percentages (25%, 50%, 75%, and 100%) to simulate the variability of disasters. Restoration strategies are applied based on factors such as distance to the centre and road priority, and the effectiveness of these strategies is then measured using the aforementioned metrics.

The reliability of the results is ensured by repeating the simulations 100 times with a fixed random seed and applying a 95% confidence interval. For the simulations and analysis, Python and the NetworkX package will be used, taking into account the impact of network topology, road capacity, and speed on the recovery process. This systematic approach provides valuable insights into how various urban networks respond to disruptions and which recovery strategies are most effective for maintaining critical infrastructure.

This research holds both scientific and societal significance, aligning with the CoSEM master's program focused on transport and logistics, where complex issues are approached from a multidisciplinary perspective. By applying the principles of systems engineering and socio-technical analysis to network recovery following disasters, this study provides both theoretical and practical insights. The evaluation of recovery strategies offers policymakers valuable guidance in selecting the most appropriate recovery measures based on the priorities of specific scenarios. This contributes to enhancing the functional value of the road network for users, which is essential for restoring a network after disruptions.

From a scientific standpoint, it contributes to the expansion of knowledge regarding the resilience and robustness of urban road networks, particularly in light of the increasing impacts of climate change and extreme weather events. The inclusion of multiple cities with diverse network conditions allows for broader applicability of the findings, aiding in the development of more advanced recovery models globally.

This research holds significant societal relevance due to the increasing frequency of extreme weather events and the urgent need for rapid and effective responses to natural disasters. The findings from this study can assist policymakers and urban planners in formulating more resilient recovery strategies that minimize the recovery time of transportation networks, restore mobility swiftly, and ensure the safety of urban areas. The applicability of this research extends beyond the American networks examined, offering broader implications for other geographical contexts, such as the German city of Munich, thereby providing internationally applicable recommendations for urban infrastructures worldwide.

The structure of this thesis is as follows: Chapter 2 presents a literature review that examines previous studies on the impact of climate change on natural disasters, the effects of disasters on transportation networks, and potential recovery strategies. This literature review provides valuable insights into the variability of impacts and discusses various strategies for the restoration of damaged infrastructure. Chapter 3 focuses on the methodology employed in this research. It explains how appropriate methods are applied to address the research questions, with particular emphasis on the networks being analysed, the recovery strategies considered, and the metric indicators used to evaluate the effectiveness of these strategies. Additionally, this chapter delves into the execution of the research and the approach taken in the case studies. The analyses are conducted in chapter 4 on the networks of Sioux Falls, Eastern Massachusetts, Anaheim and Munich. Chapter 5 offers a reflection on the findings and discusses the limitations of the study and recommendations for further research. Finally, Chapter 6 presents the conclusion of this research..

2 Literature study

In this chapter, section 2.1 will first look at the impact of climate change on natural hazards. This is followed by a discussion of the structural and functional consequences of such hazards in section 2.2. This section will also look at the distinction between hazard-specific and hazard-agnostic approaches. Section 2.3 then addresses various strategies for resolving issues in road networks, particularly when parts of the network become inaccessible due to natural hazards. The chapter wraps up with section 2.4, which addresses the current knowledge gaps and examines the first two sub-questions of the research, providing answers to them as well.

2.1. The influence of climate change on natural hazard frequency

In recent years, there has been a notable increase in the frequency and intensity of natural hazards, a trend often linked to climate change (B. Wang et al., 2020). In addition, climate change will also cause more intense and more frequent impacts (Bles et al., 2023). Global warming contributes to more extreme precipitation patterns, rising sea levels, and higher ocean and atmospheric temperatures, all of which increase the likelihood and severity of various hazards—including floods, tropical cyclones, and storm surges (Camici et al., 2014; Knutson et al., 2020).

For example, a study focusing on central Dresden, Germany, demonstrates significant shifts in hydrological patterns, with increases in precipitation (17.10%), surface run-off (12.66%), and recorded flood incidents (63.26%) (Yang et al., 2024). Research also indicates a growing intensity in tropical storms and hurricanes globally (Knutson et al., 2020). These storms bring not only wind-related destruction but also vast quantities of rainfall and storm surges, resulting in inland and coastal flooding. As the IPCC notes, climate change is likely to amplify the effects of such hazards, calling for broader hazard-resilient planning in infrastructure systems (Camici et al., 2014).

In addition to the impacts of climate change related to flooding, tropical storms and hurricanes, the risk of wildfires is also increasing. Rising temperatures and prolonged dry spells create increasingly favourable conditions for the outbreak of wildfires, particularly in regions that are naturally prone to such events (Fekete & Nehren, 2024). Wildfires can cause significant damage to road infrastructure, especially unpaved roads. Therefore, implementing appropriate recovery measures is crucial, especially in steep areas that have been severely affected by fires (Sosa & MacDonald, 2016). This highlights that climate change can influence various types of hazards and that the repercussions for road networks can be substantial.

2.2. Impact of natural hazards on road infrastructure

Natural disasters can impact road infrastructure in various ways. These effects can be both functional and structural. This section will explore the different types of natural disasters and the specific consequences they may have on road networks. In addition, this section will first look at more hazard-specific impacts, after which the focus will slowly shift to a more hazard-agnostic approach.

2.2.1. Structural impact

When analysing different natural hazards, it becomes clear that each type of disaster has unique structural consequences. Despite these differences, there is a clear connection in the way infrastructure is affected. Whether it concerns earthquakes, floods, volcanic eruptions or wildfires, each type of disaster causes disruptions within vital networks and makes it more difficult to reach affected areas. The structural consequences per natural hazard will be further elaborated on.

Earthquakes often have a devastating effect on the physical infrastructure. The force of seismic shocks can lead to the collapse of bridges, tunnels and roads, which causes direct damage to the transport network (Kilanitis & Sextos, 2018). The sudden nature of this disaster causes acute problems with accessibility and emergency services. The damage is not limited to transport connections; vital networks such as electricity and telecommunications can also be disrupted. Electricity poles could potentially collapse as a result of the earthquake, which in turn may lead to the outbreak of wildfires (Fekete & Nehren, 2024).

Flooding causes various forms of damage to asphalt roads by saturating underlying layers and eroding the road surface. Common damage effects include rutting, edge cracking, ravelling and potholes (Ashish et al., 2024; Sultana et al., 2016; W. Wang et al., 2020). In addition, cracks such as alligator cracking, longitudinal cracking and transverse fractures occur, which indicate structural weakening (Ha et al., 2022; Helali et al., 2008). These effects significantly reduce the bearing capacity of the road surface and accelerate the deterioration of the network, leading to higher maintenance costs and reduced accessibility.

Volcanic eruptions also pose a serious threat to infrastructure. An average of 30 to 40 eruptions are recorded annually, which in some cases can last for years (Tomassen, 2023). Lava, ash rains and pyroclastic flows have the potential to completely destroy roads, airports and other transport links (Hayes et al., 2022). Additionally, volcanic eruptions can lead to a decrease in the skid resistance of roads (Blake et al., 2017). The impact is often local, but can spread rapidly when essential connections are disrupted. Even without global attention, these disasters cause long-term disruptions to accessibility and logistics.

Wildfires affect infrastructure in indirect but significant ways. By increasing erosion on unpaved roads and increasing run-off, they damage surfaces and exacerbate sediment flows into nearby waters (Sosa & MacDonald, 2016). Recovery measures are complex, especially in mountainous areas that have been severely affected. Additional risks arise when wildfires are triggered by other natural phenomena, such as lightning strikes or earthquakes that knock down power lines. This creates a chain reaction of damage to various infrastructure elements, including electricity supplies (Fekete & Nehren, 2024). Furthermore, heat could also lead to the expansion of pavements or bridges (Bles et al., 2023). Consequently, the heat generated by wildfires may contribute to this effect.

Table 2.1 provides a clear overview of the main structural impacts of these four disasters, including the associated literature references. This table provides insight into how each natural hazard causes its own pattern of damage, but ultimately, all contribute to the disruption of critical networks.

Table 2.1: Structural impact of natural hazards on road networks

Natural hazard	Impact	Sources
Earthquakes	• Collapse of bridges • Collapse of roads • Collapse of tunnels • Collapse of power lines and poles which could cause fires	Fekete and Nehren, 2024; Kilanitis and Sextos, 2018
Flooding	• Rutting • Edge cracking • Ravelling • Potholes • Alligator cracking • Longitudinal cracking • Transverse fractures	Ashish et al., 2024; Ha et al., 2022; Helali et al., 2008; Sultana et al., 2016
Volcanic eruptions	• Reduction of skid resistance on roads • Coverage of roads by ash • Coverage of roads by lava	Blake et al., 2017; Hayes et al., 2022
Wildfire	• Erosion of road surface • Increased sedimentation • Expansion of pavement and bridges	Bles et al., 2023; Sosa and MacDonald, 2016

2.2.2. The functional impact of natural hazards on infrastructure networks

Due to (natural) hazards, road networks may not be accessible because they have been destroyed and need to be repaired, as a result, travellers are often unable to reach their intended destinations, are forced to make extensive detours, or must abandon their journeys altogether. This situation worsens traffic congestion and significantly decreases vehicle speeds throughout the network (He et al., 2024). Over time, the persistent risks associated with recurrent hazards can accumulate into substantial costs. These costs stem from the loss of economic assets and livelihoods, the interruption of public services, and the adverse effects on business operations and individual well-being (B. Wang et al., 2020).

These hazards disrupt the continuity of origin-destination connections, especially in areas where alternative routes are lacking. This leads to network fragmentation and limits mobility between critical locations such as residential areas, workplaces, and hospitals, while also delaying emergency services due to impassable roads and increased congestion (Wassmer et al., 2024). In the long term, these recurring disruptions undermine the reliability of the transportation network and disrupt the daily functioning of both individuals and institutions.

For example, wildfire-related evacuations may require rapid and large-scale road closures; landslides can isolate mountain communities entirely; and earthquakes can cause structural failures in bridges and tunnels, making critical connections unsafe or unusable. Between 1989 and 2000, 32.8% of all recorded bridge failures in the United States were directly related to extreme weather events (Wardhana & Hadipriono, 2003), highlighting the vulnerability of essential links.

2.2.3. Hazard-specific and hazard-agnostic perspectives on road networks

Although natural disasters such as earthquakes, floods, wildfires and volcanic eruptions differ greatly in their origins and physical behaviour, they show striking similarities in their impact on critical infrastructure. They almost always lead to disruptions in connectivity, reduced accessibility and damage to essential links in the road network. These shared consequences highlight the limitations of traditional, threat-specific approaches, in which each type of disaster is analysed and addressed separately.

A more future-proof alternative is the so-called threat-agnostic resilience approach. This focuses on the ability of a system to maintain essential functions, regardless of the type of threat (Trump et al., 2025). Instead of assuming specific scenarios, the emphasis is on the robustness, adaptability and redundancy of the system itself.

The need for a broader approach is reinforced by the increase in so-called multi-hazard disasters, in which multiple threats follow one another or occur simultaneously, such as a tsunami after an earthquake (Ba et al., 2021). Such complex situations require models that can analyse multiple threats simultaneously or sequentially (Zhou et al., 2024).

Yet many studies still focus on only one type of disaster at a time, while the nature and consequences of natural disasters vary widely. To fully understand damage to infrastructure worldwide and to assess the value of adaptation measures, a broader and integrated approach is essential (Koks et al., 2019).

Therefore, it is important to focus more on hazard-agnostic approaches. By making risks less dependent on specific scenarios, resilient systems can be designed that are better able to withstand a wide range of disasters, even in unpredictable or combined circumstances.

2.3. Recovery strategies

The concept of hazard-agnostic has been explored as an overarching approach to analysing disruptions within a network. In this section, the focus shifts to the question of how these disruptions can be effectively resolved. Special attention will be paid to determining the right priorities for recovery efforts, which can often be a challenge. Several strategies can be applied during the recovery process, especially when it comes to determining which roads to tackle first. The article by Aydin et al., 2018 offers four strategies that are further elaborated in this context.

2.3.1. Proximity to main resource centre

The initial strategy to be examined focuses on a singular variable, specifically the "proximity to the main resource centre." The humanitarian logistics and emergency management services can reach a rural area from the nearest metropolitan area. In this context, the distance from the resource centre to the roads that are currently obstructed and require repair will be evaluated. Subsequently, a distribution plan will be established that prioritizes the closest roads to repair. The primary objective is to accelerate the restoration of the overall network connectivity.

2.3.2. Proximity and road hierarchy

The second strategy focuses on the concepts of proximity and road hierarchy. This approach builds upon the first strategy by incorporating an analysis of the classification of roads into primary, secondary, and tertiary categories. The fundamental premise is that prioritizing repairing the most critical road segments, specifically the primary ones, will facilitate quicker restoration efforts. Consequently, the road repair process is determined by two factors: 1) the hierarchical classification of each road segment and 2) its distance from the nearest emergency centre. For example, the primary road segments closest to an emergency centre will be addressed first, followed by secondary and tertiary segments, according to their respective distances to the emergency facility.

2.3.3. Proximity and time to recover

The third strategy builds upon the foundation established by the first strategy. In this approach, the main consideration is the proximity of the road segments in conjunction with the time required for recovery. In the article of Dall'Asta et al., 2006, the duration necessary to restore each closed segment was assessed based on the volume of debris on the roadway, determined through surveys conducted with the relevant authorities. These surveys were instrumental in identifying response times and operational capacities, including the work schedules of clearance teams. Although recovery times for each segment were used to develop cumulative recovery functions in all strategies, this particular strategy was specifically designed to prioritise the sequencing of road recoveries. The objective is to clear road segments in an order that minimises recovery time, focusing on those with the least debris and those located closest to a resource centre.

2.3.4. Dynamically simulating a sequence based on the time variable

The final strategy does not consider the distance to the resource centre, rather, it focuses solely on the time aspect. This approach evaluates the duration required to restore a road segment. In this context, Strategy 4 emphasises the dynamic simulation of a sequence driven by the time variable. Initially, the time necessary to reopen a closed road segment was determined using probability density functions (PDFs). Subsequently, these segments were arranged in ascending order according to the identified time variable to establish the most effective restoration sequence.

2.4. Conclusion drawn from the literature and knowledge gaps

This section examines the structural and functional consequences of multiple natural hazards on road networks and the recovery strategies currently applied. This chapter addresses the sub-question: "What are the structural and functional consequences of different types of natural hazards for road networks?"

Natural hazards can damage road networks in a variety of ways, affecting both structural and functional aspects. The nature and severity of these consequences vary per type of hazard, but ultimately lead to reduced accessibility of the network and disruption of mobility.

Each hazard has characteristic structural effects. For example, earthquakes can lead to the collapse of bridges, roads, tunnels or electricity infrastructure. Floods often cause damage such as rutting, edge cracking, alligator cracking, potholes, and longitudinal or transverse cracks in the road surface. Volcanic eruptions can cover roads with ash or lava, and also cause a reduction of the skid resistance of the road surface. Wildfires cause erosion of road surfaces, increased sedimentation, and can cause expansion of pavements and bridges due to extreme heat.

Despite the diversity of physical damage, a common consequence of these hazards is the reduction in accessibility of the road network. This translates into functional impacts: reduced accessibility, reduced connectivity, and disruption of traffic flows. Critical services such as ambulance transport, fire brigades, and logistics can be severely hampered. From this perspective, the analysis shifts from a hazard-specific approach to a more hazard-agnostic approach, focusing on the functional consequences of damage, regardless of the type of hazard underlying it.

In summary, natural hazards can lead to significant structural damage to road networks, with the main functional consequence being a reduction in mobility and accessibility. Despite differences in cause, many hazards result in similar functional disruptions, such as reduced accessibility and accessibility. This emphasizes the value of a hazard-agnostic approach, where recovery strategies are developed based on functional impact rather than hazard type.

In addition, this sections also looks at the second sub-question: "What recovery strategies exist to make damaged road networks functional again? This section shows that different strategies are applied to minimize the impact of hazards and accelerate the recovery process. In many cases, roads are prioritized based on their proximity to the main resource centre, their road hierarchy within the network and the required recovery time. Strategic choices play a crucial role in deploying resources more efficiently and restoring network connectivity as quickly as possible.

These findings underline the need for well-considered recovery policies and resilient infrastructure planning. Natural hazards are an increasing threat to road infrastructure, making effective recovery strategies essential to ensure the connectivity and safety of road networks.

At the same time, the literature review reveals several knowledge gaps that are directly related to the objective of this study. Although various recovery strategies are described in the literature, there is a lack of in-depth insight into how these strategies perform when applied to different networks and tested on different metrics. It was shown that all four strategies have been applied to a network, but that comparing these strategies is only done using a minimal number of metrics. This leaves it unclear which strategy would be best when you have different goals. In addition, there is little information available on how these strategies can be applied to different networks and what the outcome would be.

Existing research often focuses on recovery strategies within the context of a specific hazard, utilizing empirical damage data. However, this study adopts a hazard-agnostic approach, concentrating on the functional impact of disruptions regardless of the type of hazard involved. This methodology enhances the comparability and generalizability of insights regarding which strategies perform best compared to the other strategies.

To reduce these knowledge gaps, this study will apply the strategies described in the literature to multiple networks. Initially, a smaller network will be analysed, after which the study will be expanded to increasingly larger networks. The effectiveness of the different recovery strategies is assessed using relevant indicators, providing insight into which strategy is most suitable in different contexts and under different requirements. In this manner, the study contributes significantly to informed decision-making for the recovery of road networks following disruptions, irrespective of the nature of the triggering hazard.

3
Research methology

This chapter first discusses in section 3.1 the research design and methodology underlying this study. Initially, it addresses the structure and framework of the research, explaining the methods and approaches used to answer the research question. Subsequently, in section 3.2, a general definition of a network is explored, which is crucial for understanding the context in which the further analysis occurs. This definition serves as a foundation for the explanation of various recovery strategies in section 3.3 and also provides a reference framework for evaluating the performance indicators used to analyse the effectiveness of these strategies. The different performance indicators and which of them will be elaborated on further in the research will be discussed in section 3.4. This structure provides a logical and structured picture of the methodology and core concepts central to this study.

3.1. Research design

This section describes how disasters and the resulting road inaccessibilities are modelled, which simulations and strategies are used, and which parameters and assumptions underlie the model. Furthermore, the main assumptions and parameters underlying the model are clarified. This provides an overview of the design of the model and how different network characteristics are taken into account in the analysis.

3.1.1. Methodological approach

The course of this research can be divided into a number of phases. First, the design of the analysis is discussed. This looks at the different percentages of edge removal that are included in the simulations, as well as the number of runs that are performed per simulation to arrive at robust results. Then, the focus will shift to the strategies that are central to the research and the metrics with which these strategies are evaluated. Together, these elements form the framework in which the effectiveness of each strategy can be assessed. Finally, the actual analysis will be performed. The results obtained are then interpreted and discussed based on the chosen strategies and metrics. Some of the important steps in the research will be further explained below.

Edge removal percentages

The simulation phase of this research focuses on modelling disasters by randomly removing network segments (edges). This disturbance represents the variable nature of damage that can occur during disasters. For this purpose, four levels of damage are applied: 25%, 50%, 75% and 100%. The choice of these specific steps is based on the need to model a wide range of scenarios without unnecessarily increasing the complexity of the model.

The chosen 25% steps provide a balanced coverage of the damage range, allowing clear trends in network functionality to be observed without excessive detail. They make it possible to identify critical points at which network performance noticeably deteriorates or abruptly collapses. In the context of hazard-agnostic research, it is also essential to be able to represent the impact of different types of disasters. For example, an earthquake could damage almost the entire road network (100%), while a disaster often only affects parts of the network (such as 25% or 50%).

By using four clearly distinct damage percentages, a representative distribution is created that on the one hand provides sufficient differentiation to analyse trends, and on the other hand keeps the model manageable. Using too many intermediate percentages could lead to excessive computation time and possibly confusing results due to too much detail. On the other hand, limiting it to only one or two damage percentages would risk missing important patterns in the deterioration of the network.

These scenarios need to be independently simulated because each level of damage represents a distinct state of the network with unique structural characteristics and consequences. Aggregating or overlapping simulations could obscure the specific effects of each damage level, making it difficult to isolate how performance metrics evolve in response to increasing disruption. Independent simulation ensures that the impact of each damage scenario is clearly measurable, allowing for robust comparison and trend identification. Furthermore, it avoids interaction effects that could arise if simulations were combined, thereby preserving the integrity and interpretability of the results.

It is also important to note that the damage scenarios are not sequentially linked in a reversible manner. That is, a simulation in which 75% of the edges are removed cannot simply be 'converted' back to the 50% scenario by assuming a 25% recovery. This is because each scenario involves a different random or strategy-driven selection of edges. The 75% damage scenario may remove a specific set of edges, and any recovery process (e.g., guided by a prioritisation strategy) will tend to restore the most critical edges first. In contrast, the 50% scenario may include some of those same critical edges in its initial set of removals. Therefore, starting from a repaired 75% scenario does not result in the same network structure as a freshly simulated 50% damage scenario. Each level thus needs to be simulated independently to maintain consistency and avoid biased or misleading results.

The chosen design therefore forms a deliberate balance between level of detail, feasibility and analytical value, and makes it possible to draw robust conclusions about the performance of the network under different forms and degrees of disturbance.

Number of runs

In this analysis, 100 runs were chosen for the 25%, 50%, and 75% removal rates. This number provides a good balance between reliability and computation time. As networks grow larger, the number of possible sets of edges to remove increases exponentially, making it impractical to test all sets. With 100 runs, a stable average can be calculated, reducing the influence of random deviations. This number of runs provides a reliable approximation of the true value without unnecessarily consuming a lot of computational power. It provides a good balance between accuracy and efficiency, as more runs (such as 1000) are time-consuming, while fewer runs (such as 10) reduce reliability. When looking at removing 100% of the edges, only one run is performed for this. This is because there are no different ways to remove all edges, the result is always the same. Therefore, performing multiple runs has no added value in this specific case.

Metrics and recovery strategies

In this study, several metrics are used to analyse the impact of disruptions on the network. The choice of which metrics are included or excluded is further explained in section 3.4. Based on simulated scenarios, it is then investigated how the network can be restored as effectively as possible. For this purpose, a set of recovery strategies has been developed, which are based on three main criteria: the functional hierarchy of the road segments, the distance to a designated recovery centre, and the estimated recovery time per segment. By combining these factors, the model attempts to provide a realistic picture of the priorities and choices that play a role in recovery planning after a disaster. The specific strategies applied within this study are discussed in detail in section 3.3.

Network modelling and statistical evaluation

This research utilizes Python in conjunction with the NetworkX package to simulate and analyse network structures. NetworkX is a robust and widely utilized library for modelling, manipulating, and visualizing complex networks and graphs. It offers a variety of functionalities for network modelling, algorithm implementation, and the analysis of network statistics.

In order to compare the analyses from Python, a t-test is performed. This allows us to investigate whether the different strategies differ significantly under different metrics and edge removal percentages. According to Wadhwa and Marappa-Ganeshan, 2023, a t-test is a statistical method that determines the significance of the difference between the means of two groups, taking into account their variance. There are three main types of t-tests: the one-sample t-test, the independent t-test, and the paired t-test, depending on the design of the study.

Multiple independent t-tests are performed to determine which strategies specifically differ from each other. For this test, each pair of strategies is compared for all different statistics. Since the values of each strategy for that statistic change during the process, the measurements are dependent on each other. Therefore, the independent t-test is chosen. In addition, a paired samples t-test is also performed. For the paired t-test, the hypotheses are as follows:

- **Null hypothesis**: The mean values of the two groups are the same, indicating that there is no distinction between them.
- **Alternative hypothesis**: The mean values in the two groups are different, indicating that there is a distinction between them.

To investigate whether a comparison between two strategies is statistically significant for a given statistic, both the t-value and the p-value are needed. The t-value can be calculated using the following formula (DATAtab, n.d.):

$$t = \frac{\bar{x_1} - \bar{x_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{3.1}$$

Where:

- $\bar{x_1}$ and $\bar{x_2}$ are the mean values of sample 1 and 2
- s_1^2 and s_2^2 are the standard deviations of sample 1 and 2
- n_1 and n_2 are the number of cases in sample 1 and 2

The t-value of the test indicates how large the difference is between the means relative to the spread of the data. The p-value tells us whether the observed difference between the means is statistically significant. If the p-value is less than 0.05, we consider the difference to be significant.

Choosing the right significance level is essential for making accurate, data-driven decisions. A commonly used significance level is 0.05, which means that there is a 5% chance of incorrectly rejecting the null hypothesis when it is true. Which is a commonly used significance level and strikes a balance between minimising false positives and detecting real effects (Virag, 2024).

The results of these tests are stored in an Excel file so that the findings can be systematically analysed and interpreted for further decision-making.

3.1.2. Reliability and validity

To ensure the reliability and validity of the results, three key measures are implemented. One of these is the use of a fixed random seed for the generator. This ensures reproducibility, as simulations can be repeated consistently under identical conditions. The seed is assigned an integer, which ensures that the pseudo-randomly generated outputs are always the same across repeated runs (Nafis, 2021). As long as no multiple threads are active, reusing the same seed value will always produce the same output. This is essential to ensure that others can obtain exactly the same results when re-running the code. Secondly, variability is minimized by conducting each simulation 100 times, effectively capturing the influence of changing network settings and the impact of disasters. This approach guarantees that the results are robust, consistent, and scientifically sound. Additionally, the values of the various metrics are normalized, enabling straightforward comparisons of the performance across different networks and varying removal rates.

3.2. General definition of a network

A graph serves as a means to define relationships among a collection of objects. It comprises a set of objects known as *nodes*, with specific pairs of these objects connected by edges (Kleinberg & Easley, 2010). In the context of a road network, the nodes can be considered as the junctions, while the sections of the roads represent the edges.

When an asymmetric relationship is necessary, such as A pointing to B but not vice versa, a *directed graph* is used. In a directed graph, each edge possesses a specific direction, represented as an arrow from one node to another. In contrast, when it is explicitly stated that a graph is undirected, it is referred to as an *undirected graph*. In the case of a road network, directed graphs will be utilized, where each connection from A to B or from B to A is treated as a distinct edge.

Mathematically, a graph G is defined as a collection of nodes and a collection of edges. This is commonly denoted as can be shown in equation 3.2.

$$G = (V, E) \tag{3.2}$$

where:

- V represents the set of nodes. Where each node can be denoted as $v_1, v_2, ..., v_n$, where $i, j, k, ...$ are indices that refer to specific nodes within the set N.
- E denotes the set of edges that connect pairs of nodes. An edge connects two nodes and can be denoted as (v_i, v_j), where v_i and v_j are the nodes connected by the edge.

The collection of nodes and edges can be mathematically represented as follows:

$$G = \left(V = \{v_1, v_2, ..., v_n\}, E = \{(v_i, v_j) \mid v_i, v_j \in V\}\right) \tag{3.3}$$

where:

- $V = v_1, v_2, ..., v_n$ denotes the set of nodes, with v_i representing a specific node within the graph.
- $E = (v_i, v_j)|v_i, v_j \in V$ signifies the set of edges, where each edge represents a connection between two nodes v_i and v_j from the set V.

This notation is employed to mathematically describe the structure of a graph (Salama et al., 2012). It can also be stated with these equations that $N = |V|$ represents the number of nodes in the graph. This indicates that N reflects the cardinality (size) of the set, or the total number of nodes in V.

3.3. Recovery strategies

Section 2.3 outlined four significant recovery strategies for road restoration following disasters. In this study, in addition to the four strategies presented in the article by Aydin et al., 2018, a fifth strategy is introduced, which resembles the third strategy, but employs a different order of priorities. These strategies will be applied to various networks in the later stages of this study and subsequently assessed. The five strategies included in this research are:

- *Proximity to the main resource centre*: This strategy focuses on restoring road segments based on their distance from the main emergency centre. Roads that are closer to the emergency centre are prioritised in the repair process.
- *Proximity and road hierarchy*: This approach adds an extra layer of complexity by considering not only the proximity of road segments to an emergency centre but also the hierarchy of the roads. In this case, primary roads, which are crucial for network connectivity, are prioritised over secondary roads. The strategy thus combines both the distance to the emergency centre and the hierarchy of the road segment.
- *Proximity and recovery time*: This strategy goes a step further by combining the proximity of road segments with the estimated recovery time of each segment. The goal is to restore the road segments with the shortest recovery times and the quickest access to resources first, so that the overall recovery of the network is achieved more quickly.

- *Recovery time and proximity*: This strategy reverses the priority order. It first considers the estimated recovery time of each road segment, and only then the distance to the resource centre. Road segments with the shortest repair time are prioritized, regardless of their location, and then it is determined which of these segments are closest to the resource centre.
- *Dynamically simulate a sequence based on the time variable*: The last strategy focuses exclusively on the time variable. Instead of the proximity to a resource centre or the road hierarchy, this approach considers the expected recovery time for each segment. This approach aims to determine the most efficient recovery order by focusing on the fastest recoverable road segments, regardless of their location in the network.

These strategies were chosen to be used in this study because they build on previous research and at the same time provide sufficient variation to compare different approaches to network restoration. The strategies all differ in their structure and in the way in which factors such as proximity to a centre, road hierarchy and recovery time are taken into account. This provides a representative and broad set of recovery strategies that together can simulate different realistic scenarios.

In previous research, these strategies were applied to a situation where the network was affected by an earthquake-triggered landslide. In this study, however, the strategies will be applied to a more hazard-agnostic situation, where the focus is on network restoration independent of the specific type of natural disaster. This allows for a broader view of the effectiveness of recovery strategies, regardless of the nature of the disruption.

In addition, a fifth strategy was chosen: a variation on the third strategy, where the priority is on recovery time, followed by distance to the response centre. This addition allows us to investigate whether the order in which recovery criteria are applied (first recovery time or first proximity) has an impact on the efficiency of the recovery process. It also provides insight into whether proximity still plays a significant role when recovery time is already included as the most important criterion.

By using this combination of existing and adapted strategies, a nuanced comparison can be made between different recovery approaches and better insight is gained into which factors contribute most to an effective network recovery – regardless of the type of natural disaster.

3.4. Performance indicators for recovery strategies

When evaluating a network, the concept of resilience frequently arises, particularly in the context of network recovery. However, there exist additional indicators that can be utilized to assess a network recovery strategy. In this way, performance-based metrics could also be considered, or more specifically accessibility. This section will explore the various indicators that can be used to compare different recovery strategies.

3.4.1. Accessibility

Accessibility is defined as the extent to which nodes within a network can be reached from a specific node in a fixed number of steps h. A distinction is made between "out-accessibility," the number of nodes that can be reached from a starting node in h steps, and "in-accessibility," the number of nodes that can reach the reference node in h steps (Viana et al., 2013). For accessibility, two different approaches will be investigated. First, betweenness accessibility will be considered, and second, a simplified approach to accessibility will be investigated by looking at degree centrality. Both approaches are further explained below.

Betweenness accessibility

Previous discussions have addressed the concept of accessibility; however, in this study, it is relevant to examine betweenness accessibility. Given that this analysis focuses on road networks, it is logical to approach accessibility through the lens of betweenness centrality. Betweenness accessibility measures how often a node is on the shortest routes between other nodes, taking into account the interaction between these nodes. This is especially useful in transportation networks, where the position of certain roads or intersections determines how important they are for the flow of traffic. The formula for betweenness is given in equation 3.4 (Sarlas et al., 2020):

$$C_{B_W}(l_i) = \sum_{j,k \in V, j \neq k} \frac{\sigma(v_j, v_k | v_i)}{\sigma(v_j, v_k)} w_{jk} \tag{3.4}$$

where:

- $\sigma(v_j, v_k|v_i)$ denotes the number of shortest paths between nodes j and k that pass through node i. This indicates how often node i is a relay point for traffic between other nodes.
- $\sigma(v_j, v_k)$ denotes the total number of shortest paths between nodes j and k, without regard to whether they pass through node i. This acts as a normalization factor to prevent nodes with a higher probability of lying between other nodes from automatically getting a higher value.
- w_{jk} gives a weight factor that represents the degree of interaction between nodes j and k. In the case of transportation networks, this could be, for example, the number of travellers, vehicles, or other forms of traffic between these nodes. For social networks, this could be, for example, the frequency of communication between users or the number of files shared.

In short, this equation calculates the betweenness accessibility of a node l by looking at the number of shortest paths passing through this node, weighted by the degree of interaction between the different pairs of nodes. In this study, betweenness accessibility is analysed, originally using the formula in equation 3.4. This formula takes into account the number of shortest paths between nodes and adds a weighting factor w_{jk} to account for the interaction between nodes.

For practical implementation, a simplified approximation of this formula is used, applying the weighted interaction term w_jk based on the volume over the road segment. This results in the betweenness centrality, which indicates how often a node is on the shortest routes between other nodes.

Degree centrality

Degree centrality (DC) serves as a straightforward measure of centrality, representing the number of direct connections associated with a node (El-Sharkawy et al., 2019). A node exhibiting a high degree centrality typically possesses numerous connections and often assumes a pivotal role within the network's structure. This metric is particularly beneficial for pinpointing nodes that enable rapid access to multiple other nodes, thereby enhancing the effectiveness of the network restoration process.

The degree centrality of a node v_i is determined using equation 3.5 (Bamakan et al., 2019):

$$DC(v_i) = \frac{1}{N-1} \sum_{j=1}^{N} \alpha_{i,j} \tag{3.5}$$

In equation 3.5 is $\alpha_{i,j} = 1$ if a direct connection exists between v_i and v_j, with $i \neq j$. In the context of a directed network, degree centrality can account for both incoming and outgoing connections. A high value of $DC(v_i)$ indicates that the node v_i has numerous direct connections to other nodes within the network, rendering it essential for overall connectivity (Golbeck, 2015). When applying degree centrality, the number of nodes that are reachable from a specific node is considered. Since there are different strategies by which a resource centre (partly) determines the order of recovery, degree centrality can be used to optimize accessibility. This is done by strategically adding nodes to improve accessibility within the network.

Choice of accessibility measure

In this analysis, both betweenness accessibility and degree centrality have been selected as metrics for evaluating accessibility. In this study, betweenness accessibility is referred to as *betweenness*, while degree centrality is denoted as *accessibility*. This choice is made because these two metrics illuminate fundamentally different dimensions of accessibility within the network.

Betweenness provides insight into the frequency with which a node appears on the shortest paths between other nodes, which is crucial for understanding flow dynamics and critical connections within the network. Conversely, degree centrality assesses the number of direct connections a node has, serving as an indicator of local connectivity. By including both measures, a more complete picture is obtained of the network structure and how it will recover after disruptions.

3.4.2. Connected components

In the context of restoring a road network after a disaster, it is important to assess the extent to which the network is fragmented. This can be determined by analysing how many separate parts the network contains after it has been disrupted. Each of these separate parts, also called weakly connected components, consists of nodes that are interconnected but have no direct connection to other parts of the network (Memgraph, 2021).

To assess the degree of fragmentation, the focus is on the number of distinct network components (N_{cc}). A higher value indicates a more fragmented network, while a lower value suggests that the network remains well-connected, even in the event of damage.

An alternative method for describing the connectivity of the network is to examine the connectivity score, defined as the inverse of the number of weakly connected components:

$$C(G) = \frac{1}{N_{cc}} \tag{3.6}$$

This approach is employed because a higher score intuitively signifies a better-connected network. If there is only one component ($N_{cc} = 1$), then the value $C(G) = 1$ indicates a fully connected network. As the network becomes more fragmented (with an increase in N_{cc}), the value of $C(G)$ approaches 0. This metric is thus easier to interpret: a higher value reflects a more robust network, whereas a lower value indicates significant fragmentation.

This insight is crucial for the recovery process as it indicates the extent to which network components need to be reconnected to enhance overall accessibility (Ahuja et al., 1993). By utilizing this metric, it becomes possible to analyse how various strategies contribute to a more efficient restoration of the network. This is the rationale behind the decision to incorporate this metric.

3.4.3. Efficiency

Efficiency can be measured by looking at how effectively information is exchanged across a network. This can be done by using the concept of small-world networks, which are efficient at both the global and local levels (Latora & Marchiori, 2001). In the case of road networks, efficiency refers to the capacity of a network to transport information or traffic quickly and effectively between different nodes (such as cities or transport hubs). Efficiency is therefore one of the network characteristics described in the literature that depends on the shortest path concept and can be measured using the following formula (Viana et al., 2013):

$$L = \frac{1}{N(N-1)} \sum_{v_i \neq v_j} \frac{1}{d(v_i, v_j)} \tag{3.7}$$

Where $d(v_i, v_j)$ is the topological distance between nodes v_i and v_j (where $1 \leq i, j \leq N$) along the shortest path. This formula calculates the efficiency of a network by considering the shortest distances between all possible pairs of nodes. It takes the inverse of each shortest distance between two different nodes (the shorter the distance, the greater the contribution to efficiency) and adds them together. Then, the result is divided by the number of possible pairs of nodes in the network, giving the average. This average represents the overall efficiency of the network: the shorter the distances between nodes, the more efficient the network is at moving information or traffic quickly.

This efficiency metric is useful to look at when assessing a network affected by a disaster, as it provides insight into how well the network functions after the disruption. When a disaster damages parts of the network, certain nodes and connections (edges) may no longer be reachable. By measuring efficiency, you can quickly see how severe the impact is on the overall connectivity and therefore efficiency will be taken into account.

3.4.4. Performance

When evaluating performance-based network metrics, it is essential to consider several key indicators, such as total travel time, total travel distance, traffic flow, and traffic capacity (Hosseini et al., 2024). These indicators offer valuable insights into the effectiveness of a transportation network and are vital for assessing the impact of any remediation efforts. This section will provide a more in-depth analysis of the total travel time and total costs.

Total travel time

One of the most important measures of the efficiency of a transportation network is the total travel time (TTT). This indicates the amount of time vehicles spend in the system and is calculated by summing the travel times on all roads in the network, weighted by the amount of traffic on those roads (Zhao & Zhang, 2020). This metric is particularly relevant for recovery measures, as it provides insight into which roads have the greatest impact on travel time. By minimizing travel time, the efficiency of the network can be restored more quickly.

Total costs

In addition to travel time, total costs are also an important factor in assessing network performance. Costs depend on effective planning of recovery activities and efficient allocation of resources (Zhao & Zhang, 2020). Disasters can impose significant costs on road users, road authorities and the economy as a whole.

For example, road users face operational costs such as additional fuel consumption and longer travel times. Road authorities bear the direct costs of infrastructure recovery and may lose budgetary space due to the reallocation of resources. In addition, disasters can cause indirect economic damage, such as loss of productivity, reduced competitiveness and a decrease in national income.

Choice of Performance metric

A deliberate choice was made to disregard both total travel time and total costs in this analysis. This choice was made because disasters affects the accessibility of the edges within a network, resulting in a reduction in the number of available edges and therefore in re-routing. No data are available on this re-routing, nor on the associated consequences for travel time, which makes it impossible to include travel time in the analysis in a valuable way.

In addition, it is difficult to assign a concrete monetary value to road repair within this model, because infrastructure repair involves many variables, such as the nature of the damage, the materials needed, the duration of the work, and the influence of external factors such as weather conditions and labour costs. Furthermore, there may be different approaches to repairing different types of damage, which makes cost estimation difficult. The lack of detailed data on these variables makes it difficult to make an accurate and uniform financial valuation of road repair. Nevertheless, both the total travel time and the total cost remain crucial factors in making well-considered choices regarding road repair work. It is therefore important to consider in the future how these elements can be appropriately incorporated into the decision-making process.

3.4.5. Resilience

A commonly referenced metric for a network is resilience, which can be understood in various dimensions. Resilience may be categorized based on the mitigation strategies implemented prior to a disaster to enhance the system's robustness; the emergency response measures enacted immediately following the event; and the long-term recovery process, during which the system is progressively restored through the reconstruction of the affected network (Gokalp et al., 2021). Additionally, resilience can be defined as the ability of a system to absorb, resist, and swiftly recover from external threats (Meng et al., 2023). Another perspective on resilience is the capability of a city's transportation infrastructure, particularly its road network, to endure, adapt to, and recuperate from various shocks and stressors (Hosseini et al., 2024).

As shown in paragraph 3.2, the road network can be represented as $G(N, E)$, where N signifies the nodes, such as intersections or cities, and E represents the edges connecting these nodes, which correspond to the roads. When roads are damaged by, for example a flooding, the affected connections $R \subset E$ are removed from the graph, resulting in a modified graph $G_r(N, E \setminus R)$. This revised structure reflects the network with the subset R of the total edges E removed. This modification simulates the physical damage to the network. The consequences of road closures and network breaks can be quantified by analysing the effect of this change.

In addition to this resilience based on traffic flow metrics, Zhao and Zhang, 2020 identifies two distinct categories of resilience measures specifically for transportation systems: those based on *network topology* and those based on *system performance*. The measures grounded in *network topology* encompass several factors, including origin-destination (O-D) connectivity, average reciprocal distance, average degree, diameter, cyclicity, betweenness, network coverage, and the diversity of travel alternatives. Conversely, *system performance*-based measures focus on aspects such as travel time, travel cost, environmental considerations, travel demand, and resilience measures derived from consumer surplus.

Some of these metrics could be used to assess a network's resilience in the disaster case. Further attention will be given to the following network topology measures: origin–destination (O-D) connectivity, and travel alternative diversity.

Origin-destination (O-D) connectivity

O-D (origin-destination) connectivity refers to the number of links in a network that support travel between specific origin and destination pairs (Zhang et al., 2015). In classical connectivity analysis, an O-D pair is considered connected if there is a path with positive capacity between the origin and destination. The network is strongly connected if there is a path for each O-D pair.

As elaborated in section 3.2, a graph can be represented as $G = (V, E)$, where the nodes V and the edges E symbolize the network. The set of O-D pairs W is then defined as a subset of the Cartesian product of the nodes.

$$W \subseteq V \times V \tag{3.8}$$

This means that W is a selection of possible connections of nodes, but does not necessarily contain all possible connections. It only contains the relevant origin and destination pairs that are analysed in the network.

The resilience in terms of O-D connectivity (ROD) is defined as the highest level of connectivity between O-D pairs within a specific scenario, divided by the initial connectivity of those O-D pairs. This relationship is mathematically represented as:

$$\text{Resilience - O-D connectivity (ROD)} = \max E_{\xi}\left(max \sum_{w \in W} \varphi^{w}(\xi)\right) \Big/ \sum_{w \in W} \Gamma_{w} \tag{3.9}$$

where:

- W is the set of all O-D pairs.
- $\varphi^{w}(\xi)$ is a binary variable indicating whether the O-D pair w is connected under scenario ξ,
- Γ_{w} is a measure of the original connectivity of the O-D pair w (=1 if connected, =0 otherwise).

This formula measures the percentage of O-D pairs that remain connected after a disruption, by dividing the number of connected pairs by the total number of pairs. Connected O-D pairs are those pairs for which a path exists in the network, while the total number of O-D pairs includes the total number of pairs evaluated.

Travel alternative diversity

Travel Alternative Diversity refers to the number of alternative routes between an origin and destination pair (O-D pair). This metric helps determine the resilience of the transportation system, as more alternative routes provide more travel options in the event of disruptions. The set of available routes for an O-D pair (v_i, v_j) is denoted as K_{v_i,v_j}, where $|K_{v_i,v_j}|$ represents the number of routes. For example, if only one route is available ($|K_{v_i,v_j}| = 1$), a disruption on this route can completely block the connection (Xu et al., 2015). More alternative routes therefore increase the resilience of the network by providing additional travel options.

Choice of resilience metric
Based on the three metrics of O-D connectivity, average degree, and travel alternative diversity, the decision was made to include O-D connectivity in further analyses. This choice was made because it serves as a direct indicator of the network's performance during disruptions. O-D connectivity provides insight into the network's ability to maintain transport flows between critical points, even after significant changes such as road closures. This aspect is particularly vital in urban areas, where the mobility of people and goods is essential for economic activities and daily necessities. By analysing O-D connectivity, it becomes possible to identify vulnerabilities within the network and develop strategies to enhance its resilience in the face of future disasters.

3.4.6. Robustness
Robustness is the ability of a network to maintain its functionality, such as moving people between nodes, despite unexpected disruptions or the loss of nodes and links (Oehlers & Fabian, 2021). In this case, robustness means that the network is able to continue to meet necessary transportation needs even if some parts of the network fail, for example due to a flood. The network remains operational by providing alternative routes, depending on the degree of redundancy the network has. This means that the network continues to function even when it is exposed to failures that may eliminate or interrupt some parts. The degree of robustness is influenced by the existence of critical links: links that, when removed, severely disrupt the network. A robust network often has redundant routes, so that alternative paths between nodes remain available if some links fail (Vodák et al., 2015). The degree of robustness is also influenced by the existence of critical links: links that, when removed, severely disrupt the network. To assess the robustness of a network, degree centrality on both weighted and non-weighted graphs can be used, which are further elaborated in the following paragraphs.

Degree centrality
A first way to measure the robustness of a network is by looking at the degree centrality. This metric indicates the connectivity of individual nodes by looking at the number of direct connections (edges) from each node (El-Sharkawy et al., 2019). When nodes with high degree centrality fail, this can disrupt the overall network connectivity, affecting the robustness of the network. Nodes with a high degree centrality typically have many connections and therefore play a crucial role in the network structure. A high degree centrality indicates that the node is essential for connecting different parts of the network, meaning that the failure of such nodes can significantly weaken the network. The average node degree gives a global picture of the connectivity and thus an indication of the overall robustness of the network.

The Degree Centrality of a node v_i is determined using the following equation (Bamakan et al., 2019):

$$DC(v_i) = \frac{1}{N-1} \sum_{j=1}^{N} \alpha_{i,j} \tag{3.10}$$

where

- N denotes the total number of nodes in the network,
- $\alpha_{i,j} = 1$ if a direct connection exists between v_i and v_j, with $i \neq j$.

Here we can see that the degree centrality of a node indicates how well it is connected within the network by counting the number of direct connections (edges) to other nodes. In the context of a directed network, Degree Centrality can account for both incoming and outgoing connections. A high value of $DC(v_i)$ indicates that the node v_i has numerous direct connections to other nodes within the network, rendering it essential for overall connectivity (Golbeck, 2015).

Degree centrality in weighted graphs
Degree centrality measures the connectivity of a node by counting the number of direct connections (edges) (El-Sharkawy et al., 2019). However, in this study, it concerns a directed network (directed graph), in which a distinction is made between in-degree (the number of incoming connections) and out-degree (the number of outgoing connections) (Powell & Hopkins, 2015).

In addition, the network is weighted, which means that not only the number of connections counts, but also their strength. This means that nodes with heavier connections can have a greater influence on the network. A node with a high in-degree receives a lot of traffic, while a high out-degree indicates that a node has many connections to other nodes. This helps to identify crucial nodes that have a large impact on network robustness in the event of disruptions.

Choice of Robustness metric

In this study, the network is not only directed, but also weighted. This means that connections are not all equally weighted: some roads or nodes play a greater role in the network structure than others. Degree centrality helps determine which nodes are most connected, but in a weighted network there will be looked at the number of connections, but also at their strength. This is essential in a transport network, where some roads carry much more traffic than others.

In addition, the directionality of the network makes an important difference. A node can have a high in-degree (many incoming connections, such as a busy intersection) or a high out-degree (many outgoing connections, such as a traffic hub that directs traffic to different destinations). By combining both aspects, a more realistic picture of which nodes are crucial for the robustness of the network and where disruptions have the greatest impact can be obtained.

3.4.7. Metrics included in further analysis

The further analysis uses six network parameters: accessibility, betweenness, efficiency, connected components, resilience, and robustness. These metrics measure respectively: the local reachability of nodes, the significance of roads in facilitating network flows, the number of fragmented networks, the shortest distance between nodes, the preservation of O-D connectivity, and the importance of a node within the network. Each of these parameters is calculated quantitatively based on graph-theoretic principles, and together they provide a complete picture of the functioning of the network under stress.

3.4.8. Importance of metrics for policymakers and residents

For policymakers, it is essential to understand where the network is vulnerable, which areas should be prioritized for recovery, and how disruptions affect the daily mobility of residents. The selected network parameters help to answer these questions in a substantiated manner.

Accessibility indicates how many nodes are accessible from a specific, centrally located node. For policymakers, this provides valuable information about which areas are quickly isolated after a disruption. If far fewer locations are accessible from a strategic centre, such as a hospital or public transport node, there is a direct reason to focus recovery efforts there. This helps to ensure the functional accessibility of essential facilities for residents in surrounding areas. *Betweenness* identifies nodes that are crucial for the flow of traffic. Identifying these 'critical links' helps to prioritize recovery or reinforcement to reduce network delays and congestion, which provides both economic and societal benefits. *Connected components* provide a picture of the fragmentation of the network. This information is valuable in determining how quickly and at what scale the network as a whole needs to be restored to function as a coherent system again. *Efficiency* measures how effectively travel within the network is performed. By identifying areas with low efficiency, policymakers can address bottlenecks that lead to detours, extra travel time, and higher costs for citizens and businesses. *Resilience*, expressed in terms of maintaining O-D connectivity, helps to assess whether people can still get from A to B. Policy measures can therefore be aimed at restoring essential connections that ensure mobility and accessibility, even in the event of disruptions. *Robustness* is measured based on the weighted degree of a node, which is the sum of the weights of the connected edges. This provides insight into how important a node is within the network, not only based on the number of connections, but also on their strength or capacity. For policymakers, this is crucial: nodes with high robustness often play a key role in the network and are potential 'single points of failure'. By identifying these nodes, measures can be taken to make the network more robust.

By combining these parameters, a clear, multidimensional picture of the network emerges that helps policymakers to set priorities, justify investments and minimize the social impact of disruptions. For residents, this means faster recovery times, more continuity in their daily journeys, and a future-proof transport system.

3.5. Modelling, optimization and evaluation of recovery strategies

This section answers the sub-question: *"How can different recovery strategies for a disrupted road network be modelled, optimized, and evaluated using multi-objective graph metric recovery?"*

The restoration strategies in this research were developed using multi-objective graph metric recovery. This means that the road network was represented as a network (graph) of nodes (e.g. intersections) and edges (road segments), where different restoration strategies were modelled based on multiple criteria. For each of these strategies, specific weights and priorities were assigned to restoration criteria such as proximity to the centre, restoration time and road hierarchy. The strategies are defined as follows:

- *Proximity to the centre*: Segments the network based on the distance to a central node, determined via proximity centrality. Nearby roads are prioritized for restoration.
- *Proximity and hierarchy*: Combines proximity with the classification of roads (primary, secondary, tertiary). Primary roads are restored first.
- *Proximity and recovery time*: Prioritizes recovery based on a combination of proximity and expected recovery time, which depends on segment length and number of lanes.
- *Recovery time and proximity*: Evaluates recovery time first; if recovery time is equal, segments closer to the centre are restored first.
- *Dynamic recovery*: Focuses solely on recovery time, without additional criteria.

These strategies have been optimized by looking at different removal percentages within each network. A simulation of 25%, 50%, 75% and 100% edge removal is included, so that it became clear which situation was most effective in a given situation. Different networks are also considered, namely Sioux Falls, Eastern Massachusetts, Anaheim and Munich.

The strategies were evaluated based on six performance indicators:

- Accessibility: the extent to which nodes remain accessible.
- Betweenness: the importance of roads in network flows.
- Connected components: number of fragments in the network.
- Efficiency: average shortest paths between nodes.
- Resilience: preservation of origin-destination connectivity.
- Robustness: importance of nodes for network coherence.

By modelling recovery strategies using different criteria, optimizing based on network-specific conditions and evaluating via multi-objective graph metric indicators, insight can be gained into the effectiveness of different recovery strategies under different disruption scenarios.

4

Analysis of recovery strategies based on case studies

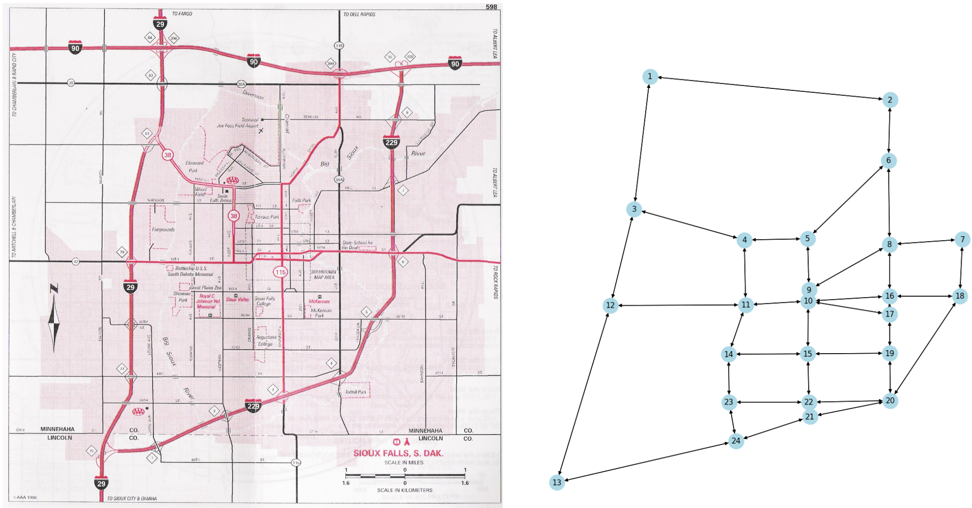
This chapter will discusses the different networks examined in this study, as well as the application of the five recovery strategies to these networks. The objective is to analyse how the selected recovery strategies affect the performance of the networks and how they relate to six key metrics: accessibility, betweenness, connected components, efficiency, resilience, and robustness. The analysis will initially be performed for the Sioux Falls network, after which the same methodology will be applied to three other networks. The chapter concludes with a detailed comparison of the results, discussing both the similarities and differences between the networks. This comparison provides valuable insights into the effectiveness of the recovery strategies in different contexts and helps to identify the best performing strategies for network recovery after disruptions when looking at specific metrics.

4.1. Case descriptions

This section will discuss the networks that will be included in the analyses in more detail. First, the Sioux Falls network will be discussed, as this network will form the basis for the further analysis. An initial model will be developed for this network, which can later be applied to the other networks. This provides a solid starting point for the rest of the research. After discussing the Sioux Falls network, the other networks that will be included in the analyses will be explained in more detail one by one. This will provide a clear overview of the networks and their interrelationships.

4.1.1. Sioux Falls network

The Sioux Falls network serves as the basis for the initial analyses. This network originates from Sioux Falls in South Dakota, United States, and is frequently utilized in transportation research to evaluate, illustrate, and compare various methods and algorithms (Hackl & Adey, 2019). The network is illustrated in Figure 4.1. Figure 4.1a, based on Transportation Networks for Research Core Team, n.d. presents the road network in its original configuration, while Figure 4.1b offers a simplified representation of the network. This simplified model will be used further in this research. The simplified network model contains 24 nodes, and 76 edges.



(a) Sioux Falls network map obtained from Transportation Networks for Research Core Team, n.d.

(b) Sioux Falls network modelled

Figure 4.1: Overview of the Sioux Falls Network

For the Sioux Falls network, several parameters were included in the analyses. For each edge, the start and end node, the recovery time, the priority (whether it is a primary or secondary road), the travel time (in minutes), the capacity of the road segment, the volume, and the length of the road segment were considered. The values for volume, capacity, and length are based on the paper by LeBlanc et al., 1975. The speed limits for this network have been examined in Ukkusuri and Yushimito, 2009, which also presents the number of lanes.

4.1.2. Eastern Massachusetts

In addition to the Sioux Falls network, another American network is also being considered, namely that of Eastern Massachusetts (EMA). This network serves as a subset of the overall Eastern Massachusetts transportation network and represents a subsection of the roads in this area. Massachusetts ranks as the seventh smallest state in the United States, indicating that the Eastern Massachusetts network is relatively compact. Nevertheless, it comprises 74 nodes and 258 edges, making it considerably larger than the Sioux Falls network.

The Eastern Massachusetts network is illustrated in Figure 4.2. However, the visualization of this network differs from that of the Sioux Falls network due to the unavailability of precise coordinates for the nodes. Consequently, it is not feasible to create a geographically accurate reconstruction of the network structure. Instead, an alternative representation is employed to elucidate the interconnections among the nodes.

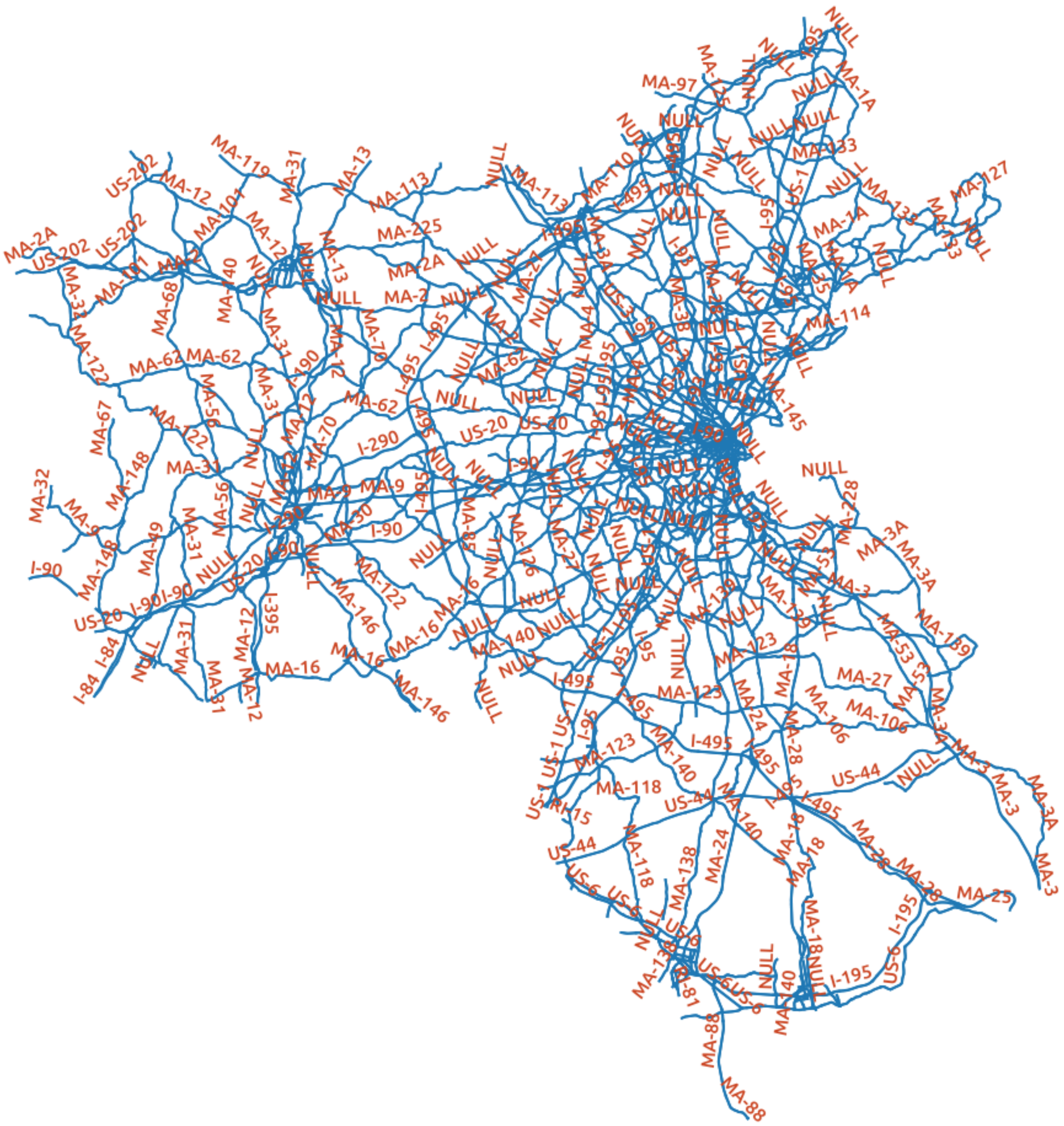


Figure 4.2: Eastern Massachusetts network obtained from Transportation Networks for Research Core Team, n.d.

4.1.3. Anaheim network

The second network to be added is the Anaheim network, located in California. It is significantly larger than both the Sioux Falls network and Eastern Massachusetts network. The Anaheim network consists of 416 nodes and 914 edges and is illustrated in Figure 4.3. A notable feature of the Anaheim network is the prominent road that extends from the upper left to the lower right. This is highlighted by the high density of nodes along this road. Additionally, significant horizontal lines can be observed at both the top and bottom of the network, again indicated by thicker blue lines and a substantial concentration of nodes. Moreover, it is important to note that the Anaheim network is situated inland, resulting in numerous connections extending outward from all directions.

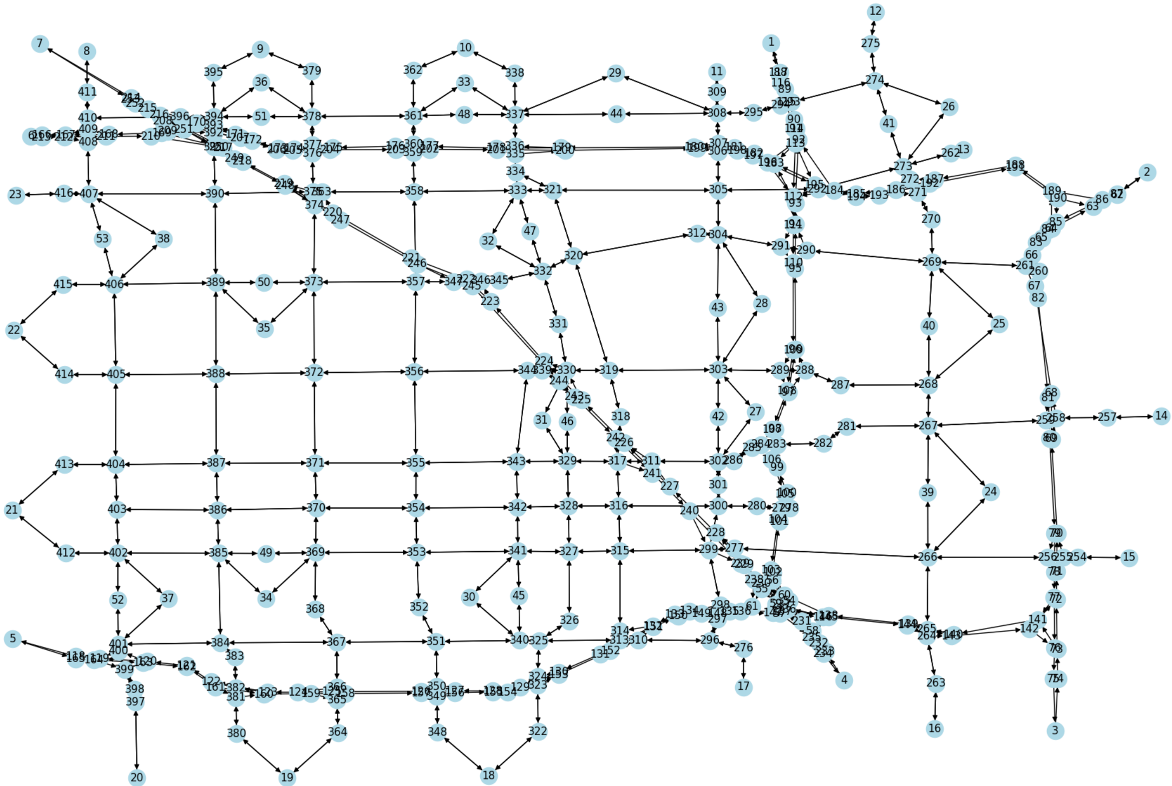


Figure 4.3: Anaheim network modelled

4.1.4. Munich network

The final network included in the analysis is that of Munich, a city located in Germany. This inclusion makes the Munich network particularly noteworthy, as it is the first and only non-American network featured in this study. With a total of 742 nodes and 1,872 edges, the Munich network is significantly larger than the Anaheim network. Another distinguishing feature is the type of data available for the Munich network. Unlike the networks of Sioux Falls and Anaheim, which provide coordinates for the nodes, the Munich network operates with solely distance data between the nodes. This leads to a different approach in representation and modelling.

Figure 4.4 illustrates the structure of the Munich network. The characteristic ring-shaped highway is prominently visible, from which various branches extend outward. The highways are marked in red, while roads with moderate speeds are depicted in blue. The roads with the lowest speeds are indicated by gray lines.

Furthermore, the numbering of the nodes in the Munich network differs from that in the other networks. The node with the lowest number is 73469, while the highest is 2146237932. Several numbers in between have been omitted, further emphasizing the unique structure of this network.

With this addition, the research not only provides insights into American urban networks but also gains a broader perspective by integrating a European road network.

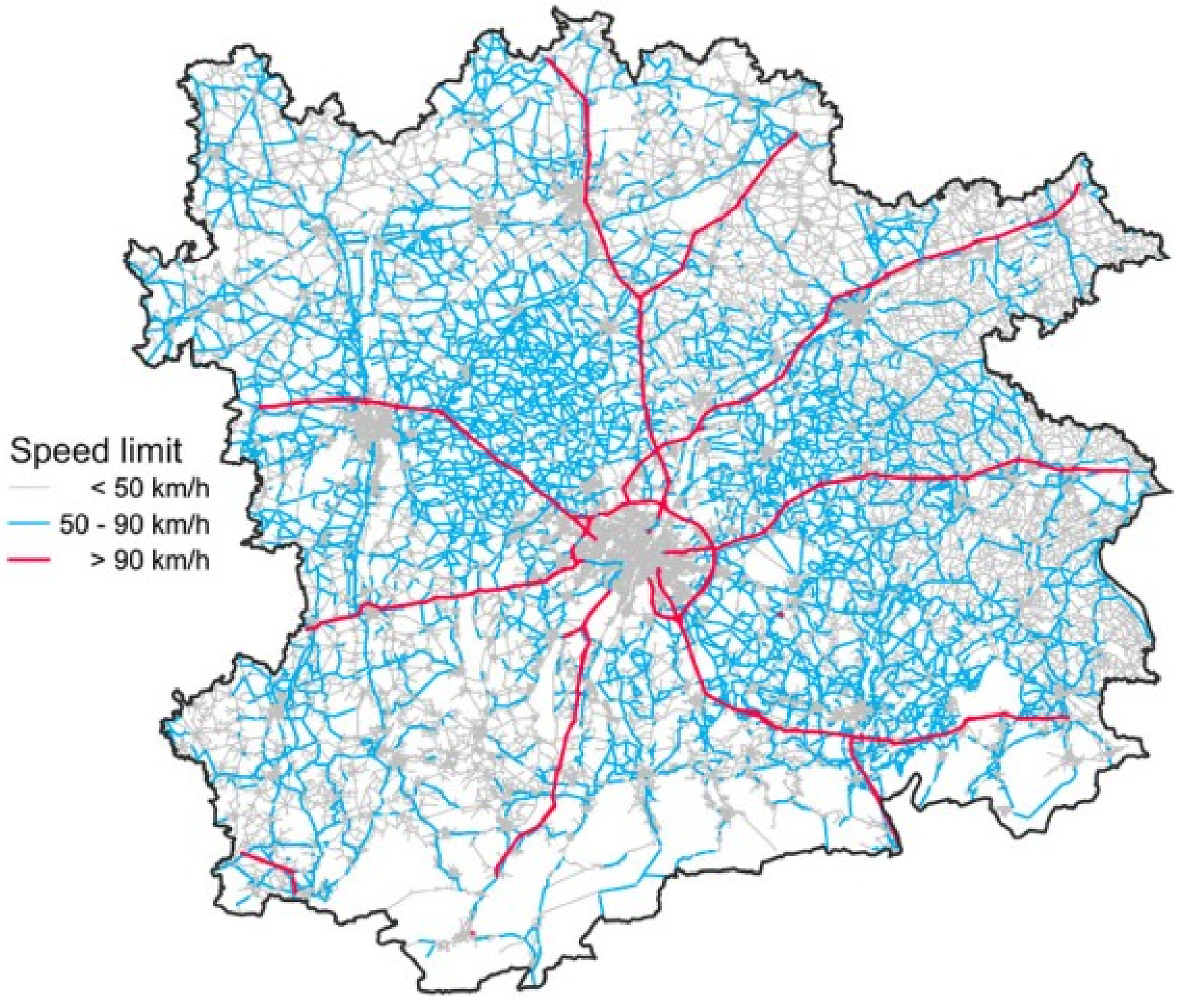


Figure 4.4: Munich network obtained from Saprykin et al., 2022

4.1.5. Comparison of network structures

In this study, betweenness, efficiency and robustness are chosen as the most important metrics to assess the initial state of the networks. These metrics provide direct insight into the core characteristics of a network, such as the degree of node centrality, the effectiveness of traffic transport and the resilience to disruptions. For example, betweenness helps to identify nodes that are essential for communication between different parts of the network, while efficiency indicates how quickly traffic is distributed and robustness reflects the stability of the network in the event of disruptions. In the early stages of the analysis, these metrics provide the most valuable information, as they provide fundamental insights into the structure and performance of the network.

However, other metrics, such as accessibility, connected components and resilience, often provide little additional information in the initial state. Accessibility often simply corresponds to the total number of nodes in the network, which says little about the structure or connections between them. Connected components gives a value of 1 in all networks, as the network is fully connected; there are no fragmented parts. Resilience will always return a value of 1 in this case, because in a fully connected network all connections between the O-D pairs are present, so there is no difference in this metric. Therefore, it is chosen to focus on the three metrics that provide the most insight into the overall functioning and resilience of the network. The values of these metrics are summarized in Table 4.1.

Table 4.1: Performance metrics of selected networks

Network	Robustness	Efficiency	Betweenness
Sioux Falls	36,566.80	0.43	0.091
Eastern Massachusetts	11,882.23	0.29	0.048
Anaheim	4,416.12	0.11	0.026
Munich	5,469.17	0.07	0.025

Table 4.1 shows that the Sioux Falls network scores higher than the other networks for all three metrics, which can be explained by the smaller size of the network, with the nodes being closer together. This makes the network more efficient in distributing traffic and increases its robustness. The Sioux Falls network, with only 24 nodes, has a robustness of 36,566.80 and an efficiency of 0.43, indicating a compact, centralized network where traffic is distributed quickly and effectively through a few key nodes.

The Munich network has a robustness of 5,469.17 and an efficiency of 0.07, indicating inefficiency in traffic despite its larger size. This network exhibits a ring-radial structure, with a main road in the middle acting as a ring, and branches emerging from it, resulting in long routes and low efficiency. The low betweenness centrality of 0.025 indicates that there are few key nodes that distribute traffic efficiently.

The Eastern Massachusetts network, with a robustness of 11,882.23 and an efficiency of 0.29, has a radial pattern. The paths radiate from the centre, and the mixed betweenness centrality of 0.048 indicates that there are both central and local nodes, which provides a balanced traffic distribution and a flexible network. The Eastern Massachusetts network is difficult to give any kind of structure to, but it most closely resembles a network with a clear core, radial structure, and high redundancy.

The Anaheim network has the lowest robustness of 4,416.12 and efficiency of 0.11, which indicates a decentralized grid. This network is distributed over a grid of nodes without strong main arteries, causing traffic to spread over many paths without central concentration points, leading to inefficiency and higher probability of congestion.

The interpretation of the performance in Table 4.1 is well reflected in the structures of the networks as described in the article by yayun, 2018. The Anaheim network exhibits the characteristics of a grid-mesh structure, with low robustness and efficiency. The Munich network has the characteristics of a ring-radial structure, with low efficiency due to long routes and few central nodes. The Sioux Falls network has a compact centralised structure, resulting in high robustness and efficiency. The Eastern Massachusetts network follows a radial pattern, with central and local nodes allowing a balanced distribution of traffic.

Table 4.2 summarises the networks with their associated structure and key characteristics. The data from Table 4.1 is included to provide an overview of the performance per network and how it reflects the underlying network structure.

Table 4.2: Traffic networks: metrics and structural interpretation

Network	Country	Structure	Key features
Sioux Falls	USA	Compact, highly centralised	Small, centralised network with short paths enabling fast and efficient traffic distribution.
Eastern Massachusetts	USA	Radial, high redundancy	Densely connected, mesh-like centre with radiating connections to the edges, which are also partly interconnected.
Anaheim	USA	Grid-mesh, decentralised	Grid layout without dominant routes causes dispersed flow and risk of congestion.
Munich	Germany	Ring-radial, low centrality	Long paths and few central nodes result in inefficient, dispersed traffic flow.

The comparison of the four networks clearly shows how the underlying structure of a traffic network influences its performance in terms of robustness and efficiency. Compact and centralized networks, such as Sioux Falls, perform best due to their short distances and efficient traffic distribution. Networks with a grid structure or ring-radial structure, such as Anaheim and Munich, show that decentralization and long connecting routes can lead to lower efficiency and reduced robustness. The Eastern Massachusetts region represents a middle ground, with a mixed structure that provides a reasonably robust and flexible network. These results underline the importance of well-considered network structure when designing urban mobility systems.

4.1.6. Network resources, central node determination and recovery methods

This section will delve deeper into the data from the four networks and how it is incorporated into the analysis. To begin, it will examine the information that serves as the foundation for analysing recovery strategies and the impact of disruptions on network performance. Furthermore, the identification of the central node within each network, the removal of edges, and the assessment of recovery time will be explored.

Data sources and network properties

These networks are expected to offer a detailed understanding of the practical application of the five different strategies. By examining the various networks, one can conduct a thorough analysis of the impact of these strategies on different statistical measures. The data for all four networks is sourced from Transportation Networks for Research Core Team, n.d. which also provides the data for the Sioux Falls model.

The dataset encompasses several elements, including the starting and ending nodes of the networks, as well as the recovery times necessary following failures. It also incorporates the prioritization of roads, distinguishing between primary and secondary routes. Additionally, the analysis utilizes travel times in minutes, the capacity of road segments, traffic volumes, and the lengths of the road sections to further model and evaluate the networks.

Determining the central node

When integrating case studies into the research design, there are several key aspects to consider. An important part of evaluating recovery strategies is to consider both the distance to a resource centre and the priority of the roads. In the article by Aydin et al., 2018, the Araniko Highway is considered the main access road within the network and therefore designated as the resource centre for recovery operations.

In the analysed networks, identifying a single central recovery point is not always straightforward. Consequently, this study focuses on determining the most central node within the network. Various methods exist for assessing centrality, and this research has opted for closeness centrality. This metric reflects the average shortest distance from a node to all other nodes in the network (Perez & Germon, 2016). It provides valuable insights into how well a node is connected to the rest of the network, which can be crucial in identifying which nodes need to be quickly accessible during a recovery process. Since the coordinates of the nodes are not available for some networks, this method serves as a reliable means of identifying the most central node. Based on this analysis, the following nodes have been identified as central: node 10 in the Sioux Falls network, node 23 in East Massachusetts, node 303 in the Anaheim network, and node 77669 in the Munich network. These nodes are situated at the core of their respective networks, making them logical starting points for analysing recovery strategies.

When examining the central nodes, it is noteworthy that for Munich, the central node is identified as node 77669. While this may seem surprising, it can be explained by the fact that the Munich network employs a different numbering sequence, as discussed in paragraph 4.1.4.

Removal of edges

Earlier in this chapter, it has become evident that the various networks analysed in this study each possess a distinct number of nodes and edges. Consequently, the effects of edge removal will differ based on the size and structure of each network. Each network features a unique quantity of connections, leading to varying amounts of removed edges at different percentages of edge removal. Therefore, the number of edges eliminated is influenced not only by the percentage applied but also by the overall size and connectivity of the network.

Table 4.3 illustrates the number of connections removed for each network at the various removal percentages applied. This table provides a clear overview of the quantitative changes occurring in the network's structure at different levels of edge removal. Understanding this data is essential, as it is critical for the subsequent analysis of the implications of edge removal and the effectiveness of recovery strategies across different networks.

Table 4.3: Number of edges removed per scenario per network

	Number of edges removed per run			
Scenario	**Sioux Falls**	**Eastern Massachusetts**	**Anaheim**	**Munich**
25%	19	65	229	468
50%	38	129	457	936
75%	57	193	685	1404
100%	76	258	914	1872

Method for calculating recovery time

The recovery time of road segments is scaled based on the maximum speed of the segment. Higher speeds are typically associated with wider roads (SWOV, 2021), resulting in a larger recovery area and therefore longer recovery time.

To better understand this relationship, one can look at the distinction between highways and non-highways, as described by Teodorović and Janić, 2017. Non-highways typically have a total width of 7.3 meters, while highways are wider and vary in width depending on the number of lanes. For example, highways with two lanes in each direction have a total width of 40.2 meters, while for three and four lanes this is 47.6 and 54.8 meters respectively. This division is in line with the speed limits as defined by Administration, 2021, where roads in residential areas and school zones have a maximum speed of 40 km/h, while rural highways have a limit of 89 km/h and rural interstate have a speed limit of 113 km/h.

The relationship between speed, road type and width forms the basis for scaling recovery times. For the Sioux Falls network, the number of lanes on a road is already established, eliminating the need to consider speed in this context. For other networks, Table 4.4 can be utilized, which provides an overview of the classification used.

Table 4.4: Relationship between speed, road type, and total width.

Speed (km/h)	Road types	Total road width (m)
≤ 40	Non-motorway	7.3
> 40	Dual 2 lanes	40.2
> 89	Dual 3 lanes	47.6
> 113	Dual 4 lanes	54.8

The distribution of speeds, the number of lanes and their associated widths can be used to calculate a scaling factor for the recovery time of the road segments.

4.2. Simulation results by edge removal rate

To gain insight into the effects of different edge removal percentages on networks, this section presents an in-depth analysis. The impact on each of the four networks is examined for each removal percentage. The emphasis is on an extensive case study of the Sioux Falls network when removing 25% of the edges. This specific situation is discussed in detail in subsection 4.2.1. Additional explanations for the other removal percentages can be found in the appendix. Subsection 4.2.2 discusses the removal of 50% of the edges, followed by an analysis of the effect of 75% removal in subsection 4.2.3. Finally, subsection 4.2.4 discusses the scenario in which all edges are removed from the network. This last analysis again focuses specifically on the Sioux Falls network, and also explains the recovery process per strategy.

4.2.1. Analysis of 25% edge removal

In the scenario where 25% of the edges are removed, a graph is presented showing the evolution of the different metrics for this network. The main findings per network are discussed, and for the other networks a similar graph and a more extensive explanation of the analysis can be found in Appendix A.

Sioux Falls

The first network configuration analysed is the Sioux Falls network where 25% of the edges have been removed. In concrete terms, this means that 19 edges have been removed from the network, leaving 57 nodes. In the context of a disaster scenario, this situation would have a relatively mild impact on the network compared to other scenarios where a larger number of edges are lost. Figure 4.5 shows the Sioux Falls network with these 25% edges removed. It shows how all strategies score on different performance metrics.

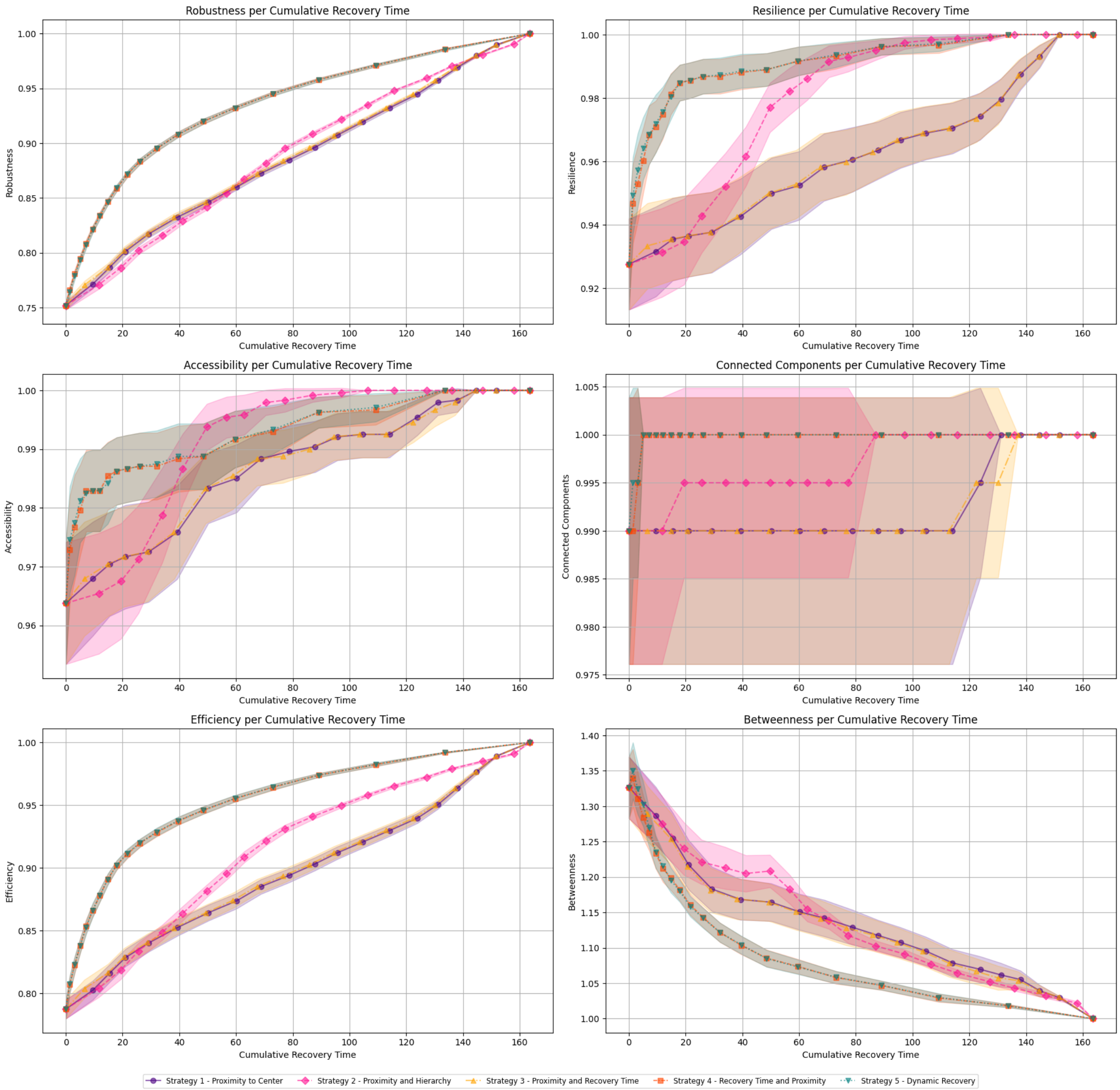


Figure 4.5: Impact of 25% edge removal on Sioux Falls network metrics

An extensive analysis of removing 25% of the edges in the Sioux Falls network can be found in Appendix A, but the key findings are discussed below.

When examining the impact of removing 25% of the edges from the Sioux Falls network, it becomes evident from Table E.1 that most metrics do not show significant differences across the various strategies. Metrics such as robustness, accessibility, efficiency, and betweenness remain statistically insignificant. However, resilience and connected components demonstrate significant variations, indicating that these aspects are more sensitive to changes in the network structure.

Connected components and weakly connected components indicate that a higher value reflects a more interconnected network. Conversely, a lower value suggests that the network is fragmenting into several isolated components, making travel between certain nodes impossible. Strategies such as *dynamic recovery* and *recovery time and proximity* significantly enhance the cohesion of the network, effectively preventing it from breaking apart into separate clusters.

Resilience measures the extent to which the original origin-destination (OD) pairs can be restored after a disruption. A high resilience score indicates that travellers can still find connections between most OD pairs, even when 25% of the links are lost. The findings reveal that strategies incorporating recovery components, such as *recovery time and proximity* and *dynamic recovery*, perform notably better in this regard. This implies that these strategies help maintain the majority of OD traffic, which is essential for the network's usability.

The results highlight that strategies featuring active recovery processes offer better protection against fragmentation and preserve a larger percentage of the original OD traffic. Practically, this means that during disruptions, the transport network remains operational, minimizing inconvenience for travellers. In contrast, a strategy lacking a recovery component, such as Proximity to Center, results in significantly greater fragmentation and reduced accessibility. This emphasizes the critical role of recovery-oriented strategies like *recovery time and proximity* and *dynamic recovery* in network planning, ensuring that a transport network is resilient to disruptions and can adapt swiftly and efficiently to maintain functionality

Eastern Massachusetts

When looking at removing 25% of the edges in the Eastern Massachusetts network, several changes appeared to be visible, but that these effects were not statistically significant. The statistical test, from which the results can be found in Table E.1, showed that no significant differences could be found in the 25% edge removal network for the accessibility, connected components, efficiency, resilience and robustness metrics. This suggests that although there may be a visual or numerical difference, there is insufficient evidence to conclude with certainty that this difference is not simply due to random variation.

When looking at the metric betweenness, a statistically significant difference appears between the strategies. In particular, the strategies *proximity and recovery time* and *dynamic recovery* perform better than the other strategies examined. The t-values for betweenness for these strategies are respectively 12.78 higher than for the strategy *proximity to centre*, and 12.66 higher than for *proximity and recovery time*. The difference is smallest for the strategy *proximity and hierarchy*, with a t-value of 3.41.

In the case of the Eastern Massachusetts network, it appears that the strategies based on *recovery time* yield the best results. These strategies ensure a rapid increase in betweenness, which can be positive in terms of network recovery. However, a high betweenness can also indicate that a small number of nodes play a disproportionately large role in the flow. This makes the network sensitive to disruptions at these crucial points, and can therefore also indicate increased vulnerability.

Anaheim network

When 25% of the edges are removed from the Anaheim network, Table E.1 shows that the *proximity and hierarchy* strategy consistently outperforms others across all metrics. This combined approach maintains strong reachability and network integrity while balancing utilisation and recovery.

While *proximity to centre* and *proximity and recovery time* perform well on specific metrics, they fall short overall. *Recovery time and proximity* and *dynamic recovery* offer little advantage compared to those two strategies, when looking at the betweenness and robustness, but are still less effective compared to *proximity and hierarchy*. In conclusion, *proximity and hierarchy* offers the most robust and balanced performance.

Munich network

When analysing the performance of the recovery strategies for the Munich network, where 25% of the edges were removed, it is noticeable from Table E.1, that *proximity and hierarchy strategy* performs best on several metrics, including accessibility, betweenness, connected components, efficiency, resilience, and robustness. This strategy shows significant improvements over the other strategies, indicating that combining proximity and hierarchy results in a more resilient network that is more resilient to disruptions.

The strategies *recovery time and proximity* and *dynamic recovery* outperform strategies *proximity to centre* and *proximity and recovery time* on the accessibility, betweenness, connected components, resilience and robustness, but still perform worse than strategy *proximity and hierarchy*.

In summary, the strategy *proximity and hierarchy* is the most robust choice for preserving network functionality when removing 25% of the edges in the Munich network. It provides significant improvements on several critical metrics and is more resilient to link loss than the other strategies. The strategies *recovery time and proximity* and *dynamic recovery* also perform well, but do not always match the results of the strategy *proximity and hierarchy*. In contrast, the strategies *proximity to centre* and *proximity and recovery time* do not show significant advantages in this specific scenario and prove to be less effective.

4.2.2. Analysis of 50% edge removal

In the same way as for the removal of 25% of the edges, the networks can be looked at when 50% of the edges are removed. The extensive analyses of this can be found in Appendix B.

Sioux Falls

When 50% of the edges are removed from the Sioux Falls network, the impact on performance is more pronounced than with 25% removal, particularly in terms of betweenness and connected components. Strategies *recovery time and proximity* and *dynamic recovery*, significantly outperform proximity-based strategies. These recovery strategies are notably more effective in maintaining network control and influence after a disruption.

In terms of connected components, recovery time based strategies also demonstrate greater resilience, better preserving the network's connectivity and weakly connected components. In contrast, proximity-based strategies struggle to maintain these components effectively.

Overall, strategies *recovery time and proximity* and *dynamic recovery* prove to be far more effective at restoring the network's original structure and ensuring connectivity after significant edge removal.

Eastern Massachusetts

Removing 50% of the edges in the Eastern Massachusetts network reveals significant differences in robustness, resilience, and betweenness. However, the differences in accessibility, connected components, and efficiency are not statistically significant.

In terms of robustness, the strategies *proximity to centre* and *proximity and recovery time* are better than *proximity and hierarchy*, with a difference of 3.75. In terms of resilience, or the recovery of the original OD pairs, the strategies *proximity to centre*, *proximity and hierarchy*, and *proximity and recovery time* are found to significantly reduce the difference the most, although there is no significant difference between these three. For betweenness, *proximity to centre* and *proximity and recovery time* show lower values than the other strategies. The difference with *proximity and hierarchy* is 7.89, and with *recovery time and proximity* and *dynamic recovery* causes 6.72 and 6.73. However, there is no statistically significant difference between *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery*.

In summary, the analysis shows that strategies that induce recovery mechanisms, such as *recovery time and proximity*, in many cases outperform the more proximity-oriented strategies, especially in terms of robustness and resilience. This suggests the importance of recovery-oriented strategies for maintaining network structure after disruptions.

Anaheim
When removing 50% of the edges from the network, the *proximity and hierarchy* strategy is found, in Table E.2, to consistently perform best on all of the metrics. This strategy clearly shows superior results compared to the other strategies, suggesting that combining proximity and hierarchy provides a robust approach to improving network performance under disruptions.

When looking at the other four strategies, it can be seen that they do not perform best on any of the metrics. In summary, it appears that the *proximity and hierarchy* strategy is the best choice for improving overall network performance.

Munich
When 50% of the edges in the Munich network are removed, the different strategies show significant differences in all of the metrics. The more detailed explanation of removing 50% of the edges in the Munich network can be found in Appendix B or Table E.2. Strategies *recovery time and proximity* and *dynamic recovery* score lower on accessibility than strategies *proximity to centre* and *proximity and recovery time*.

When looking at the comparison of the different strategies, it can be seen that strategy *proximity and hierarchy* performs best of the five strategies for a number of metrics. For example, it performs best for betweenness, efficiency and robustness. Regarding accessibility and resilience, *proximity to centre* and *proximity and recovery time* perform better and regarding the connected components, strategies *recovery time and proximity* and *dynamic recovery* perform better.

4.2.3. Analysis of 75% edge removal

Similar to the analysis for the removal of 25% and 50% of the edges, the networks are also evaluated after removing 75% of the edges. The detailed analyses can be found in Appendix C.

Sioux Falls
In the Sioux Falls network, the *proximity and hierarchy* strategy significantly outperforms the other strategies for accessibility, betweenness, and resilience. For the connected components, *recovery time and proximity* and *dynamic recovery* are the best performing strategies. However, no significant differences were found for efficiency and robustness.

When looking at the Sioux Falls network, it can be seen that for accessibility, betweenness and resilience, strategy *proximity and hierarchy* performs significantly better than the other four strategies. This means that this strategy ensures that other nodes are reachable from the central node sooner, that a number of nodes in the network are important for facilitating network flows and that the connections between origin and destination points are restored faster. For the connected components, these are strategies *recovery time and proximity* and *dynamic recovery*. This means that these strategies are better able to reduce the number of separate components in the network sooner. For robustness, no statistically significant differences can be seen.

Eastern Massachusetts
In terms of accessibility for removing 75% of the Eastern Massachusetts network, *proximity to centre* and *proximity and recovery time* perform significantly better than the other strategies. This suggests that these two strategies best enable the network to quickly access nodes even after loss of connections. The same holds true for connected components. Here, *proximity to centre* and *proximity and recovery time* perform best. This suggests that these strategies can best restore the network, optimally preserving the network's connectedness despite loss of edges. In terms of efficiency, the results also show that *proximity to centre* and *proximity and recovery time* are the most efficient. This indicates that these strategies ensure a more effective distribution of network resources and a faster recovery of the network after disruptions.

However, for betweenness and robustness, other strategies perform better. In both cases, *proximity and hierarchy*, as well as *recovery time and proximity* and *dynamic recovery*, are found to perform statistically significantly better than the other strategies. This means that when the focus is on betweenness or robustness, these strategies are preferred because they are better able to preserve the intermediate connections in the network and keep the network robust in the event of disruptions.

In terms of resilience, *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time* are found to perform best. This indicates that these strategies are able to quickly and effectively restore the network to its original state, even after removing a large number of connections.

Anaheim
When analysing the performance of the strategies for the Anaheim network, where 75% of the edges were removed, Table E.3 shows that the *proximity and hierarchy* strategy performed best on almost all metrics. For the metrics connected components and efficiency, several other strategies also achieved similar scores.

The *proximity and hierarchy* strategy showed significant improvements over the other strategies, indicating that the combination of *proximity and hierarchy* creates a stronger and more resilient network that is better able to withstand connection loss.

In addition, the *proximity to centre* and *proximity and recovery time* strategies also performed well. They scored significantly better than *recovery time and proximity* and *dynamic recovery* on efficiency, but did not always outperform proximity and hierarchy.

Interestingly, *recovery time and proximity* and *dynamic recovery* actually outperformed *proximity to centre* and *proximity and recovery time* on maintaining connected components. However, again, no statistically significant difference was found compared to proximity and hierarchy.

Munich
In terms of betweenness and robustness, following from the results of the statistical test, which can be seen in Table E.3, it can be found that *proximity and hierarchy* performs significantly better than the other four strategies.

In terms of accessibility, efficiency and resilience, both *proximity to centre* and *proximity and recovery time* performed better than the other strategies, indicating that recovery mechanisms play an essential role in improving network resilience. This suggests that the combination of proximity and recovery time not only optimises network resilience but also efficiency. Recovery mechanisms provide a better distribution of network resources.

When looking at the connected components, strategies *recovery time and proximity* and *dynamic recovery* perform the best over the five strategies.

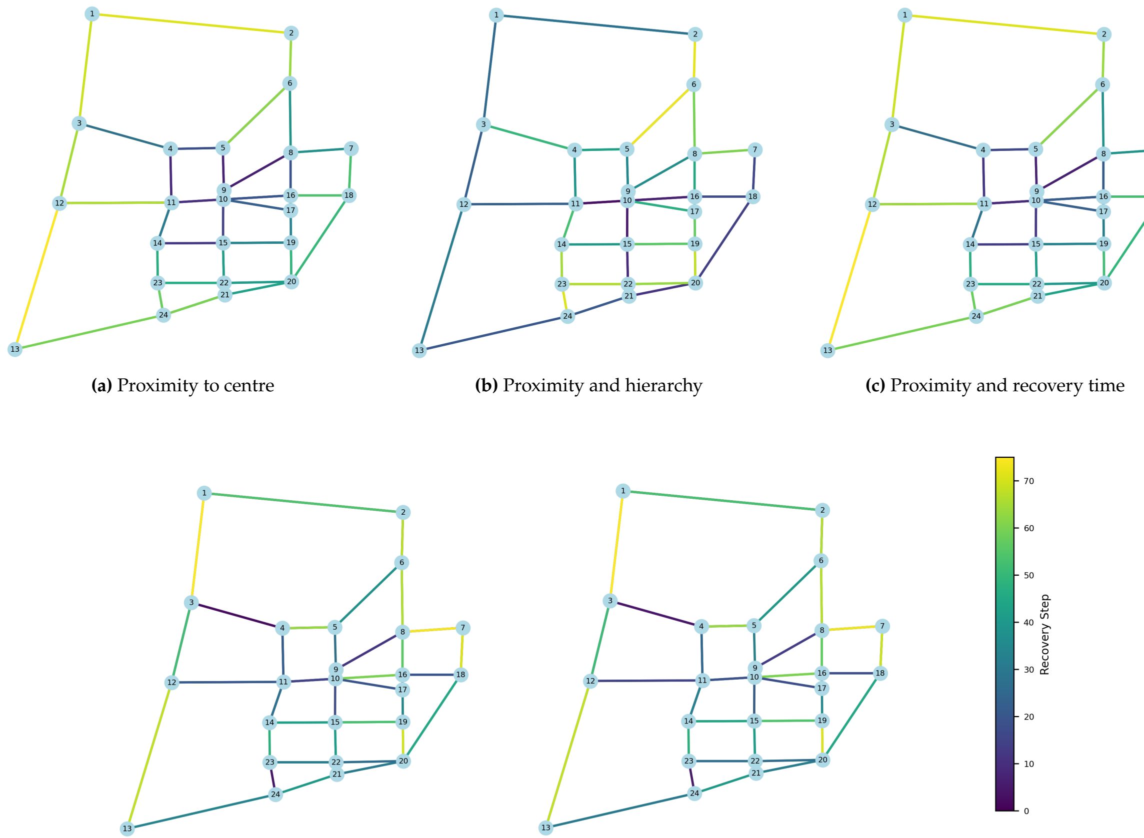
4.2.4. Analysis of 100% edge removal

As with the analyses for removing 25%, 50% and 75% of the edges, the networks were also evaluated after removing 100% of the edges. The detailed analyses of this can be found in Appendix D. However, there is an important difference here: because all edges are removed, there are no simulations over 100 runs, since there is only one way to empty the entire network. For the Sioux Falls network, the edge recovery process was also specifically examined. This allows for a detailed analysis per strategy in which parts of the network and at what point in the recovery process new connections are made. This provides valuable insights into the effectiveness and behaviour of the different recovery strategies.

Sioux Falls
In the Sioux Falls network, the *proximity and hierarchy* strategy significantly outperforms the other strategies in terms of accessibility and resilience. In terms of betweenness, *proximity and hierarchy* and *dynamic recovery* are found to perform best. This is remarkable, since for most conventional removal rates, *recovery time and proximity* and *dynamic recovery* often show identical results. In this case, however, there is no statistically significant difference between these two strategies. While *dynamic recovery* typically performs significantly better than *proximity to centre* and *proximity and recovery time*, this is not the case for *recovery time and proximity*. In terms of connected components, *recovery time and proximity* and *dynamic recovery* are the best performing strategies. However, no significant differences were observed for efficiency and robustness.

In summary, the *proximity and hierarchy* strategy ensures that nodes are faster to reach from the central node, that important nodes for network flows are used effectively, and that the connections between origin and destination points recover faster. For the connected components, it is *recovery time and* *proximity* and *dynamic recovery* that connect the network faster by reducing the number of separate components. However, for robustness, there is no significant variation between the strategies.

In addition to examining the impact of removing all edges on the six metrics, an overview of the recovery process can also be made. This overview offers a clear understanding, as there is no variation in the edges removed across different iterations. The recovery process is illustrated in Figure 4.6. Here, the dark purple color indicates which edges are restored first and the yellow color indicates which edges are restored last. It shows that different recovery strategies lead to different outcomes. Notably, the majority of strategies prioritize the restoration of inner edges, whereas strategy *proximity and hierarchy* emphasizes the outer edges earlier in the process. This is because outer edges often have a higher speed and, therefore receive a higher priority within this strategy. This makes it more important to recover these first when looking at proximity and hierarchy.



(a) Proximity to centre

(b) Proximity and hierarchy

(c) Proximity and recovery time

(d) Recovery time and proximity

(e) Dynamic recovery

Figure 4.6: Recovery order for five different strategies, visualised with edge-based colouring based on recovery step.

The recovery patterns of strategy *proximity to centre* and *proximity and recovery time* exhibit similarities. This similarity accounts for the comparable outcomes observed across the six metrics during analysis. Such results align with the inherent definitions and network structure of these strategies. Strategy *proximity to centre* focuses on recovering edges based on their proximity to the central node, whereas strategy *proximity and recovery time* prioritises proximity before considering edges with the shortest recovery times. Given the minimal variation in recovery times within the Sioux Falls network, the similarities between these strategies are pronounced.

When evaluating these five strategies, it is important to emphasise that a different choice for the centre node can lead to different results. This would mainly affect the strategies in which proximity plays a major role. These would therefore deviate more from the other strategies. For example, if node 1 were chosen as the central node (a node that is not in the physical centre of the network, but can be seen strategically as a resource centre node), the recovery pattern would look significantly different. Strategy *dynamic recovery* would remain unchanged, because it works independently of the central node and focuses exclusively on the shortest recovery time. In contrast, strategies *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time* would be strongly affected, because they recover from the new central node. This would result in a delayed recovery of the more distant parts of the network.

If for example in the Sioux Falls network, node 1 is chosen as the central node, which is in the upper left part of the network, than the lower right part of the network will be recovered significantly later in some of the strategies, because it is further away from the central node. This shows that the location of the resource centre node plays a crucial role in the recovery process and has a significant effect on the final recovery time of the network.

Eastern Massachusetts
Based on the statistical analyses, the results of which are shown in Table E.4, the following conclusions can be drawn for the Eastern Massachusetts network after removing 100% of the edges. For the metrics accessibility and connected components, the strategies *proximity to centre* and *proximity and recovery time* appear to perform best. Both strategies provide a more accessible network structure and preserve network connectivity most effectively after removing the edges.

For betweenness and robustness, *proximity and hierarchy* appears to perform significantly better than the other strategies. This suggests that this strategy is the most robust against disruptions and effectively protects the network against loss of connections. For efficiency and resilience, the strategies *proximity to centre*, *proximity and hierarchy*, and *proximity and recovery time* show better performances than the other strategies. These three provide the best balance between network efficiency and resilience to disruptions.

Anaheim
The analysis of the different strategies for removing 100% of the edges in the Anaheim network provides important insights into how each strategy performs on different metrics. The *proximity and hierarchy* strategy emerges as the best choice for some of the analysed metrics. This is evident from the significant improvement it provides in betweenness, resilience, and robustness. In particular, the high t-values compared to the other strategies suggest that combining proximity and hierarchy is a robust approach for improving network performance and maintaining network connectivity after removing edges. This strategy thus appears to be the most balanced and robust approach for optimising the network in the face of disruptions.

When looking at accessibility and efficiency, there can be seen that the strategies *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time* perform best. This makes sense for accessibility, as these strategies focus on recovery from a specific node, while accessibility is also calculated from this node. In terms of efficiency, this combination makes travelling between two points in the Anaheim network easier.

For the connected components metric, the analysis shows that the *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* strategies contribute most effectively to quickly recovering disconnected components, which restores the network structure after connection loss.

Munich
When removing 100% of the edges in the Munich network, it turns out that different strategies perform better for different metrics. For accessibility, efficiency, and resilience, the strategies *proximity to centre* and *proximity and recovery time* perform best. This means that these strategies recover the network faster, make nodes more reachable, and maintain network functionality after disruptions. They especially help to improve connectivity and efficiency when the network is completely disrupted.

For betweenness and robustness, *proximity and hierarchy* performs best. This strategy provides better protection for the network by preserving important nodes even after losing all edges. For connected components, *recovery time and proximity* and *dynamic recovery* perform best, because they make the network function as a whole faster. This shows that there is no strategy that performs best everywhere; each strategy has strengths depending on the specific metric.

4.3. Comparison of networks at different edge removal rates

When analysing different recovery strategies and their performance on various metrics, it is noticeable that the degree of fragmentation within a network has a significant impact on the performance differences between strategies. As a network becomes more fragmented, the statistically significant differences between strategies increase. This is first visible by the increase in red boxes in Table 4.5, indicating that there is no statistically significant difference between some strategies and others. In addition, it can be seen that the best-performing strategy strongly depends on the network structure and the degree of fragmentation.

To provide a clear overview of the performance of the different strategies, Table 4.5 summarises the performance per network and per removal percentage. Colour coding is used to visually emphasise the best strategies:

- **Red** : a strategy is not statistically significantly better than another strategy for any metric.
- **Orange** : A strategy performs statistically significantly the best out of the five strategies on at most two of the six metrics.
- **Yellow** : A strategy performs statistically significantly the best out of the five strategies on three or four of the six metrics.
- **Green** : A strategy performs statistically significantly the best out of the five strategies on five or six of the six metrics.

This colour coding allows for quick identification of which strategies perform better under different network conditions. The different network conditions will also be included later as scenarios. In this study, there are 16 different scenarios, of the four networks with each of the four different removal percentages.

Table 4.5: Comparison of strategies with different removal percentages across four networks.

Network	25%	50%	75%	100%
Sioux Falls	Proximity to centre	Proximity to centre	Proximity to centre	Proximity to centre
	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy
	Proximity and recovery time	Proximity and recovery time	Proximity and recovery time	Proximity and recovery time
	Recovery time and proximity	Recovery time and proximity	Recovery time and proximity	Recovery time and proximity
	Dynamic recovery	Dynamic recovery	Dynamic recovery	Dynamic recovery
EMA	Proximity to centre	Proximity to centre	Proximity to centre	Proximity to centre
	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy
	Proximity and recovery time	Proximity and recovery time	Proximity and recovery time	Proximity and recovery time
	Recovery time and proximity	Recovery time and proximity	Recovery time and proximity	Recovery time and proximity
	Dynamic recovery	Dynamic recovery	Dynamic recovery	Dynamic recovery
Anaheim	Proximity to centre	Proximity to centre	Proximity to centre	Proximity to centre
	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy
	Proximity and recovery time	Proximity and recovery time	Proximity and recovery time	Proximity and recovery time
	Recovery time and proximity	Recovery time and proximity	Recovery time and proximity	Recovery time and proximity
	Dynamic recovery	Dynamic recovery	Dynamic recovery	Dynamic recovery
Munich	Proximity to centre	Proximity to centre	Proximity to centre	Proximity to centre
	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy
	Proximity and recovery time	Proximity and recovery time	Proximity and recovery time	Proximity and recovery time
	Recovery time and proximity	Recovery time and proximity	Recovery time and proximity	Recovery time and proximity
	Dynamic recovery	Dynamic recovery	Dynamic recovery	Dynamic recovery

Sioux Falls network: compact and centralised
The Sioux Falls network has a compact, centralised structure, which allows the network to exhibit both the highest robustness (36, 566.80) and efficiency (0.43). The *proximity and hierarchy* strategy is found to be most effective as the network becomes more fragmented. In centralised networks, restoring central connections is critical because these nodes carry the most traffic and provide the most connections between different network components. The *proximity and hierarchy* strategy is particularly effective in this network because it focuses on restoring the connections closest to the central nodes. This approach makes sense because the centralised nature of the network means that restoring connections between central nodes has the most impact on overall network performance. Quickly restoring these central connections minimises disruption to network functionality and allows the network to quickly regain its efficiency..

Eastern Massachusetts network: radial and high redundancy
The Eastern Massachusetts network has a radial structure, meaning that there is a central node with connections extending to the edge of the network. The network also has high redundancy, meaning that there are multiple routes to different nodes, which increases the resilience of the network. This network exhibits a mixed betweenness centrality (0.048), indicating a balanced distribution of traffic between both central and peripheral nodes. At 25% link removal, strategies that focus on *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* appear to perform best. In a radial

structure, it is important to quickly restore connections to and from the central node, especially when significant fragmentation occurs. Restoring connections leading to and from the centre ensures that communication within the network can be quickly re-established, which is essential for maintaining overall network functionality. As the degree of fragmentation increases, it becomes even more effective to restore connections from the centre, which provide the fastest and most robust routes for traffic. This highlights the critical role of the central node in radial networks such as Eastern Massachusetts, where restoring connections to the centre of the network is essential to maintaining the robustness of the entire system.

Anaheim network: grid-like structure

The Anaheim network has a decentralised grid-mesh structure, meaning that there are no clear central nodes and connections are evenly distributed across the network. This results in low robustness $(4, 416.12)$ and efficiency (0.11), as the network is vulnerable to disruptions without central nodes to coordinate traffic. In such a network, it is essential to employ multiple recovery strategies that focus on restoring connections at different levels and areas of the network. The *proximity and hierarchy* strategy proves to be the most effective in this network, as it focuses on restoring connections that connect the network at different levels. This is important in decentralised networks, as the network has no central nodes to focus on. Restoring connections at different layers of the network ensures that traffic can be distributed effectively and that the network maintains its robustness even when multiple connections are lost. This approach enables the network to be rebalanced by restoring connections that route traffic to different parts of the network, which is essential for maintaining overall network functionality.

Munich network: ring radial with low centrality

The Munich network exhibits a ring-radial structure, where the connections are organised in a ring shape around a few central nodes. The network has low efficiency (0.07) and relatively low robustness $(5, 469.17)$, which makes the network vulnerable to disruptions, especially given the long routes and the limited number of central nodes. The low efficiency is caused by the fact that there are long routes between the nodes and that the central nodes are not optimally utilised. When 25% of the connections are removed, the *proximity and hierarchy* strategy is found to perform best, because it focuses on restoring the central connections. This makes sense since the ring structure of the network relies on the central nodes to maintain connections between different parts of the network. At higher levels of fragmentation, when the central nodes have less influence, the strategy that focuses on *proximity to the centre* and *proximity and recovery time* is found to be more effective. This indicates that while central nodes are important, restoring connections that reconnect peripheral nodes to the centre is essential to maintaining network robustness. Restoring these peripheral connections prevents further network fragmentation and ensures that the network retains its resilience and functionality even after significant disruption.

Relation between network structure, fragmentation and the choice of recovery strategies

In a network such as Sioux Falls, with a more centralised structure, it can be seen that recovery strategies that focus on proximity and hierarchy are particularly effective. Because a relatively small number of central nodes carry a large portion of the traffic, restoring these central connections allows network performance to be restored quickly. In a network such as Eastern Massachusetts, with a radial structure and high redundancy, it seems especially important to quickly restore connections to and from the centre. This helps maintain the overall functionality of the network, especially as fragmentation increases. In a network such as Anaheim, with a more decentralised structure, where there is no clear centre and traffic flows are scattered across the network, it appears that employing multiple recovery strategies, focusing on both proximity and hierarchy, is necessary to effectively restore connections. Finally, in a ring-radial network such as Munich, it can be seen that maintaining connections around the central ring is initially important, but that with greater fragmentation, restoring connections to peripheral nodes becomes increasingly crucial to ensure network robustness.

As the degree of fragmentation increases, the effectiveness of the different recovery strategies changes significantly. At low fragmentation, it is often sufficient to strategically restore a few key connections to quickly improve network functionality. However, at higher fragmentation, when larger parts of the network become disconnected, the restoration of multiple connections, and often also of less central or peripheral nodes, becomes increasingly important. Especially in networks with a clear central structure, such as Sioux Falls and Eastern Massachusetts, the importance of robust and redundant connections around the centre becomes increasingly important when fragmentation is severe. In decentralised or ring-radial networks such as Anaheim and Munich, the focus shifts to restoring connections that can connect regional clusters, in order to prevent parts of the network from becoming completely isolated, when fragmentation is high. Fragmentation therefore, forces a more differentiated and dynamic recovery strategy, where the choice of which connections to restore depends strongly on the structure and the degree of damage to the network.

4.4. Comparison of strategies when looking at the metrics

The results can be presented in another way, where we look at the different removal rates and networks to determine how often each strategy comes out on top per metric. This is visually represented in Figure 4.7, which shows the different strategies on the x-axis and their corresponding scores on the y-axis. The procedure is as follows: when a strategy scores best on a specific metric, it is given a value of 1. However, if two strategies achieve the same, statistically significant result, they are both given a value of 1. The same is true when one strategy outperforms three others, but there is no statistically significant difference between the two best-performing strategies.

Furthermore, there are also a number of situations in which there are no statistically significant differences between the different strategies. This is for example the case for the robustness metric in the Sioux Falls network. Here, the comparison of the different pairs of strategies shows that there is no statistically significant difference for any of the removal percentages. In these cases, it was decided not to include the strategic comparisons without a significant difference in the score.

To further illustrate this, consider the network where 75% of the edges of the Sioux Falls network are removed. In this case, the analysis of the resilience metric shows that the *proximity to centre* and *proximity and recovery time* strategies perform statistically worse than the *proximity and hierarchy* strategy. However, there is no statistically significant difference between the other strategies. Therefore, only the strategy *proximity and hierarchy* is given a value of 1, as this strategy performs statistically significantly better than two of the other strategies, while for the other comparisons, no clear statistical difference can be observed.

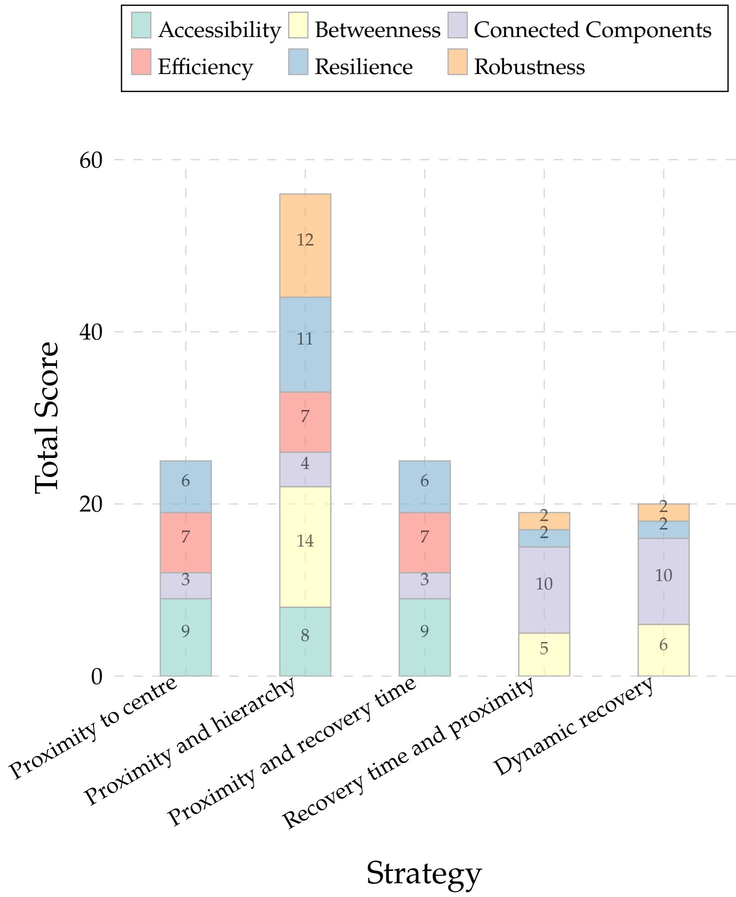


Figure 4.7: Stacked bar chart showing scores per strategy across six metrics

In the analysis of the different networks, presented in Table 4.7, it is seen that the *proximity and hierarchy* strategy achieves the highest score. This means that this strategy performs best across all networks and for the different removal rates, and can therefore be considered the most robust choice in various scenarios.

When looking at accessibility, which measures the degree of network reachability from central nodes, it can be seen that the strategies *proximity and hierarchy*, *proximity to centre*, and *proximity and recovery time* perform best. This is because these strategies focus on restoring connections that are close to the centre and restoring important nodes within the network. This means that these strategies help to improve the reachability of the network, especially when the network is disrupted. For policymakers, it can be important to focus on accessibility, especially when accessibility from a certain point is important.

Betweenness measures how important a node is to the flow of traffic or information by looking at nodes that are on many shortest paths. Strategies such as *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* score high on betweenness because they prioritise the recovery of these critical nodes. However, because nodes with high betweenness are so important, they also make the network more vulnerable. A disruption at these nodes can lead to delays or downtime in the entire network. Therefore, despite lower betweenness scores, strategies such as *proximity to centre* or *proximity and recovery time* may sometimes be a better choice. These strategies focus on quickly restoring connections close to the network centre, which improves overall accessibility and reduces network vulnerability. Policymakers should consider finding a balance between optimising betweenness and enhancing overall network stability so that the network is less susceptible to disruptions.

Connected components measure how the network is fragmented in the event of disruptions. It is crucial that the network reconnects quickly to continue to function as a single entity. The *recovery time and proximity* and *dynamic recovery* strategies are most effective here. These strategies focuses on restoring edges based on the recovery time, which helps to quickly restore key connections and prevent large parts from becoming isolated. For policymakers, this means that these strategies reduce network fragmentation and promote overall stability. This helps to quickly restore residents' mobility and access to vital services, even in the event of disruptions.

Efficiency measures how effectively travel is performed within the network by evaluating the shortest distances between nodes. Strategies such as *proximity to centre*, *proximity and hierarchy*, and *proximity and recovery time* perform best here. These strategies ensure that connections close to the centre of the network are quickly restored, leading to a decrease in the average shortest distance between nodes. This results in higher network efficiency, allowing people to travel faster between different points. For policymakers, this means that networks that rely on fast throughput and travel time minimisation can benefit from these strategies. Improving efficiency can not only reduce travel time, but also strengthen the overall connectivity within the network, optimising network performance.

Resilience is measured by the ability of the network to maintain connectivity between key origin and destination (O-D) points, even in the face of disruptions. While each strategy performs well in certain scenarios, *proximity and hierarchy* is the best choice for improving network resilience in most cases. This strategy ensures that connectivity between key points is quickly restored, resulting in a rapid restoration of mobility. By focusing on networks that can quickly recover from disruptions and quickly restore essential routes, policymakers can ensure that the impact of disruptions on the mobility and accessibility of residents is minimised.

Robustness measures the ability of the network to withstand disruptions, especially when key nodes or connections fail. In terms of robustness, it is notable that the *proximity to centre* and *proximity and recovery time* strategies do not perform best in any of the scenarios. In contrast, the *proximity and hierarchy* strategy performs best in many different scenarios. This strategy focuses on quickly restoring key connections (edges), especially those that carry a lot of traffic. Restoring these strategic connections increases the robustness of the network because these connections are essential for maintaining overall network functionality. The more traffic a connection carries, the more important it becomes to the robustness of the network. By prioritising the restoration of these key connections, the network can quickly resume operation, even if some parts fail.

The choice of a strategy is highly dependent on which network metric is given the highest priority. Each metric emphasises a different aspect of the network, meaning that different strategies perform better depending on the situation. However, the analysis shows that the *proximity and hierarchy* strategy performs well in almost every scenario. This strategy ensures that important nodes and connections can be quickly restored, increasing the overall resilience and robustness of the network. Since *proximity and hierarchy* performs consistently well across multiple metrics, it can be considered a safe and reliable choice for network management. For policymakers, this strategy offers the assurance of a robust, resilient and efficient network structure, regardless of the specific situation or disruption.

4.5. Conclusions and implications for recovery strategies

In this chapter, five recovery strategies for disaster-affected road networks were evaluated using multi-objective methods. These strategies used different priorities such as proximity to the centre, hierarchy, recovery time, or a combination of these. The performance of these strategies was tested on four networks, Sioux Falls, Eastern Massachusetts, Anaheim, and Munich, at different levels of disturbance.

The analyses show that the effectiveness of a strategy strongly depends on both the network structure and the level of disturbance. Networks like Sioux Falls with a centralised structure or Eastern Massachusetts with a radial structure show different recovery patterns than networks like Munich with a more decentralised networks. It also appears that recovery strategies that focus on proximity and hierarchy, or on recovery time, yield varying results under different conditions.

The next chapter will further interpret and contextualise these findings by systematically answering the research questions and by comparing the results with existing literature and real-world applications.

5
Discussion

In this chapter, the main findings of this research are analysed and put into perspective. First, the results are summarized and compared with existing literature to determine to what extent they correspond with previous studies. Next, the limitations of the research are discussed. Finally, suggestions are made for future research to gain further insights within this research area.

5.1. Reflection on the Results

This section of the discussion presents and analyses the main findings of this research, with a focus on the recovery of networks after a disaster. First of all, it is important to note that the findings based on the graphs showing the trajectory of the strategies on different metrics differ somewhat from the results that actually prove to be statistically significant. Although the graphs sometimes give the impression that certain results are significant, the detailed statistical analysis shows that the statistically significant findings provide a more nuanced picture.

In examining the fourth research question: *"How do different road network structures influence the performance of recovery strategies under varying levels of disruption?"*, several findings can be highlighted. The analysis showed that the structure of a road network does indeed play a role in the effectiveness of recovery strategies. This was evident from the analysis of the network structures summarised in Table 5.1,

Table 5.1: Network structures and recommended recovery strategies by edge removal percentages

		Best recovery strategy			
Network	**Structure**	25%	50%	75%	100%
Sioux Falls	Compact, centralised	Proximity and hierarchy, Recovery time and proximity, Dynamic recovery	Proximity and hierarchy, Recovery time and proximity, Dynamic recovery	Proximity and hierarchy	Proximity and hierarchy
Eastern Massachusetts	Radial, high redundancy	Proximity and hierarchy, Recovery time and proximity, Dynamic recovery	Proximity to centre, Proximity and hierarchy, Proximity and recovery time	Proximity to centre, Proximity and hierarchy, Proximity and recovery time	Proximity to centre, Proximity and hierarchy, Proximity and recovery time
Anaheim	Grid-mesh, decentralised	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy	Proximity and hierarchy
Munich	Ring-radial, low centrality	Proximity and hierarchy	Proximity and hierarchy	Proximity to centre, Proximity and recovery time	Proximity to centre, Proximity and recovery time

Table 5.1 shows that networks such as Sioux Falls, which has a more centralized structure, or a network such as Eastern Massachusetts, which has a more radial structure, tend to perform well with recovery strategies that focus on *proximity and hierarchy*, especially under larger disruptions. These networks clearly show that recovery focused on restoring connections to the centre is prioritised under larger disruptions, while this is less important under smaller disruptions.

On the other hand, a network such as Anaheim, which has a more decentralised structure, tends to perform better under recovery strategies that focus on overall network connectivity, regardless of the level of disruption. This suggests that the degree of centrality in a network is an important element in choosing the right recovery strategy, underscoring the relevance of network structure in recovery strategies.

Furthermore, analysis of networks such as Munich, which has a ring-radial design, indicates that recovery strategies that focus on restoring connections to the centre are more effective for larger disruptions. This is an important observation because it shows how this lower centrality network structure seems to require different recovery strategies than more centralised networks.

In summary, the effectiveness of recovery strategies seems to be strongly dependent on network structure. Centralised networks seem to benefit more from recovery strategies that focus on the centre, while decentralised networks may benefit from strategies that maintain overall connectivity. It is essential to tailor recovery strategies to the specific network structure and disruption conditions.

This section also addresses the final sub-question: *"What recommendations can be made for choosing the most appropriate recovery strategy for a disrupted network?"* In this context, it appears that recovery strategies are highly dependent on the specific network parameters. Table 5.2 provides an overview of these metrics, briefly explains what they measure within the network, and links the most effective strategies to them based on the analyses performed.

Table 5.2: Recovery strategies linked to network metrics

Metric	Description of the metric	Recommended strategy/strategies
Accessibility	How connected the network is from the centre node.	Proximity to centre, Proximity and recovery time, Proximity and hierarchy
Betweenness	The importance of particular roads in facilitating network flows.	Proximity and hierarchy, Recovery time and proximity, Dynamic recovery
Connected components	Number of fragmented networks	Recovery time and proximity, Dynamic recovery
Efficiency	The average shortest distance between nodes.	Proximity to centre, Proximity and hierarchy, Proximity and recovery time
Resilience	The extent to which connections between origin and destination points are restored.	Proximity and hierarchy (mostly), other strategies sometimes also
Robustness	Recovery of the most important connections with the highest volume (critical infrastructure).	Proximity and hierarchy, Recovery time and proximity, Dynamic recovery
Overall performance	Average performance across all scenarios and metrics.	Proximity and hierarchy

The choice of recovery strategy depends largely on the specific network properties and the disruption. To improve accessibility, i.e. the number of nodes reachable from the centre, strategies such as *proximity to the centre*, *proximity and recovery time*, and *proximity and hierarchy* are most effective. These strategies provide fast access to the network, especially for larger disruptions.

For betweenness (importance of connections for network flows), *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* are best, because they restore critical connections quickly. When the goal is to restore connected components, so to reduce the number of fragmented networks, *recovery time and proximity* and *dynamic recovery* are the recommended choices.

When improving efficiency, the average shortest distance between nodes, strategies focused on *proximity to the centre* and *proximity and hierarchy* are most suitable, because they restore the shortest connections. For resilience, i.e. restoring connections between origin and destination points, *proximity and hierarchy* usually provide the best results.

To increase network robustness, recovery of key connections, *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* are most effective. Finally, for overall network performance, *proximity and hierarchy* prove to have the broadest applicability, providing a good balance between speed and stability.

In summary, recovery strategies should always be tailored to the specific network properties and disruption conditions. A combination of proximity, hierarchy, recovery time, and dynamic recovery can restore the network quickly and efficiently.

5.2. Findings in relation to existing literature

An important contribution of this study is the broader approach it takes compared to the literature. While previous studies, such as that of Aydin et al., 2018, focused on specific networks, this study extends the analysis to four different networks. This allows us to investigate how the effectiveness of recovery strategies varies depending on the structure and scale of the network. This extension provides a broader and more detailed insight into how different networks respond to disruptions and which strategies are most suitable for different contexts.

In the existing literature of Aydin et al., 2018, the dynamic recovery strategy is was considered the most preferred strategy for restoring road networks after disruptions. However, the findings in this study suggest that in most cases this strategy is not always the most suitable choice. This may mainly depend on the specific network structure or the metrics that are analysed. In some cases, a different recovery strategy, such as *proximity and hierarchy*, was found to be more effective, depending on the level of disruption or the complexity of the network.

This study distinguishes itself by taking a more holistic approach, examining different networks with different topologies and functionalities. The effectiveness of recovery strategies appears to vary greatly in this broader context, suggesting that the choice of recovery strategy is context-dependent. This may also explain why the dynamic recovery strategy is not always the best choice for all network types. For example, while a network with a high degree of redundancy is better able to recover quickly via *dynamic recovery* methods, a network with a lower degree of interconnectivity may benefit from a different approach.

Furthermore, the literature has often focused on a limited number of metrics for evaluating recovery strategies. This study extends this by integrating multiple metrics, including network accessibility, betweenness, connected components, efficiency, resilience and robustness. This comprehensive approach allows to not only determine which strategy is generally most effective, but also to analyse which strategy is best suited for networks of different sizes and complexity. This allows for a more nuanced analysis that takes into account different performances and scenarios.

What further distinguishes this study from previous studies is the integration of varying degrees of disaster impact. Many studies have limited themselves to networks directly affected by a specific type of disaster, analysing damage based on specific impact data. However, this study takes a more systematic approach by removing different percentages of network components, which provides the flexibility to investigate how networks perform under different disruption scenarios. This provides a valuable addition, especially considering that detailed damage data are often not always available.

In conclusion, this study provides a valuable addition to the existing knowledge by not only evaluating the effectiveness of recovery strategies but also by testing them in different networks and under different levels of damage. The findings reinforce the methodological approaches in the literature and provide practical insights that can contribute to strengthening the resilience of transport networks to extreme disruptions. It shows that recovery strategies should be chosen context-specifically and that more flexibility in the decision-making process is needed to maximize the effectiveness of recovery in complex networks.

5.3. Limitations of the study

This chapter addresses the limitations of the research. It examines various factors, including the available data, the strategies employed, the selected networks, and the metrics utilized. These limitations may impact the results and conclusions of the study.

5.3.1. Available data from the networks

In this study, there was a lack of realistic data for the networks studied. This meant that network elements were removed arbitrarily rather than based on actual disaster patterns. This affects the representativeness of the results, as the disruptions in the network do not reflect the actual impact of a disaster. For example, the edges are currently randomly removed throughout the network, but a disaster could also cause more local damage. Furthermore, detailed information on the actual damage to the infrastructure was lacking and no direct data on recovery time was available for the affected road segments. As a result, assumptions had to be made, assuming that the damage was the same for all networks, regardless of the actual disaster conditions. The recovery time was then estimated based on the size of the road segments, which was derived from the length and number of lanes. This simplified approach does not take into account the actual damage or the complexity of the recovery process, which may affect the accuracy of the findings.

In addition, there was inconsistent data availability between the different networks used in this study. For example, for some networks, such as the Munich and Eastern Massachusetts networks, there were no coordinates available, which made the analysis of the geographic locations and distribution of network elements a bit more difficult. Also, direct speed information was not provided for each network. Instead, speed was derived based on the free flow time of the road segments, which may affect the accuracy of the speed analysis.

These incomplete and inconsistent data sets contribute to the uncertainty of the findings and may affect the effectiveness of the recovery strategies. Additional and more consistent data, such as detailed coordinates, speed information, and realistic damage data, would significantly improve the quality of the study.

5.3.2. Overview of selected strategies, networks, and metrics

This study discusses five strategies for road network recovery after disasters. However, alternative strategies are also mentioned, such as minimizing recovery costs or reducing total operational time. Cost minimization would prioritize recovery of the lower-cost parts of the network. Minimizing operational time would use online optimization and real-time decision making to achieve rapid recovery.

In addition to these strategies with different focal points, this research only looks at the step-by-step recovery of a network. In this case, only one edge is recovered per step, while in reality, multiple edges can probably be recovered at a time.

There are limitations to implementing the current strategies, particularly the proximity and road hierarchy strategy. Here, the hierarchy of the road section is investigated, but no data was available. Therefore, a classification was made based on the speed of the road sections. This classification of hierarchy for the road sections can influence the results, and a different classification of the hierarchy can possibly lead to other priorities.

The metrics included in this study can also be considered. Namely, six metrics were considered: accessibility, betweenness, connected components, efficiency, resilience, and robustness. While these metrics provide useful insights, additional data on costs and operational time would better clarify the effectiveness of the recovery strategies if that information were available.

The study includes four networks of different sizes, but due to the variations in scale, it is difficult to make direct comparisons. The limited computing power made it impossible to analyse larger urban networks, making the findings not easily applicable to larger networks such as those in megacities.

5.4. Recommendations for future research

While this research has provided important insights into recovery strategies for transportation networks after disasters, there are several areas that require further investigation. Future studies could focus on expanding the recovery strategies, improving the metrics used, and analysing larger and more diverse networks. Using realistic data, such as recovery duration data, could also increase the reliability and effectiveness of the strategies. By implementing these recommendations, further research could contribute to developing more effective solutions for infrastructure recovery after disasters.

5.4.1. More in-depth analysis about the recovery times

An important recommendation for future research is to pay more attention to the recovery times of road sections after a disaster. At present, little is known about how long it actually takes to repair a damaged road section. However, this is of great importance, since three of the strategies considered in this study explicitly make use of these recovery times. A different estimate or distribution of these times across the network could therefore lead to substantially different results. It is therefore essential to further investigate how long repair work takes in practice.

5.4.2. Parallel recovery of multiple edges

Another relevant point of attention for future research is the possibility of restoring multiple road sections (edges) simultaneously. This research assumes a scenario in which the network is built up step by step, one connection at a time. In practice, however, it will often be possible to perform multiple restoration operations in parallel. It is important to realize that in realistic situations there is no infinite amount of available resources. Certainly, in larger networks, not all connections can be restored simultaneously. Nevertheless, it is plausible that more than one edge can be tackled simultaneously. By including this limitation in future research, a more realistic and applicable picture can be sketched of the recovery process after a disruption.

5.4.3. Utilization of realistic data

Future research could benefit significantly from the use of empirical disaster data. This would involve using historical data after a variety of disasters to more accurately model road damage and analyse which segments of the network are most vulnerable. By looking at historical data, researchers can better understand which road segments are frequently affected and which specific characteristics, such as location, elevation, or infrastructure, influence the vulnerability of certain parts of the network. This information would help prioritize recovery efforts and identify the most vulnerable points in a network, which could improve the effectiveness of recovery strategies.

5.4.4. Expansion of the analysis

Future research could extend recovery strategies by focusing on cost minimization or accelerating recovery. A cost minimization strategy could include cost analysis and optimization models for the recovery procedure, while a rapid recovery strategy could use online optimization and real-time utilization.

There is also scope for the statistics used to be overly biased by economic and economic factors, which is why cost and operational time were not available in this study. Future research could focus on collecting these data to better assess the sustainability of recovery strategies.

Finally, it would be useful to investigate larger and more complex networks, such as those in large cities like Chicago or Sydney, as well as simultaneous networks from other regional regions such as Africa or Asia. This would help to better understand the dispersion of recovery strategies in different contexts.

6

Conclusion

This thesis investigated how disruptions of road networks affect the functioning of mobility systems and how recovery strategies can be effectively deployed under different circumstances. The central research question was: *How do disruptions affect road networks, and which recovery strategies are most effective under varying conditions based on different network metrics?*

The analysis first shows that natural disasters can cause significant structural and functional damage to road networks. Although the nature of the physical damage varies by disaster type and location, the functional consequences, such as reduced accessibility, delays and disruptions of critical services, show striking similarities. This underlines the importance of a risk-agnostic approach, where recovery strategies are not dependent on the type of disaster, but focus on the functional recovery of the network structure.

Within this framework, five different recovery strategies were modelled, each with its own prioritisation mechanism: based on proximity to the centre, hierarchy, recovery time, or combinations thereof, including a dynamic approach. These strategies were evaluated using six network metrics: accessibility, betweenness, efficiency, connected components, resilience and robustness. By using a multi-objective approach, it became possible to measure not only the speed of recovery, but also the quality of recovery in terms of network functionality.

The results convincingly show that the effectiveness of recovery strategies is strongly dependent on the underlying network structure. The Sioux Falls network, which is more centrally organised, and the Eastern Massachusetts network, which has a more radial structure, clearly benefit from strategies based on *recovery time* or *proximity and hierarchy* at the lower removal percentages. For the Sioux Falls network, it applies that as the network becomes more fragmented, *proximity and hierarchy* becomes more important. For Eastern Massachusetts, a shift can also be seen as the network becomes more fragmented, only then more towards the strategies *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time*. Networks such as Anaheim with a grid-mesh, decentralised structure, can respond better to strategies that focus on recovery based on *proximity and hierarchy*. The Munich network with a more ring-radial network and low centrality shows that as the network becomes more fragmented, the strategies based on *proximity to centre* and *proximity and recovery time* would be preferred.

In addition, it appears that the functional objective of the recovery process also determines the choice of strategy. For example, for improving accessibility, strategies such as *proximity to the centre*. *proximity and hierarchy* and *proximity and recovery time* are most suitable. If the focus is on restoring important traffic arteries with high betweenness, *proximity and hierarchy*, *recovery time and proximity* and *dynamic recovery* are more suitable. For restoring OD paths (resilience), *proximity and hierarchy* usually provide the best results. When reducing network fragmentation (connected components), strategies based on *recovery time and proximity* and *dynamic recovery* are most valuable. For efficiency, i.e. the shortest path between two nodes, strategies *proximity to the centre*. *proximity and hierarchy* and *proximity and recovery time* the most suitable. When looking at repairing the roads with the largest volume, in other words, robustness, the strong preference is for *proximity and hierarchy*.

In short, this study shows that there is no one-size-fits-all strategy. The effectiveness of recovery depends on the network topology, the degree of disruption, and the chosen optimisation objective. The contribution of this study therefore lies in explicitly linking strategies to specific network types and performance objectives within a simulated, multi-objective evaluation framework. As such, this study not only provides scientific insights into modelling network recovery, but also practical tools for policymakers and crisis planners who need to realise rapid and targeted infrastructure recovery in emergency situations.

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A

Simulation results of 25% edge removal

A.1. Sioux Falls 25% edges removed

The first network configuration analysed is the Sioux Falls network where 25% of the edges have been removed. In concrete terms, this means that 19 edges have been removed from the network, leaving 57 nodes. In the context of a disaster scenario, this situation would have a relatively mild impact on the network compared to other scenarios where a larger number of edges are lost. Figure A.1 shows the Sioux Falls network with these 25% edges removed. It shows how all strategies score on different performance metrics.

Robustness

The analysis of robustness based on cumulative recovery time shows that the strategies based on *recovery time and proximity* and *recovery times* show many similarities, while the strategies based on *proximity to centre* and *proximity and recovery time* also show similar trends. The strategy based on *proximity and hierarchy*, on the other hand, deviates from the other strategies.

The results shown in Figure A.1 seem to suggest a preference for strategies based on *recovery time and proximity*, as well as the strategy focused solely on *dynamic recovery*, in comparison to other strategies. However, an examination of the statistical test outcomes, as shown in Table E.1, reveals that there is no statistical significance among the various pairs of strategies. This indicates that the effect observed in the figure lacks statistical support. Consequently, due to the robustness of the test results, it is not possible to favour any particular strategy over another strategy in the Sioux Falls network with a 25% edge removal.

Resilience

When analysing resilience, it is noticeable that the 95% confidence intervals are significantly larger. This indicates that a different set of removed connections can have a different impact on the recovery of the network in terms of resilience. The uncertainty in this metric is therefore higher. The use of the 95% confidence interval is essential to better understand the variability of the measurements and to assess whether observed differences between strategies are significant or could be due to random fluctuations. The larger the interval, the greater the uncertainty and the potential variation in the performance of a strategy.

Based on the analysis of the statistical tests in Table E.1, it appears that the performance of the strategies differs significantly. This evaluation is supported by the significance values, where strategies *proximity to centre* and *proximity and recovery time* perform less well than *proximity and hierarchy* with t-values of 2.13 and 2.15 respectively. They also perform less well than *recovery time and proximity* with t-values of 2.58 and 2.61 and than *dynamic recovery* with t-values of 2.72 and 2.75.

The differences here are not very large everywhere, but clear enough to say that strategies *proximity to centre* and *proximity and recovery time* perform the least of the five strategies.

Furthermore, there is no statistically significant difference between *proximity and hierarchy* and *recovery time and proximity*, just as there is between *proximity and hierarchy* and *dynamic recovery*. So it can be said that the differences here are not very large, but clear enough to say that strategies *proximity to centre* and *proximity and recovery time* perform the least of the five strategies.

Accessibility
Further analysis of the accessibility shows that this metric increases very strongly for all five strategies. This means that it is possible to reach all other connections in the network from the central node (node 10) quite quickly. In addition, the model quickly ensures that a large number of nodes become accessible again, which explains why the accessibility metric increases so quickly.

When evaluating the effectiveness of various strategies at a 25% removal rate within the Sioux Falls network, it becomes evident that the five strategies yield similar results, complicating the identification of a definitive superior option. This observation is also reflected in Table E.1, where none of the effects on accessibility are statistically significant. This indicates that the differences observed are not substantial enough to conclude that one strategy is superior to another.

Connected components
During the simulation with 25% of removed connections, it was noticed that the number of connected components was slightly above 1. Due to the way the value is calculated and subsequently normalised, it may be slightly above 1. Although this effect was not fully anticipated, it is likely to have a limited impact on the overall analysis and interpretation of the results.

In addition to resilience, the results of the statistical tests in Table E.1 show significant differences between the strategies in terms of connected components, i.e. the extent to which the network becomes fragmented after disruption. This shows that strategies that implement recovery mechanisms generally outperform strategies that focus solely on proximity.

The analysis shows that *proximity to centre* performs significantly worse than both *proximity and hierarchy* with $t = -3.22$, *recovery time and proximity* with a t-value of -4.91 and *dynamic recovery* with $t = -5.43$. This suggests that a single focus on proximity is insufficient to ensure coherence within the network.

In contrast, *proximity and hierarchy* significantly outperforms *proximity and recovery time* with $t = 3.57$, showing that a combination of hierarchy and proximity has a beneficial effect on network structure after disruption. However, *proximity and hierarchy* underperforms *dynamic recovery* with $t = -2.37$, implying that a dynamic recovery strategy is more effective in maintaining a well-connected network.

Furthermore, there is a significant difference between *proximity and recovery time* and *recovery time and proximity* ($t = -5.35$), as well as between *proximity and recovery time* and *dynamic recovery* with $t = -5.94$, with the latter two strategies maintaining a more robust network structure.

In summary, strategies that integrate dynamic recovery, such as *recovery time and proximity* and *dynamic recovery*, are shown to maintain network cohesion significantly better than strategies that rely solely on proximity. This emphasises the importance of flexible and adaptive recovery mechanisms for limiting network fragmentation after disruptions.

Efficiency
When analysing the robustness and efficiency graphs, they show a similar pattern. Efficiency is calculated as a measure of the shortest distances between nodes. Normally, a decreasing graph would be expected, since the loss of connections leads to longer distances between nodes. However, because an inverse normalization is used here, the graph shows an increasing pattern.

Figure 4.5 seems to indicate that the strategies based on *recovery time and proximity*, as well as the strategy based on *dynamic recovery* alone, outperform the other three strategies. However, when the results in Table E.1 are analysed, it appears that there is no statistically significant difference between the different strategies. This implies that no clear conclusion can be drawn from this analysis about which strategy is superior to the other in this case.

Betweenness
Another important metric is betweenness centrality. It shows that the value initially starts above 1 and then slowly decreases towards 1. Although one might expect that the fully restored network would have the optimal betweenness centrality, this is not necessarily the case. In the Sioux Falls network, removing certain connections can cause some nodes to have high betweenness centrality. This is because these nodes are then on many shortest paths and therefore become more important in the network structure. An extremely high betweenness centrality value for a particular connection can have a strong effect on the average. When a connection is subsequently restored, this can cause the betweenness centrality of that specific connection to decrease sharply, while the betweenness centrality of other connections only increases slightly. As a result, the average betweenness centrality can decrease when a new connection is added. This effect is also visible in the Sioux Falls network.

The results in Table E.1 show that there are no significant differences between the strategies in terms of betweenness, or the degree to which certain nodes play a central role in network traffic.

All t-values are close to zero and the p-values are significantly higher than the threshold of 0.05, suggesting that no strategy has a statistically significant impact on this metric. This may imply that betweenness is a less suitable metric to distinguish the effectiveness of the strategies, or that the adjustments within the strategies do not directly affect the structural centrality of the network.

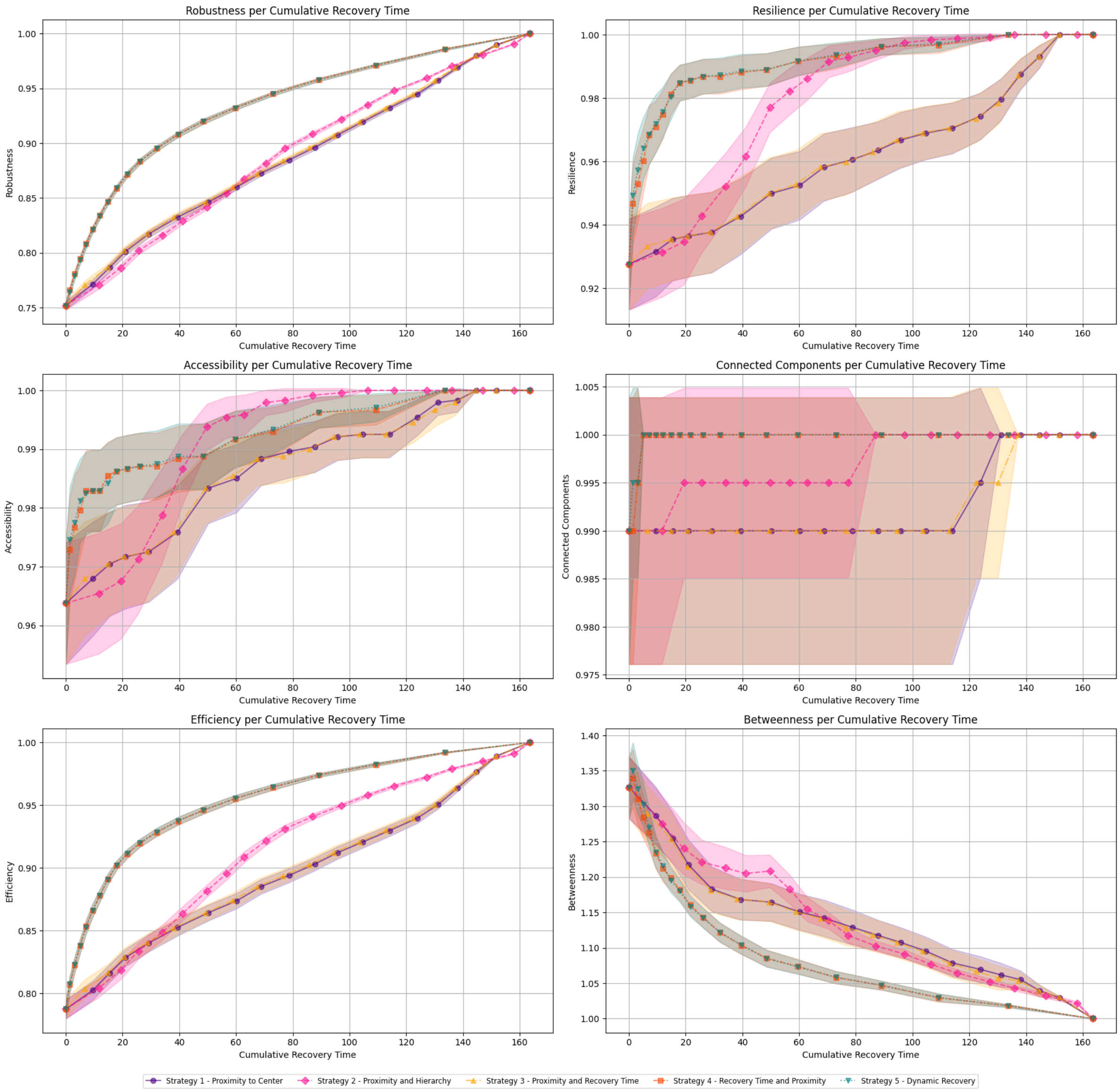

Figure A.1: Impact of 25% edge removal on Sioux Falls network metrics

A.2. Eastern Massachusetts 25% edges removed

When 25% of the edges are removed from the Eastern Massachusetts network, the network performance is affected. In this case, removing 25% of the edges means that 65 edges disappear, leaving 193 edges. This scenario can be interpreted as a mild disruption, such as a partial disaster, where most of the network remains functional. In this section, the impact of different recovery strategies on the six metrics is analysed.

Robustness

Robustness, or the importance of a node within the network based on the weights of its edges, is restored fastest by strategies *recovery time and proximity* and *dynamic recovery*. This is because these strategies prioritize restoring high-volume roads or important connections before tackling weaker connections. This means that if the goal is to restore the roads with the highest volume first, strategies *recovery time and proximity* and *dynamic recovery* are the best choices.

When examining the robustness of the network, as illustrated in Table E.1, it is evident that there are no statistically significant differences among the various strategies for the Eastern Massachusetts network. This indicates that, despite the differences in how each recovery strategy restores connections within the network, none of the strategies significantly outperforms the others in enhancing the network's robustness.

Resilience
In the first half of the recovery process, all strategies show a similar development in resilience. From the halfway point of the process, however, strategies *recovery time and proximity* and *dynamic recovery* perform better than the rest. This means that when the goal is to restore OD pairs (origin-destination relationships) as quickly as possible, strategies *recovery time and proximity* and *dynamic recovery* are preferred. For the further recovery process, the choice is less clear-cut, because strategy *proximity and hierarchy* initially scores better than strategies *proximity* and *proximity and recovery time*, but later lags behind.

When examining the robustness of the network, as illustrated in Table E.1, it is evident that there are no statistically significant differences among the various strategies for the Eastern Massachusetts network. This indicates that, despite the differences in how each recovery strategy restores connections within the network, none of the strategies significantly outperforms the others in enhancing the network's robustness.

Accessibility
Figure A.2 shows that in the first phase of the recovery process, the five strategies are close to each other in terms of accessibility. Later in the process, strategies *recovery time and proximity* and *dynamic recovery* outperform strategies *proximity* and *proximity and recovery time*, while strategy *proximity and hierarchy*lags behind. This means that with strategies *recovery time and proximity* and *dynamic recovery*, a larger number of nodes become accessible from the central node more quickly. This can be desirable in situations where the network needs to be fully connected again as quickly as possible.

When examining the accessibility of the network, as illustrated in Table E.1, it is evident that there are no statistically significant differences among the various recovery strategies for the Eastern Massachusetts network. This indicates that the differences in how these recovery strategies enhance network accessibility are not substantial enough to be deemed statistically significant.

Connected components
Looking at the connected components, it can be seen that the range of the 95% confidence interval is a lot larger than with the other metrics. This means that there is more uncertainty in the value of the connected components and that another set of 25% of the edges that are removed can produce quite different results. However, it can be said that if the goal is to ensure that the network becomes a whole again as quickly as possible and that there are therefore no separate components, then it is best to look at strategies *recovery time and proximity* and *dynamic recovery*. These have a higher value for the connected components more quickly and will therefore ensure that the network is connected sooner than strategies *proximity*, *proximity and hierarchy* and *proximity and recovery time*.

An analysis of the connected components within the network, as illustrated in Table E.1, reveals that there are no statistically significant differences among the various recovery strategies for the Eastern Massachusetts network. This indicates that the differences in the effectiveness of these strategies in restoring the number of connected components are not substantial enough to be deemed statistically significant.

Efficiency
Efficiency, or the speed at which someone can travel between two points, is recovered fastest by strategies *recovery time and proximity* and *dynamic recovery*, followed by strategies *proximity* and *proximity and recovery time*. Strategy *proximity and hierarchy* lags behind and contributes least to a fast return to the original network structure. This means that strategies *recovery time and proximity* and *dynamic recovery* are best suited for situations where a fast recovery time of the shortest routes is crucial.

When examining the efficiency of the network, as shown in Table E.1, it becomes evident that the Eastern Massachusetts network also does not exhibit any statistically significant differences between the different recovery strategies. This suggests that the variations in the performance of these strategies in terms of restoring connected components are insufficient to be considered statistically significant.

Betweenness

The betweenness decreases as the recovery process progresses. This is probably because after removing 25% of the edges, some nodes are on a disproportionately high number of shortest paths, leading to high betweenness. Restoring connections distributes traffic more evenly, which reduces betweenness. Strategies *proximity* and *proximity and recovery time* cause a rapid decrease in betweenness, which is beneficial because the network becomes less vulnerable to the failure of a specific node. If the intention is to keep some nodes on many shortest paths, then strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* are more suitable.

When examining the betweenness, Table E.1 reveals that most of the comparisons among the various strategies are statistically significant. The strategies labelled as *proximity* and *proximity and recovery time* demonstrate significantly better performance compared to the strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery*, with average values that are higher by 0.05, 0.08, and 0.08, respectively.

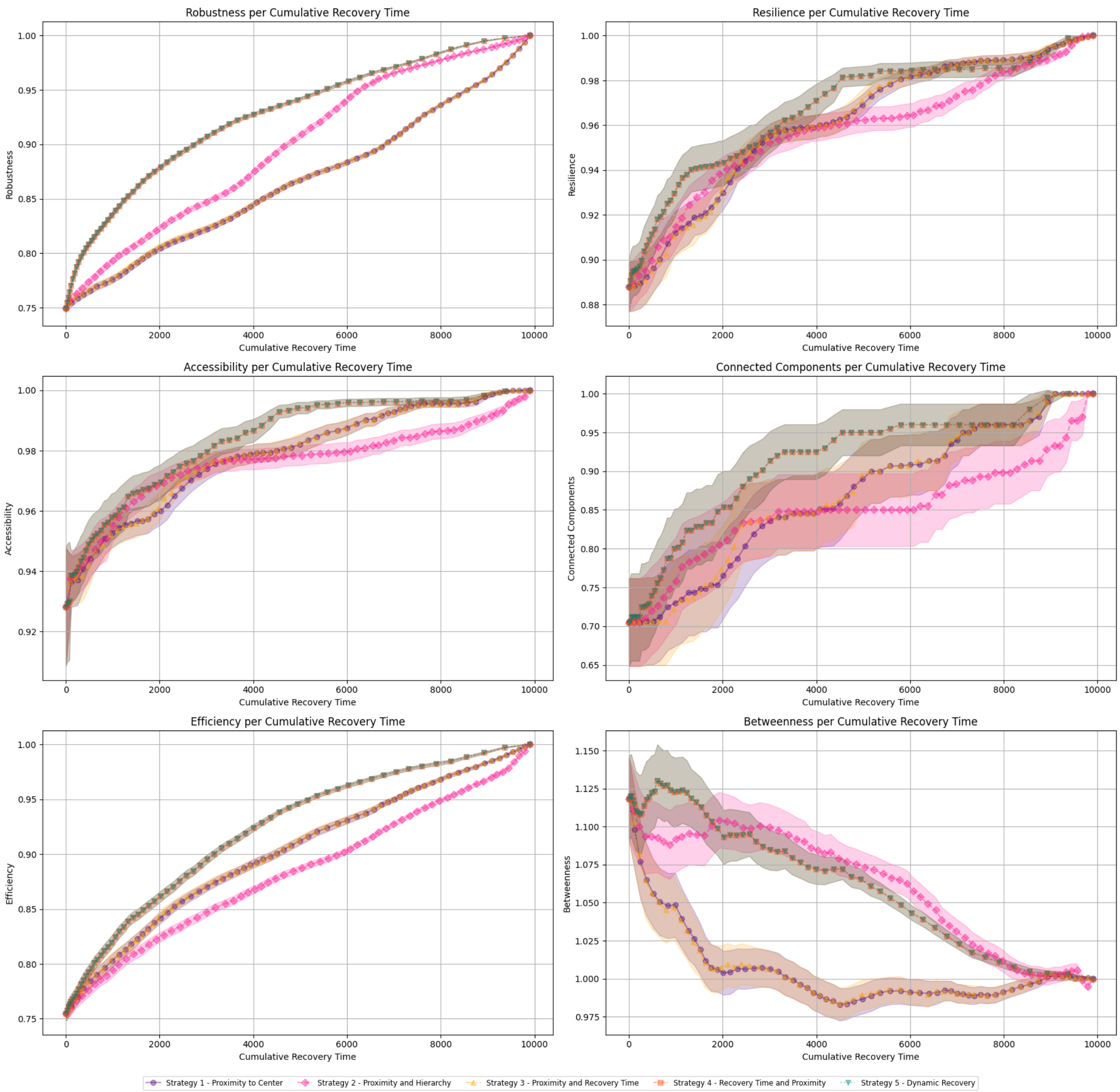

Figure A.2: Impact of 25% edge removal on Eastern Massachusetts network metrics

A.3. Anaheim 25% edges removed

When 25% of the connections in the Anaheim network are removed, different recovery strategies are compared based on their impact on various network metrics. Below is an analysis by metric following from Figure A.3, discussing the performance of the strategies in relation to their impact on the network.

Robustness

Here, strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* perform best, while strategies *proximity to centre* and *proximity and recovery time* score significantly lower. Strategy *proximity and hierarchy* has a strong start and initially shows the best performance. Later in the process, strategy *dynamic recovery* performs slightly better, but overall strategy *proximity and hierarchy* remains the most effective choice for robust network restoration.

Looking at Table E.1, the robustness analysis shows that *proximity and hierarchy* significantly outperforms the other strategies, with t-values of 7.09, 7.09, 10.25, and 10.21 compared to *proximity to centre*, *proximity and recovery time*, *recovery time and proximity*, and *dynamic recovery*, respectively. Furthermore, *proximity to centre* and *proximity and recovery time* outperform *recovery time and proximity* and *dynamic recovery*, with t-values of 2.83 and 2.78, respectively. This indicates that strategies emphasizing a balanced distribution of proximity and recovery opportunities are more robust in terms of structural stability.

Resilience

There is no clear winner here: initially, strategy *proximity and hierarchy* performs best, but later in the recovery process, strategy *dynamic recovery* takes over. This means that if the goal is to increase resilience as quickly as possible, strategy *proximity and hierarchy* is the best choice. However, if it is more important to ultimately have a more robust and resilient network, strategy *dynamic recovery* is the better option. The other strategies clearly lag behind.

The *proximity and hierarchy* strategy again shows a clear advantage in terms of resilience within the network. The t-values for the comparison with *proximity to centre*, *proximity and recovery time*, *recovery time and proximity* and *dynamic recovery* are 5.99, 5.99, 6.13 and 6.02, respectively. This implies that strategies combining hierarchical and proximity factors generate a higher degree of resilience to disturbances. No significant differences were observed between the other strategies.

Accessibility

Strategy *proximity and hierarchy* performs best here, meaning that it ensures that many other nodes are reachable from the central node as quickly as possible. This is followed by strategies *recovery time and proximity* and *dynamic recovery*, and then strategies *proximity to centre* and *proximity and recovery time*. It is notable that strategy *recovery time and proximity* initially outperforms strategy *dynamic recovery*, but later in the recovery process, strategy *dynamic recovery* becomes more effective. This suggests that strategy *recovery time and proximity* provides a faster initial reconnection, while strategy *dynamic recovery* ultimately ensures a more sustainable recovery.

The *proximity and hierarchy* strategy shows significantly superior performance in terms of accessibility compared to other strategies. The differences compared to *proximity to centre* and *proximity and recovery time* are both significant with a t-value of 7.86. Furthermore, *proximity and hierarchy* outperforms *recovery time and proximity* and *dynamic recovery*, with respective t-values of 7.97 and 7.75. This suggests that combining proximity and hierarchy provides a more robust approach for accessibility improvements. No statistically significant differences were observed between the remaining strategies.

Connected components

Strategy *proximity and hierarchy* starts out very strong, indicating that it quickly restores a large part of the network. However, this improvement tapers off later in the process. Strategy *dynamic recovery* shows a strong increase halfway through, while strategy *recovery time and proximity* performs similarly at first but lags behind later. This means that strategy *proximity and hierarchy* is preferable when a fast initial recovery is desired, while strategy *dynamic recovery* is better when a sustainable and rapid increase in long-term connectivity is desired.

The results for connected components show that *proximity and hierarchy* again significantly outperforms all other strategies. The t-values for the comparisons with *proximity to centre* and *proximity and recovery* *time* are 12.21, while compared to *recovery time and proximity* and *dynamic recovery* they are 11.58. This implies that strategies with a strong emphasis on hierarchical connectivity can create more coherent networks. No significant differences were found between the other strategies, indicating that these strategies have a similar impact on the network topology.

Efficiency

Strategies *recovery time and proximity* and *dynamic recovery* perform best here, with strategy *dynamic recovery* being the slightly better option. Strategy *proximity and hierarchy* follows at some distance, while strategies *proximity to centre* and *proximity and recovery time* clearly lag behind. This means that strategies *recovery time and proximity* and *dynamic recovery* are the most effective for a network that recovers quickly in terms of travel speed and efficiency.

In terms of efficiency, *proximity and hierarchy* also achieves superior results compared to the other strategies. The differences with *proximity to centre*, *proximity and recovery time*, *recovery time and proximity*, and *dynamic recovery* are significant with respective t-values of 2.95, 2.95, 3.97 and 4.03. This suggests that combining proximity and hierarchy results in a more optimal utilisation of network efficiency. No significant differences were found for the other strategies.

Betweenness

Strategy *proximity and hierarchy* causes a strong spike in this metric, indicating that some paths are restored that are crucial for many shortest paths. However, this can also introduce vulnerability, as a sudden dependency on certain nodes makes the network more susceptible to disruptions. Strategies *recovery time and proximity* and *dynamic recovery* have a more gradual increase and recover faster than strategies *proximity to centre* and *proximity and recovery time*. Of these strategies, *dynamic recovery* performs best, indicating that it provides a balanced recovery process with reduced dependency on individual nodes.

When looking at table E.1, in terms of betweenness, *proximity and hierarchy* significantly outperforms *proximity to centre* and *proximity and recovery time*, with a t-value of 18.21. This strategy also outperforms *recovery time and proximity* and *dynamic recovery*, with t-values of 15.02 and 14.07, respectively. Interestingly, both *recovery time and proximity* and *dynamic recovery* in turn outperform *proximity to centre* and *proximity and recovery time*. The t-values of these betweenness differences are 6.88 for *recovery time and proximity* and 7.59 for *dynamic recovery*. This emphasises that strategies that combine recovery with proximity can be more robust in terms of network betweenness. The differences between *proximity to centre* and *proximity and recovery time*, as well as between *recovery time and proximity* and *dynamic recovery*, were not found to be significant.

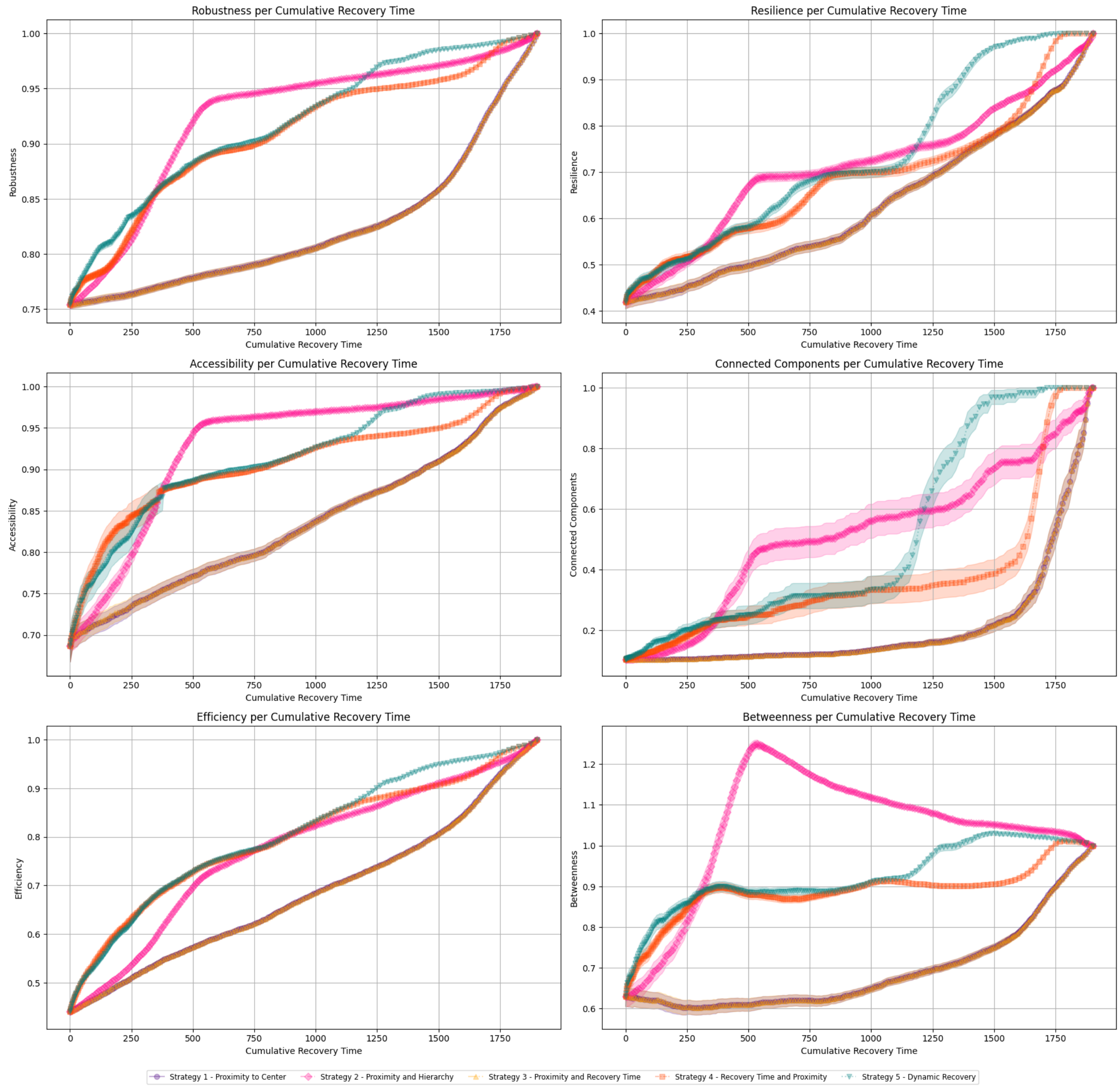

Figure A.3: Impact of 25% edge removal on Anaheim network metrics

A.4. Munich 25% edges removed

When 25% of the connections in the Munich network are removed, different recovery strategies are compared based on their impact on various network metrics. Below is an analysis by metric following from Figure A.4, discussing the performance of the strategies in relation to their impact on the network.

Robustness

When looking at the robustness of the network, measured by removing 25% of the edges in the Munich network, we see that the *proximity to centre* and *proximity and recovery time* strategies show the worst performance. This means that when a significant percentage of the connections within the network are removed, these strategies are less able to bridge the loss of connections and effectively recover the network. This may indicate an insufficiently resilient structure, where important connections are not restored quickly enough, leading to larger disruptions in the network.

In contrast, the *recovery time and proximity* and *dynamic recovery* strategies are the most robust. These strategies seem to react faster to the loss of connections and recover more efficiently, keeping the network relatively stable even in the face of disruptions. This suggests that with these strategies, the network is better able to maintain connectivity or recover quickly after removing edges. The *proximity and hierarchy* strategy is in the middle, indicating that this approach has moderate resilience: the network can recover with some delay, but does not perform as well as the previously mentioned strategies.

The results in table E.1 show that *proximity to centre* performs significantly worse than *proximity and hierarchy* (t = -9.79). This indicates that a hierarchical structure makes the network more robust to disturbances.

In addition, there is no significant difference between *proximity to centre* and *proximity and recovery time* (t = 0.01), suggesting that recovery mechanisms do not directly improve robustness.

Resilience

When looking at the resilience of the network, we see a similar pattern. Strategies *recovery time and proximity* and *dynamic recovery* again perform best. This means that these strategies are able to quickly recover the network after disruptions, making the network more resistant to long-term or repeated damage.

The *proximity and hierarchy* strategy scores third, indicating that the network also has some resilience here, but not on the same level as the top strategies. At the bottom of the scale are the strategies *proximity to centre* and *proximity and recovery time*, which are the least effective in maintaining stability after disruptions. This suggests that these strategies are less flexible in their recovery capacity and may be more vulnerable to network risks.

The results show that *proximity to centre* performs significantly worse than *proximity and hierarchy* (t = -5.53). This means that a hierarchical structure helps to maintain resilience in the network.

In addition, *proximity to centre* performs worse than both recovery time and proximity (t = -5.54) and *dynamic recovery* (t = -5.53), suggesting that recovery strategies are important for resilience.

However, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.01), which means that both strategies have similar effects.

Accessibility

When looking at the accessibility of the network, we see that the *recovery time and proximity* and *dynamic recovery* strategies again perform best. These strategies ensure that the network remains quickly accessible, even when parts of the network are disrupted. Access points remain open, and the network remains user-friendly despite the loss of connections.

The *proximity and hierarchy* strategy again comes in third, suggesting that the network retains some degree of accessibility with this approach, but may be less efficient at recovering access points than the top strategies. Strategies *proximity to centre* and *proximity and recovery time* are the least effective, meaning that users in these networks will often have more difficulty gaining access, especially in disrupted conditions.

The results show that *proximity and hierarchy* significantly outperforms *proximity to centre* with a t-value of -14.34. This suggests that a hierarchical structure significantly increases the accuracy of the network.

In addition, *proximity to centre* significantly underperforms both *recovery time and proximity* (t = -5.91) and *dynamic recovery* (t = -5.90), suggesting that recovery strategies play an important role in improving accuracy.

Furthermore, the comparison between *proximity and hierarchy* outperforms both *recovery time and proximity* (t = 6.89) and *dynamic recovery* (t = 6.90). This confirms that hierarchy is a determining factor in improving accuracy.

Finally, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.01), indicating that both strategies have similar effects on accuracy.

In summary, *proximity and hierarchy* is the most effective strategy for accuracy, while strategies based on recovery times provide an improvement over a simple proximity strategy.

Connected components
For the connected components we again see a clear pattern where the strategies *recovery time and proximity* and *dynamic recovery* perform best. These strategies ensure that the network remains well connected, even when parts of the network are removed. This means that the network is less likely to split into smaller, isolated components, which improves the overall robustness and performance.

The strategy *proximity and hierarchy* is between the top strategies and the weaker options. This indicates that the network in this strategy has slightly more fragile connections, but it remains relatively well connected compared to the weaker strategies. The strategies *proximity to centre* and *proximity and recovery time* perform worst, but the difference between *proximity and hierarchy* and the weaker strategies is smaller than for the other metrics. This may indicate that the hierarchy in these strategies provides some stability, but not enough to keep the network topology robust under stress.

The results in table E.1 show that *proximity and hierarchy* significantly outperforms *proximity to centre* (t = -11.18). This indicates that hierarchy contributes to preserving network structure during disruptions.

In addition, *proximity to centre* underperforms *recovery time and proximity* (t = -16.14) and *dynamic recovery* (t = -16.14). This suggests that recovery strategies play a crucial role in preserving connected network components.

Furthermore, the comparison between *proximity and hierarchy* and recovery strategies shows a mixed picture. Although *proximity and hierarchy* outperforms *proximity and recovery time* (t = 11.17), and it is inferior to *recovery time and proximity* (t = -6.89) and *dynamic recovery* (t = -5.90).

Finally, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.00).

In summary, *recovery time and proximity* and *dynamic recovery* perform best in preserving network components, while *proximity to centre* is the least effective.

Efficiency
With regard to efficiency, the pattern is again consistent: the strategies *recovery time and proximity* and *dynamic recovery* perform best. This suggests that these strategies allow the network to function efficiently even when part of the network infrastructure is lost. Efficiency is not only maintained, but in some cases also optimized by the fast recovery and the effective distribution of resources within the network.

The strategy *proximity and hierarchy* again comes in third, suggesting that this approach does provide some efficiency, but not on the same level as the top strategies. Strategies *proximity to centre* and *proximity and recovery time* score lowest, indicating that they function less efficiently in situations of disruption, possibly due to a less dynamic approach to recovery and redistribution of network resources.

The results show that *proximity and hierarchy* performs significantly better than *proximity to centre* (t = -5.77). This indicates that a hierarchical structure contributes to a more efficient network.

In contrast, recovery strategies do not show a significant improvement, as there is no difference between *proximity to centre* and *proximity and recovery time* (t = 0.01), and there is also no statistical significance between *recovery time and proximity* and *dynamic recovery* (t = 0.00).

Betweenness
When analysing the betweenness, we see that the strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* show a steep increase in betweenness at the beginning, which then levels off. This means that these strategies quickly generate influential connections in the network, but this influence decreases as the network recovers. This points to a strategy that quickly becomes effective, but then shows a stabilizing trend.

The strategies *proximity to centre* and *proximity and recovery time* have a more exponential curve, with the betweenness in the network increasing gradually. This means that these strategies exert influence more gently, possibly through a more gradual approach to recovery and the strengthening of network connections. This allows the network to recover more slowly, but ultimately in a more stable and controlled manner.

The results show that *proximity and hierarchy* significantly outperforms *proximity to centre*, with a t-value of -35.28. This indicates that hierarchy helps to more effectively utilize the central nodes in the network.

In contrast, there is no significant difference between *proximity to centre* and *proximity and recovery time* (t = -0.01), suggesting that adding a recovery mechanism does not directly affect betweenness centrality. Also, the comparison with *recovery time and proximity* and *dynamic recovery* (t = 0.00) shows that these strategies do not provide a decisive improvement.

Furthermore, *proximity and hierarchy* outperforms *proximity and recovery time* (t = 35.29) and also outperforms *recovery time and proximity* (t = 8.57) and *dynamic recovery* (t = 8.57). This confirms that hierarchy plays a crucial role in maintaining central nodes in the network.

In summary, *proximity and hierarchy* offers the best performance, while *proximity to centre* and *proximity recovery time and* do not offer significant improvement.

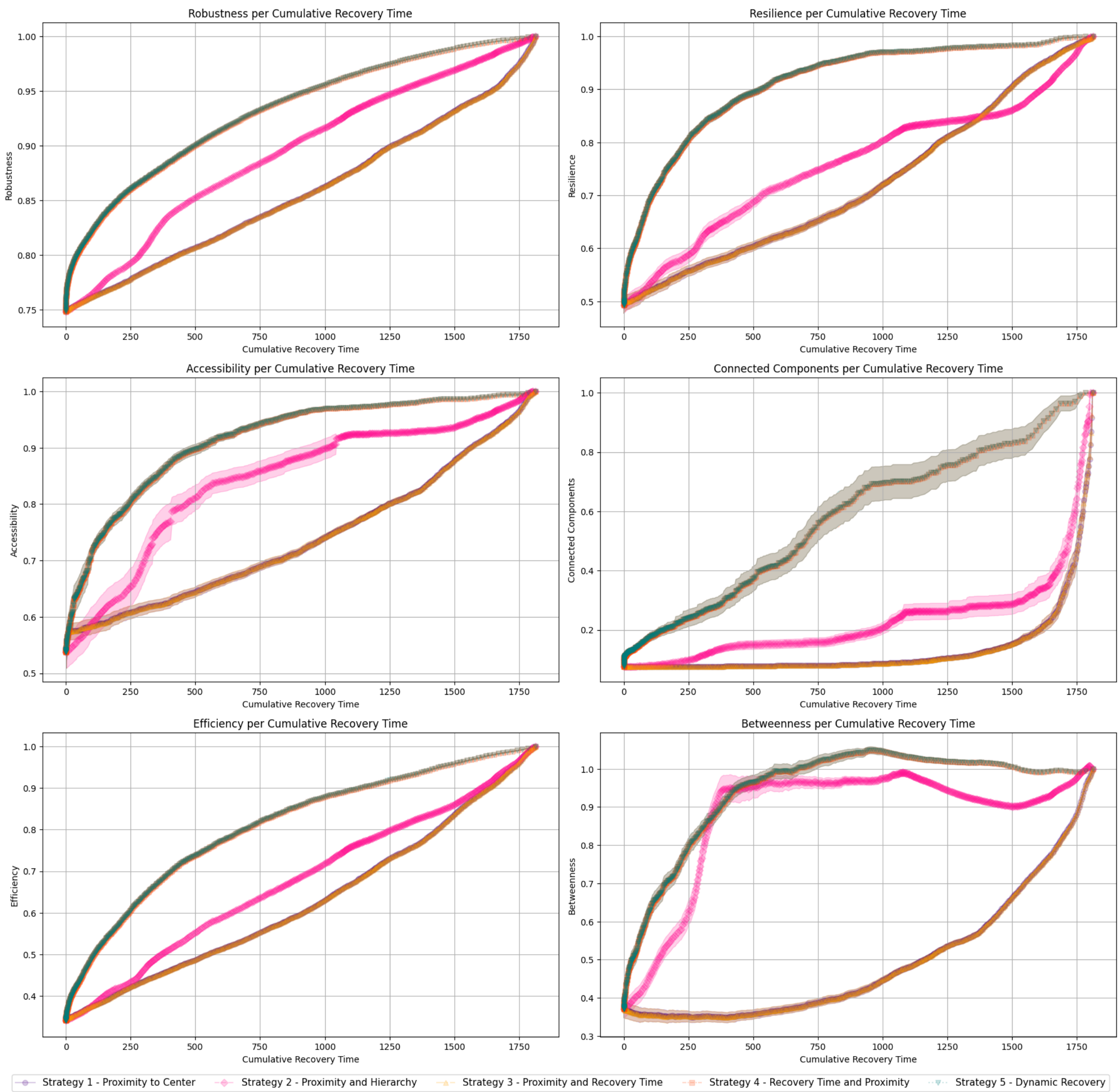

Figure A.4: Impact of 25% edge removal on Munich network metrics

B

Simulation results of 50% edge removal

B.1. Sioux Falls 50% edges removed

Removing 50% of the edges in the Sioux Falls network has a significant impact on the structure and functionality of the network. Figure B.1 shows the modified network, which shows how removing these connections affects various network metrics.

Robustness

The robustness metric shows that the network initially has difficulty recovering, but as the recovery time progresses, robustness steadily increases. This suggests that the network is slowly able to restore larger connections and become functional again. The initial decrease in robustness is caused by the large loss of connections, which means that fewer alternative routes are available.

Table E.2 shows that there is no statistically significant difference between the different strategies for robustness. This means that no conclusions can be drawn from these results about the superiority of one of the strategies compared to the other.

Resilience

The resilience metric shows that the recovery continues in a slowly increasing line. This indicates that the network is resilient, but that the speed at which the number of functional routes recovers is relatively low. The 95% confidence interval is wider here, which indicates that there is greater uncertainty about the exact recovery speed.

When looking at resilience, the effects that are shown in E.2 are also not statistically significant, so here, can also not be demonstrated clear preference for a particular strategy based on significance.

Accessibility

The accessibility of the network increases rapidly as more connections are restored. This means that most nodes are reachable again relatively quickly, despite the large number of removed edges. The central nodes in particular are restored quickly, which makes other parts of the network accessible again.

Although these effects appear to be visible, they are also not statistically significant according to Table E.2, so no difference in average between the different strategies can be confirmed.

Connected Components

The connected components metric shows that initially many separate network elements emerge after removing 50% of the edges. This indicates that the network has been split into smaller, disjoint parts. During the recovery period, these components are reassembled, eventually resulting in a maximum value of the restored network.

Based on the reanalysis of the statistical tests in Table E.2, it appears that the performance of the strategies differs significantly. This evaluation is supported by the significance values, where strategies *proximity to centre* and *proximity and recovery time* perform less well than *proximity and hierarchy*, *recovery time and proximity* and *dynamic recovery*.

For all these effects, the difference between the strategies lies between **2.13 and 5.22 standard deviations**, indicating a moderate to large effect. In particular for connected components, i.e. the ability to keep the network structure intact in the event of disruption, strategies that integrate recovery mechanisms perform significantly better than strategies that focus exclusively on proximity.

For example, the comparison between *proximity to centre* and *recovery time and proximity* shows a significant negative effect ($t = -4.84$), implying that *proximity to centre* is inferior in terms of connected components. Likewise, *proximity to centre* shows a significantly worse performance compared to *dynamic recovery* ($t = -5.21$).

In addition, *proximity and hierarchy* is shown to perform significantly better than *proximity and recovery time* ($t = 2.04$), demonstrating that adding a hierarchical structure within the recovery process is beneficial for the network structure.

In summary, it is found that strategies that adopt **recovery time** as a core principle, such as *recovery time and proximity* and *dynamic recovery*, maintain a more robust network structure compared to strategies that rely solely on proximity. This emphasizes the importance of recovery-oriented methodologies for effectively recovering the network components.

Efficiency
The efficiency metric shows that the shortest paths between nodes are drastically affected by removing 50% of the edges. Initially, efficiency is greatly reduced, but recovery strategies increase it again. This indicates that as more connections are restored, the average range within the network improves.

When examining Table E.2, it becomes evident that no significant differences can be identified among the various strategies in terms of efficiency. This analysis indicates that the efficiency levels of the different strategies are comparable, suggesting that they perform similarly in this regard.

Betweenness
The betweenness centrality of certain nodes initially increases greatly, indicating that some nodes play a crucial role in redistributing traffic. Then, the value decreases again as alternative routes are restored and the dependency on these nodes decreases. This shows that in the early stages of recovery, some nodes are very important to the network structure, but that this dependency decreases later.

Based on the reanalysis of the statistical tests in Table E.2, it appears that the performance of the strategies differs significantly. This evaluation is supported by the significance values, where strategies *proximity to centre* and *proximity and recovery time* perform less well than strategies *proximity and hierarchy*, *recovery time and proximity* and *dynamic recovery* in terms of **betweenness**, i.e. the degree of influence or control over the shortest paths between other nodes in the network.

For all these effects, the difference between the strategies lies between **3.91 and 5.64 standard deviations**, indicating a moderate to large effect. In particular, for **betweenness**, or the extent to which a strategy maintains connectivity and influence within the network, it appears that strategies that integrate recovery mechanisms perform significantly better than strategies that focus solely on proximity.

For example, the comparison between *proximity to centre* and *recovery time and proximity* shows a significant negative effect ($t = -5.64$), implying that *proximity to centre* is inferior in terms of betweenness. Similarly, *proximity to centre* shows a significantly worse performance compared to *dynamic recovery* ($t = -5.59$).

In addition, *proximity and hierarchy* is shown to perform significantly better than *proximity and recovery time* ($t = 3.91$), demonstrating that adding a hierarchical structure within the recovery process is beneficial for betweenness.

In summary, strategies that use **recovery time** as a core principle, such as *recovery time and proximity* and *dynamic recovery*, show higher betweenness compared to strategies that rely solely on proximity. This emphasizes the importance of recovery-oriented methodologies for maintaining network control and influence during disruptions.

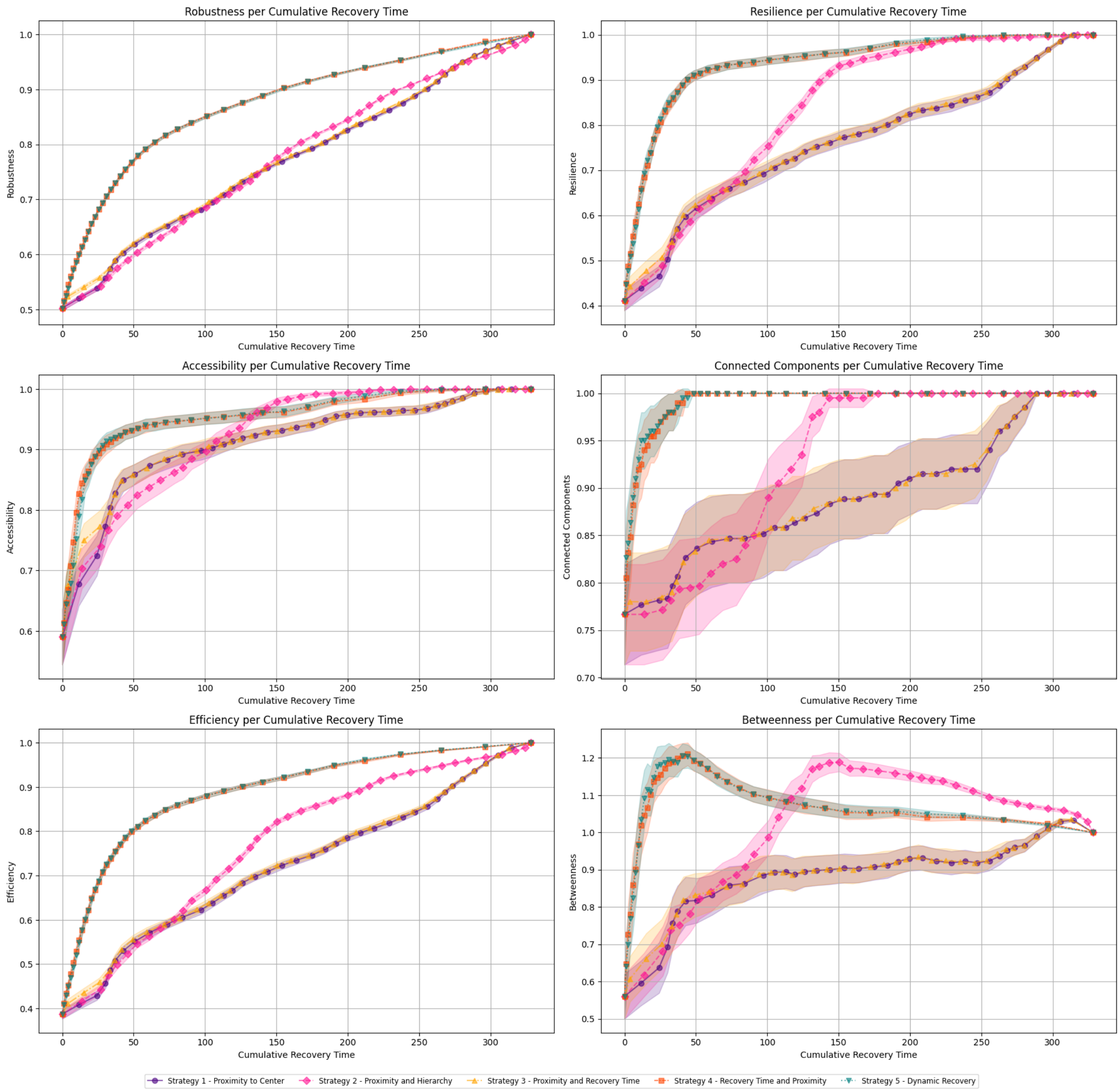

Figure B.1: Impact of 50% edge removal on Sioux Falls network metrics

B.2. Eastern Massachusetts 50% edges removed

In addition to removing 25% of the edges for the Eastern Massachusetts network, the effect of removing 50% of the edges can also be considered. This scenario represents a larger disruption to the network, such as a more severe flood, making the impact on network connectivity and robustness more significant. The findings regarding removing 50% of the edges can be found in Figure B.2.

Robustness

For robustness, strategies *recovery time and proximity* and *dynamic recovery* perform better than the other strategies. Strategy *proximity and hierarchy*scores better than strategies *proximity* and *proximity and recovery time*, which perform the least well. This indicates that strategies *recovery time and proximity* and *dynamic recovery* prioritize restoring the most important and robust connections within the network.

When comparing the findings from the figures with the results of the statistical test, it can be seen that there is a significant difference between strategy *proximity* and *proximity and hierarchy* with respect to robustness. and also between *proximity and hierarchy* and *proximity*. In both comparisons, the effect is the same and it can be concluded that strategies *proximity* and *proximity and recovery time* perform significantly better than strategy *proximity and hierarchy*, which has a lower average value of 0.07. Furthermore, no statistically significant differences can be found with respect to robustness.

Resilience
With resilience, it appears that in the initial phase all strategies have a similar course, but from one third of the recovery process strategies *recovery time and proximity* and *dynamic recovery* perform best. Strategies *proximity* and *proximity and recovery time* perform less well, while strategy *proximity and hierarchy*falls in between. This means that if the goal is to restore the original OD pairs as quickly as possible, strategies 4 or 5 are the most effective choices.

When looking at resilience, Table E.2 shows that strategy *proximity and hierarchy* performs less well than strategies *recovery time and proximity* and *dynamic recovery*. There is a difference of 0.07 in the average value for resilience, so it can be said for resilience that the strategies *recovery time and proximity* and *dynamic recovery* are preferred, with a fast recovery of resilience.

Accessibility
When looking at accessibility, it appears that strategies *recovery time and proximity* and *dynamic recovery* have a similar progression and are close to each other. Strategy *proximity and hierarchy*, on the other hand, shows a slower increase. This means that if the goal is to make the network accessible again from the central node as quickly as possible, strategies *proximity*, *proximity and recovery time*, *recovery time and proximity* or *dynamic recovery* are the best choices. Strategy *proximity and hierarchy*would be less suitable if fast connectivity from the centre node is desired.

Regarding accessibility, there is also a significant difference between some strategies. For example, *proximity* performs significantly worse than strategies *recovery time and proximity* and *dynamic recovery* and has a lower average value for both of 0.06. Furthermore, the same effect can be seen for *proximity and recovery time*, also with a difference in average value of 0.06. Due to the way these strategies are defined, this effect was also to be expected.

Connected components
The analysis of the connected components shows that strategies *recovery time and proximity* and *dynamic recovery* reconnect the network completely the fastest. If the primary goal is to get the network functioning as a whole again as quickly as possible, then these strategies are preferred. For strategies *proximity*, *proximity and hierarchy* and *proximity and recovery time*, the choice depends on preference: strategy *proximity and hierarchy*provides a faster connection of parts of the network at the beginning of the recovery process, while strategies *proximity* and *proximity and recovery time* have a more gradual increase in the connected components at the beginning, but eventually reach a higher value of the connected components more quickly.

An analysis of the connected components within the network, as depicted in Table E.2, reveals that there are no statistically significant differences among the various recovery strategies for the East Massachusetts network. This indicates that the variations in the effectiveness of these strategies in restoring the number of connected components are not substantial enough to be deemed statistically significant.

Efficiency
For efficiency, or shortest travel time between nodes, strategies *recovery time and proximity* and *dynamic recovery* perform best, meaning they achieve the fastest improvement in network connectivity. Strategies *proximity* and *proximity and recovery time* follow, and strategy *proximity and hierarchy*scores the lowest. This implies that strategies *recovery time and proximity* and *dynamic recovery* are preferred when a rapid increase in efficiency and improved accessibility is a priority.

An analysis of the efficiency of the different restoration strategies, as illustrated in Table E.2, shows that there are no statistically significant differences between the strategies within the Eastern Massachusetts network. This implies that the variations in restoration time, resource requirements, and operational costs are not substantial enough to have a significant impact on the overall efficiency of the restoration process. This suggests that none of the strategies offers a clear operational or economic advantage over the others in terms of efficiency.

Betweenness

For betweenness, it can be seen that strategies *proximity and hierarchy*, *recovery time and proximity* and *dynamic recovery* show a strong increase in the initial phase, while strategies *proximity* and *proximity and recovery time* show a more moderate increase. If the goal is to have certain nodes play a prominent role in shortest paths within the network, strategies *proximity and hierarchy*, *recovery time and proximity* and *dynamic recovery* might be preferred. However, if a more even distribution of network traffic is desired, making the network less vulnerable to disruptions, strategies *proximity* and *proximity and recovery time* would be a better choice.

The analysis of betweenness reveals that, as shown in Table E.2, the relationship between the strategies *proximity* and *proximity and recovery time* is not statistically significant. However, both strategies do exhibit statistically significant differences when compared to the strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery*, with average value differences of 0.14, 0.13, and 0.13, respectively.

Therefore, based on the betweenness analysis for the 50% edge removal scenario in the Eastern Massachusetts network, it can be concluded that the strategies *proximity* and *proximity and recovery time* are preferred. Nonetheless, the subsequent ranking of the strategies cannot be statistically substantiated.

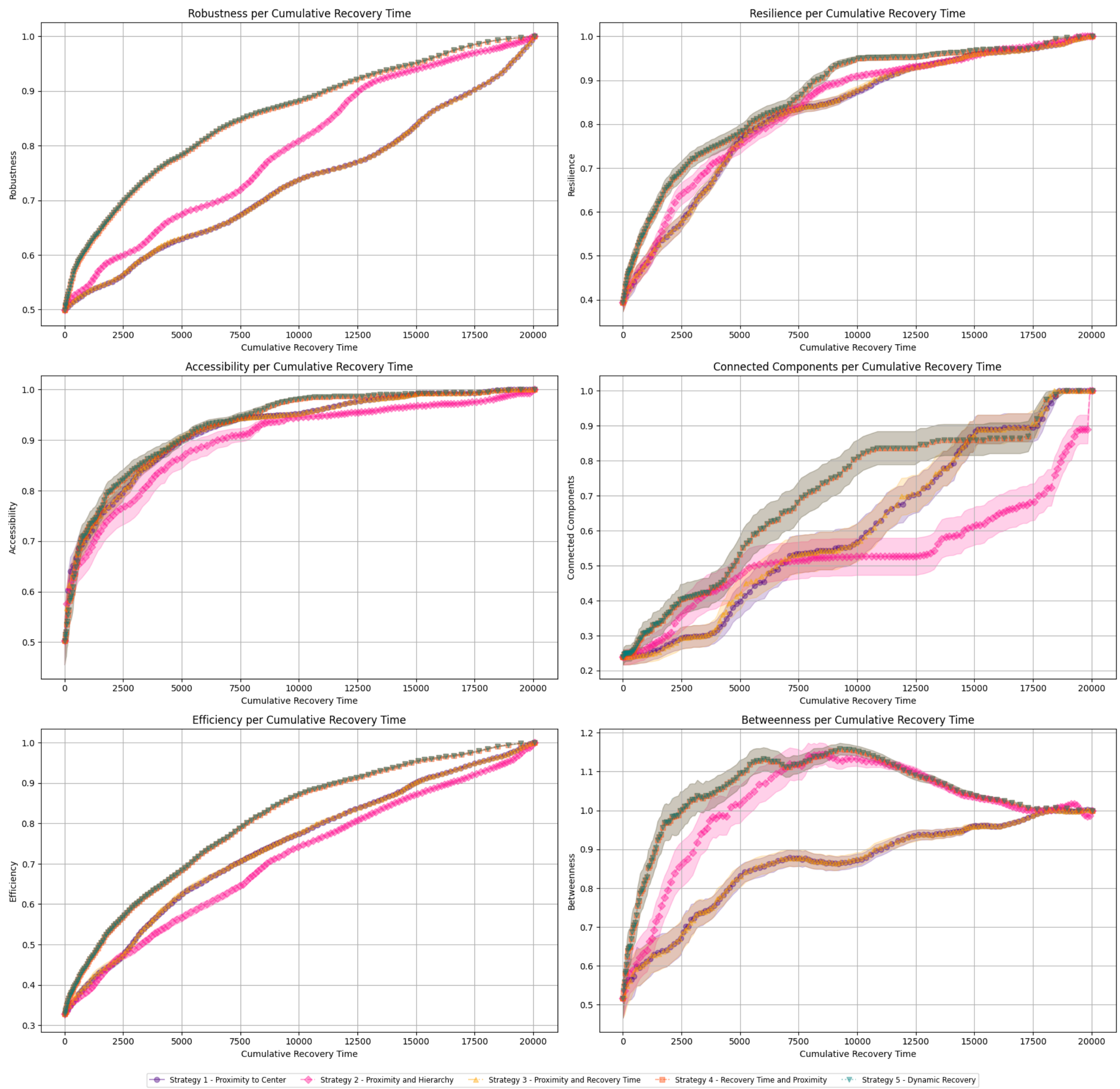

Figure B.2: Impact of 50% edge removal on Eastern Massachusetts network metrics

B.3. Anaheim 50% edges removed

Another option is to remove 50% of the edges from the Anaheim network. This is shown in Figure B.3. Below we will explain what happens for each metric and which strategy performs best.

Robustness

In this context, strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* demonstrate superior performance, whereas strategies *proximity to centre* and *proximity and recovery time* exhibit significantly lower scores. Strategy *proximity and hierarchy* begins with a strong performance, showcasing the best results initially. As the process progresses, strategy *dynamic recovery* slightly outperforms the others; however, strategy *proximity and hierarchy* remains the most effective option for ensuring a resilient network recovery overall.

In terms of robustness, which measures the structural stability of the network after perturbations, *proximity and hierarchy* significantly outperforms the other strategies, with t-values of 10.02 for *proximity to centre*, 10.02 for *proximity and recovery time*, 14.45 for *recovery time and proximity*, and 14.39 for *dynamic recovery*. This suggests that the *proximity and hierarchy* strategy makes the network the most robust against connection loss. Furthermore, both *proximity to centre* and *proximity and recovery time* outperform *recovery time and proximity* and *dynamic recovery*, with respective t-values of 3.96 and 3.95 for *proximity to centre*, and 3.89 and 3.88 for *proximity and recovery time*.

Resilience
Here, all five strategies are relatively close, but strategies *proximity to centre* and *proximity and recovery time* perform slightly worse. This suggests that while there is no clear winner, strategies *recovery time and proximity* and *dynamic recovery* may provide a more robust recovery.

In the area of resilience, which measures the network's resistance to perturbations, *proximity and hierarchy* is found to perform significantly better than all other strategies, with t-values of 7.05 for *proximity to centre*, 7.06 for *proximity and recovery time*, 7.81 for *recovery time and proximity*, and 7.68 for *dynamic recovery*. This suggests that combining proximity and hierarchy makes the network more resilient to perturbations. No statistically significant differences were observed between the other strategies.

Accessibility
Strategy *proximity and hierarchy* ultimately performs best, followed by strategies *recovery time and proximity* and *dynamic recovery*, and then strategies *proximity to centre* and *proximity and recovery time*. Interestingly, however, strategy *proximity and hierarchy* initially performs worse than the other three strategies, indicating that the recovery process is initially slower but becomes more effective later on.

In terms of accessibility, Table E.2 shows that the *proximity and hierarchy* strategy significantly outperforms the other strategies. The t-values of 5.80 and 5.81 for *proximity to centre* and *proximity and recovery time* respectively indicate a more robust approach to accessibility, with these strategies being better able to reach nodes quickly and efficiently after removing 50% of the edges. Furthermore, the *proximity and hierarchy* strategy is also better than *recovery time and proximity* and *dynamic recovery*, with t-values of 8.32 and 8.77 respectively. This suggests that combining proximity and hierarchy significantly improves the accessibility of network components. As for the remaining strategies, it is found that *proximity to centre* and *proximity and recovery time* outperform *recovery time and proximity* and *dynamic recovery*, with respective t-values of 3.07 and 3.63 for *proximity to centre*, and 3.07 and 3.62 for *proximity and recovery time*.

Connected components
All strategies start out pretty much the same here, but in the end strategy *dynamic recovery* performs best, followed by strategy *recovery time and proximity*, then strategy *proximity and hierarchy*, and finally strategies *proximity to centre* and *proximity and recovery time*. This indicates that strategy *dynamic recovery* is the most effective in reducing network islands and increasing network connectivity.

The connected components metric measures the degree of network coupling after removing edges. Here, Table E.2 shows that the strategy *proximity and hierarchy* significantly outperforms all other strategies, with respective t-values of 8.34 for *proximity to centre*, 8.35 for *proximity and recovery time*, 6.15 for *recovery time and proximity*, and 5.63 for *dynamic recovery*. This indicates that the strategy combining proximity and hierarchy preserves the most coherence in the network. Furthermore, *recovery time and proximity* outperforms *proximity to centre* and *proximity and recovery time*, with t-values of 2.14 and 2.15, respectively. Also, *dynamic recovery* outperforms *proximity to centre* and *proximity and recovery time*, with t-values of 2.52 and 2.53, respectively.

Efficiency
Strategies *recovery time and proximity* and *dynamic recovery* demonstrate superior performance in this context. Strategy *proximity and hierarchy* ranks next, albeit with a noticeable gap, while strategies *proximity to centre* and *proximity and recovery time* significantly trail behind. Consequently, it can be concluded that strategies *recovery time and proximity* and *dynamic recovery* are the most efficient for a network that prioritises rapid recovery in travel speed and overall effectiveness.

In terms of efficiency, *proximity and hierarchy* is found to significantly outperform the other strategies, with t-values of 2.71 for *proximity to centre*, 2.74 for *proximity and recovery time*, 6.07 for *recovery time and proximity*, and 6.24 for *dynamic recovery*. This indicates that the combination of proximity and hierarchy leads to a more optimised utilisation of the network capacity. Furthermore, *proximity to centre* outperforms both *recovery time and proximity* and *dynamic recovery*, with t-values of 3.32 and 3.51, respectively. *Proximity and recovery time* also outperforms *recovery time and proximity* and *dynamic recovery*, with respective t-values of 3.32 and 3.51.

Betweenness
Strategy *proximity and hierarchy* results in a strong spike in this metric, suggesting that some paths are restored that are essential for numerous shortest paths. However, this can also introduce a vulnerability, as a sudden reliance on specific nodes makes the network more susceptible to disruptions. Strategies *recovery time and proximity* and *dynamic recovery* exhibit a more gradual increase and recover more quickly than strategies *proximity to centre* and *proximity and recovery time*. Among these strategies, strategy *dynamic recovery* performs the best, indicating that it offers a balanced recovery process with reduced dependence on individual nodes.

For the betweenness metric, which indicates the degree of intermediateness of nodes in the network, Table E.2 shows *proximity and hierarchy* significantly outperforms *proximity to centre* and *proximity and recovery time*, with a t-value of 19.66. This means that the *proximity and hierarchy* strategy provides a more efficient distribution of intermediate links throughout the network, which contributes to better network functionality after edge removal. This strategy also outperforms *recovery time and proximity* and *dynamic recovery*, with t-values of 15.15 and 15.06, respectively. As for the other strategies, *recovery time and proximity* and *dynamic recovery* are shown to outperform *proximity to centre* and *proximity and recovery time*, with t-values of 5.82 and 5.83 for *recovery time and proximity*, respectively, and 5.72 for both compared to *dynamic recovery*. However, the effects between *proximity to centre* and *proximity and recovery time*, as well as between *recovery time and proximity* and *dynamic recovery*, are not statistically significant.

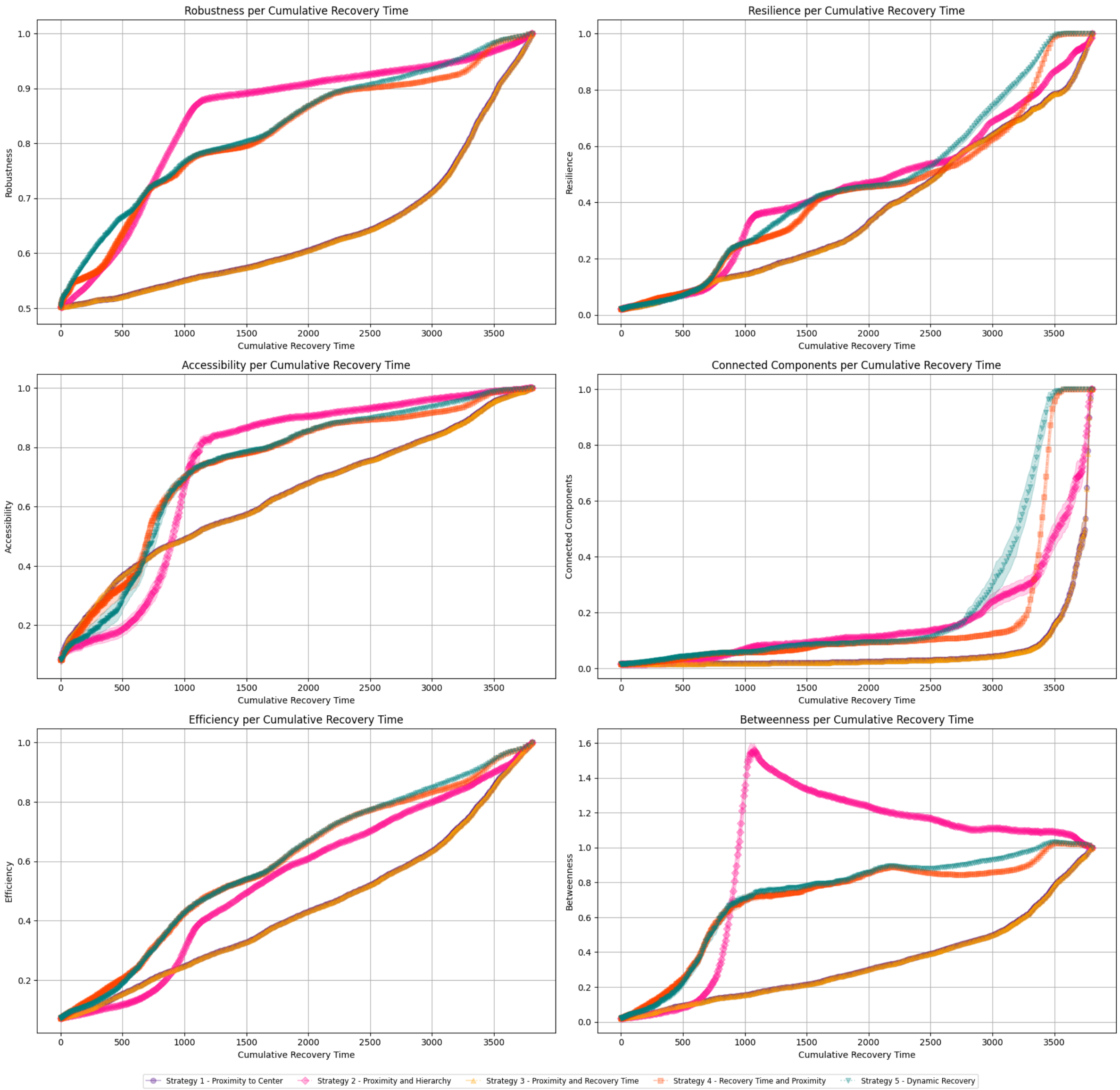

Figure B.3: Impact of 50% edge removal on Anaheim network metrics

B.4. Munich 50% edges removed

When 50% of the connections in the Munich network are removed, different recovery strategies are compared based on their impact on various network metrics. Below is an analysis by metric following from Figure B.4, discussing the performance of the strategies in relation to their impact on the network.

Robustness

When removing 50% of the edges in the Munich network, it is noticeable that the *proximity to centre* and *proximity and recovery time* strategies are the least robust. This means that the network fragments faster and is less resilient to disruptions with these strategies. In contrast, *recovery time and proximity* and *dynamic recovery* perform best, suggesting that these strategies are better able to maintain network functionality. The *proximity and hierarchy* strategy is in between these two extremes in terms of performance and shows moderate robustness.

The results in Table E.2 for robustness show that *proximity and hierarchy* performs significantly better than *proximity to centre* and *proximity and recovery time*, with both t-values of 9.79. This indicates that a hierarchical network structure produces a more robust network under disturbances.

In contrast, there is no significant difference between *proximity to centre* and *proximity and recovery time* (t = 0.01), suggesting that recovery mechanisms by themselves do not directly improve robustness. Also the comparison between strategies *recovery time and proximity* and *dynamic recovery* (t = -0.02) shows that these strategies do not yield significant gains.

Furthermore, *proximity and hierarchy* also *recovery time and proximity* (t = 11.00) and *dynamic recovery* (t = 10.98). This confirms that hierarchy is a decisive factor in increasing network robustness.

In summary, *proximity and hierarchy* provides the most robustness, while recovery strategies do not show a significant improvement over proximity strategies.

Resilience

When assessing the resilience of the network after removing 50% of the edges, a different pattern is visible. Strategies *proximity to centre* and *proximity and recovery time* show relatively good performances here, while *proximity and hierarchy* scores the worst. This means that in the event of a disruption, the network with *proximity and hierarchy* is less able to recover and regain its original functionality.

The results in Table E.2 show that *proximity and hierarchy* significantly outperforms *proximity to centre* in terms of resilience, with a t-value of 9.91. This indicates that hierarchical structures contribute to a more robust network under disturbances.

However, *proximity to centre* performs better than both *recovery time and proximity* (t = 6.80) and *dynamic recovery* (t = 6.80), indicating that recovery strategies based on proximity to the centre significantly improve network resilience.

Interestingly, there is no significant difference between *proximity and hierarchy* and *recovery time and proximity* (t = 1.18) or *dynamic recovery* (t = 1.18), suggesting that although hierarchy is beneficial, it is not clearly superior to recovery strategies.

Furthermore, *proximity and recovery time* performs significantly better than *recovery time and proximity* (t = 6.80) and *dynamic recovery* (t = 6.80), confirming that combining proximity and recovery time and proximity is a more powerful strategy than a strategy that focuses on recovery alone.

In summary, strategies *proximity to centre* and *proximity and recovery time* remain the more resilient strategies.

Accessibility

When looking at the accessibility of the network after removing 50% of the edges, *proximity to centre* and *proximity and recovery time* initially perform best. The *proximity and hierarchy* strategy initially performs the lowest, indicating that the network remains less accessible after a disruption with this strategy. However, as the recovery process progresses, from about two-thirds of the way through, *proximity and hierarchy* starts to outperform *proximity to centre* and *proximity and recovery time*. This suggests that although *proximity and hierarchy* may initially seem like a less effective strategy, it may yield better results in the long run.

The results in Table E.2 show that *proximity and hierarchy* significantly outperforms *proximity to centre* in terms of accessibility, with a t-value of 2.85. This suggests that adding a hierarchical structure within the strategy results in a more accessible network structure.

In contrast, *proximity to centre* significantly outperforms both *recovery time and proximity* (t = 7.80) and *dynamic recovery* (t = 7.81), implying that strategies that include proximity to centre mechanisms maintain better accessibility than a recovery time strategy.

An interesting pattern is visible when comparing *proximity and hierarchy* with the recovery-oriented strategies. Although *proximity and hierarchy* underperforms *proximity and recovery time* (t = -2.85), it remains superior to *recovery time and proximity* (t = 4.25) and *dynamic recovery* (t = 4.27). This suggests that hierarchy plays a more important role in accessibility than recovery mechanisms.

Finally, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.01), suggesting that both strategies have similar effects on accessibility.

In summary, strategies *proximity to centre* and *proximity and recovery time* perform the best on accessibility, while *recovery time and proximity* and *dynamic recovery* are the least effective. Recovery strategies provide some improvement, but cannot match the benefits of hierarchy within the network.

Connected components
For maintaining connected components in the network, the strategies *proximity to centre*, *proximity and recovery time* and *proximity and hierarchy* show a similar pattern. During much of the recovery process, the values remain low, indicating that the network remains highly fragmented. However, at a certain point in the recovery process, the values suddenly increase to the final recovery level. This indicates that the network recovers in a short time, rather than gradually over the entire process.

The results in Table E.2 show that *proximity and hierarchy* significantly outperforms *proximity to centre* in the area of connected components, with a t-value of 5.51. This indicates that a hierarchical network structure contributes to maintaining network coherence in the event of disruptions.

In addition, *proximity to centre* significantly underperforms both *recovery time and proximity* (t = -11.66) and *dynamic recovery* (t = -11.66). This suggests that recovery strategies play a more important role in maintaining network structure than mere proximity principles.

Strategy *proximity and hierarchy* outperforms *proximity and recovery time* (t = 5.51), *recovery time and proximity* (t = 7.19) and *dynamic recovery* (t = 7.19). This suggests that hierarchy has a positive effect.

Finally, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.00), indicating that both strategies have a similar impact on network connectivity.

Efficiency
In terms of efficiency, the *proximity to centre* and *proximity and recovery time* strategies generally outperform the other strategies. The *proximity and hierarchy* strategy achieves the lowest score, but remains relatively close to the other two. This indicates that while *proximity and hierarchy* may not be the most efficient strategy, the difference with *proximity to centre* and *proximity and recovery time* is not very large.

The results for efficiency shown in Table E.2, show that there is no significant difference between *proximity to centre* and *proximity and hierarchy* (t = 1.15). There is also no significant difference between *proximity and hierarchy* and *proximity and recovery time* (t = -1.15).

There is also no significant difference between *proximity to centre* and *proximity and recovery time* (t = 0.00), which means that adding a basic recovery mechanism does not directly improve efficiency. The comparison of *proximity to centre* and *recovery time ans proximity* and *dynamic recovery* show that *proximity to centre* outperform those other two strategies with t-values of both 8.59.

It is noteworthy that *proximity and hierarchy* not only outperforms *recovery time and proximity* (t = 7.19) but also *dynamic recovery* (t = 7.19). This confirms that hierarchy is a determining factor in improving network efficiency.

Finally, the results show that there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.00), indicating that these strategies have similar effects.

In summary, *proximity and hierarchy* is the most efficient strategy, while recovery strategies do not provide significant improvement over proximity strategies.

Betweenness
For betweenness, the strategies *recovery time and proximity* and *dynamic recovery* show a strong increase early in the recovery process, after which the values level off or even decrease. This indicates that these strategies initially contribute strongly to network reconnection, but that their effect decreases thereafter. The strategy *proximity and hierarchy* shows a similar pattern, but only starts to increase later in the recovery process and then decreases more deeply. In contrast, *proximity to centre* and *proximity and recovery time* show a more gradual, exponential growth. This suggests that these strategies contribute more consistently to network betweenness throughout the recovery process.

The results in Table E.2 for betweenness show a clear pattern where *proximity and hierarchy* significantly outperforms *proximity to centre*, with a t-value of 16.81. This indicates that a hierarchical structure leads to a more efficient distribution of network loads and fewer central nodes that become overloaded.

Furthermore, *proximity to centre* performs significantly worse than both *recovery time and proximity* (t = -7.17) and *dynamic recovery* (t = -7.17). This means that the lack of recovery mechanisms has a negative effect on the distribution of network traffic, which can lead to more vulnerable nodes in the network.

Interestingly, *proximity and hierarchy* not only significantly outperforms *proximity and recovery time* (t = 16.81), but also *recovery time and proximity* (t = 7.25) and *dynamic recovery* (t = 7.24). This confirms that hierarchy is an important factor in distributing network load and preventing bottlenecks.

Finally, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.00), indicating that these two strategies distribute network load in a similar way.

In summary, *proximity and hierarchy* is most effective in reducing node load, while *proximity to centre* leads to an uneven distribution of network traffic. Recovery mechanisms improve distribution, but cannot match the effectiveness of hierarchy.

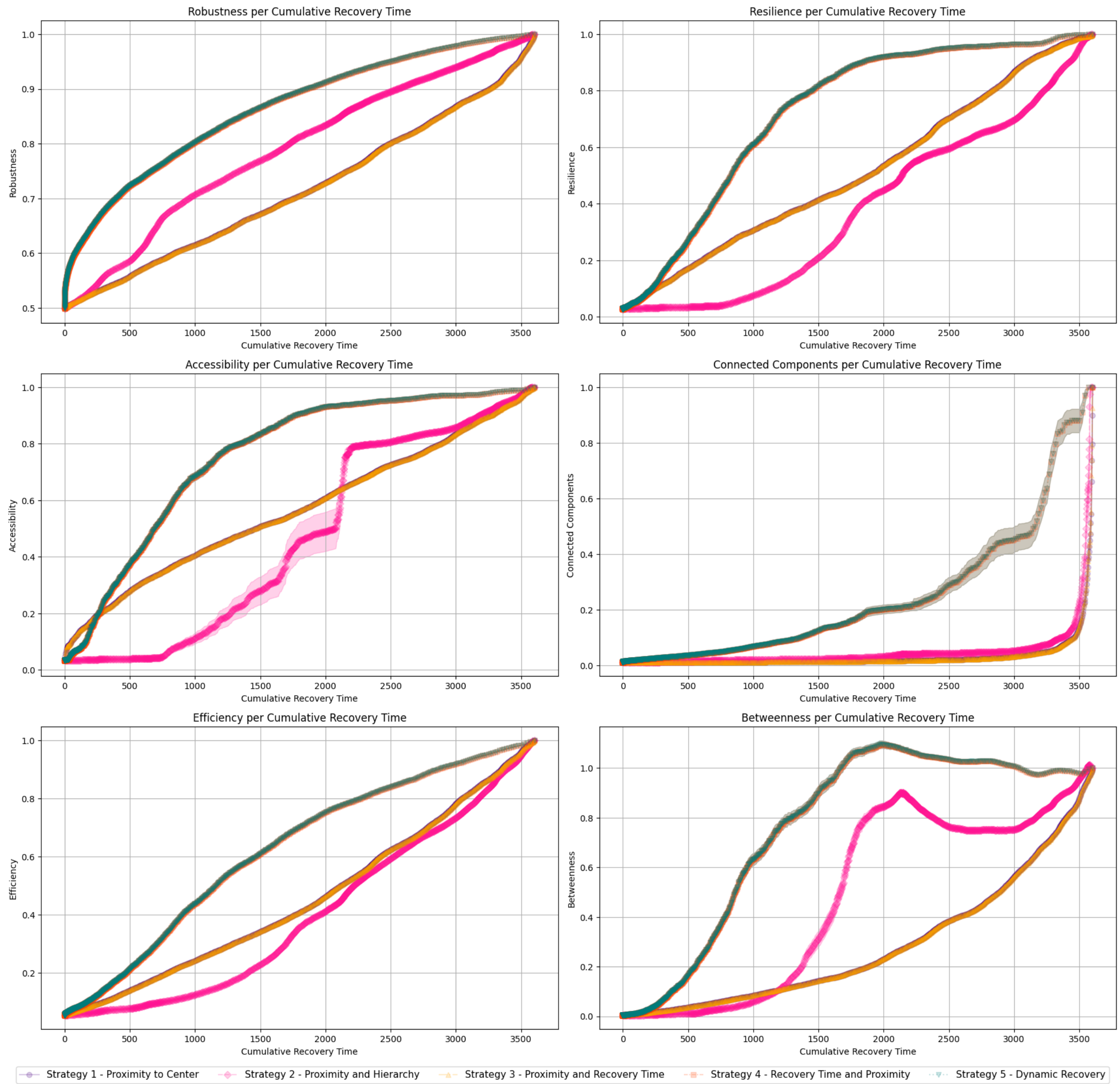

Figure B.4: Impact of 50% edge removal on Munich network metrics

C

Simulation results of 75% edge removal

C.1. Sioux Falls 75% edges removed

Removing 75% of the edges in the Sioux Falls network has a significant impact on the structure and functionality of the network. It means that there will be 57 edges removed. Figure C.1 shows the modified network, which shows how removing these connections affects various network metrics.

Robustness

Strategies *recovery time and proximity* and *dynamic recovery* score highest on robustness, indicating that these strategies focus on restoring highly connected nodes. This results in a network that stabilizes more quickly. Strategies *proximity to centre* and *proximity and recovery time* show a slower increase in robustness, indicating that these strategies may have a less structured approach to restoring key connections. Strategy *proximity and hierarchy* takes an intermediate position, with a steady but less steep increase in robustness.

When looking at the effects of the different strategies, Table E.3 shows that none of the comparisons are statistically significant. This means that the observed differences between the strategies are not large enough to be considered reliable and reproducible effects. In other words, the variations between the strategies could be coincidental or the result of other, unexamined factors, and cannot be attributed with certainty to the specific strategies that were used. Since there is no statistically significant difference, no clear conclusion can be drawn about which strategy performs better than the other.

Resilience

The resilience score shows significant differences between the strategies. Strategies *recovery time and proximity* and *dynamic recovery* show a faster increase, indicating that these strategies contribute to a more robust network in the short term. Strategies *proximity to centre* and *proximity and recovery time* lag slightly behind, suggesting that these strategies only contribute to a more resilient network later. This may mean that they give less priority to restoring critical connections in the early stages, leaving the network temporarily more vulnerable to disruptions.

Based on the reanalysis of the statistical tests in Table E.3, it appears that the performance of the strategies differs significantly. Strategies that integrate recovery mechanisms, such as *proximity and hierarchy*, perform significantly better than strategies that focus solely on proximity, such as *proximity to centre*.

For example, the comparison between *proximity to centre* and *proximity and hierarchy* shows a significant negative effect ($t = -2.18$), implying that *proximity to centre* is inferior in terms of resilience.

In addition, the comparison between *proximity and hierarchy* and *proximity and recovery time* shows that *proximity and hierarchy* performs significantly better ($t = 2.18$), which shows that adding a hierarchical structure promotes the recovery of the original OD pairs.

In summary, strategies that integrate **recovery time** and hierarchy show better resilience than strategies that focus on proximity alone.

Accessibility

At 75% of the connections removed, accessibility shows a strong increase as strategic connections are restored. Strategies *recovery time and proximity* and *dynamic recovery* score highest here, suggesting that these strategies connect important nodes in the early stages. This means that they focus on crucial corridors, which makes the network functional faster. Strategies *proximity to centre* and *proximity and recovery time* restore accessibility more slowly, suggesting that these strategies first tackle secondary connections before they strengthen the core structure of the network.

Based on the reanalysis of the statistical tests in Table E.3, it appears that the performance of the strategies differs significantly. Strategies that integrate *recovery time*, such as *recovery time and proximity* and *dynamic recovery*, perform significantly better than the strategies that are based solely on proximity.

For example, the comparison between *proximity to centre* and *recovery time and proximity* shows a significant positive effect ($t = 2.52$), which shows that *recovery time and proximity* performs better in terms of accessibility. Similarly, *proximity to centre* is found to perform significantly better than *dynamic recovery* ($t = 2.60$), which also points to the advantage of recovery strategies in terms of accessibility.

In addition, *proximity and hierarchy* performs significantly better than *proximity and recovery time* ($t = 2.64$) and *dynamic recovery* ($t = 2.72$), implying that adding a hierarchical structure improves accessibility.

In summary, strategies that integrate **recovery time** and/or hierarchy perform better in terms of accessibility than strategies that rely on proximity alone.

Connected Components

The connected components graph shows that the network is initially highly fragmented. Strategies *recovery time and proximity* and *dynamic recovery* cause the number of connected components to increase more quickly towards 1, which means that these strategies are more effective in reconnecting the network. Strategies *proximity to centre* and *proximity and recovery time* also perform well, while strategy *proximity and hierarchy* takes longer to fully recover the network. This suggests that strategies *recovery time and proximity* and *dynamic recovery* recover highly connected nodes more quickly, allowing the network to function as a whole at an earlier stage.

Based on the reanalysis of the statistical tests in Table E.3, it appears that the performance of the strategies differs significantly. Strategies that integrate *recovery time* and *dynamic recovery*, such as *recovery time and proximity* and *dynamic recovery*, perform significantly better than strategies that are based solely on proximity.

For example, the comparison between *proximity to centre* and *recovery time and proximity* shows a significant negative effect ($t = -5.03$, $p = 1.86 \times 10^{-6}$), implying that *proximity to centre* is inferior in terms of connected components. Similarly, *proximity to centre* performs significantly worse than *dynamic recovery* ($t = -5.24$, $p = 7.42 \times 10^{-7}$), again showing that recovery mechanisms perform better.

In addition, *proximity and hierarchy* is found to perform significantly worse than *proximity to centre* ($t = -2.14$, $p = 0.0342$), but here too the effect is still relatively small compared to the recovery strategies.

In summary, strategies that use **recovery time** and **dynamic recovery** as a core principle perform significantly better in terms of connected components than strategies that focus solely on proximity.

Efficiency

Efficiency increases steadily for all strategies, but with clear differences. Strategies *recovery time and proximity* and *dynamic recovery* again show the fastest increase, meaning that these strategies restore shorter routes faster. Strategies *proximity to centre* and *proximity and recovery time* follows slightly later, while strategy *proximity and hierarchy* lag behind. This confirms the previous pattern where strategies *recovery time and proximity* and *dynamic recovery* prioritize the most impactful connections, contributing to a more efficient network recovery.

When examining Table E.3, it becomes evident that there are no statistically significant differences in efficiency within the Sioux Falls network following a 75% edge removal. Consequently, it is not possible to determine which of the strategies performs better in comparison to the others.

Betweenness

The initial betweenness centrality is relatively low; however, it experiences a rapid increase for strategies *recovery time and proximity* and *dynamic recovery*. This observation indicates that these strategies introduce nodes early in the recovery phase that play a significant role in the distribution of flows. These nodes are likely to appear on numerous shortest paths, thereby enhancing their importance. As the recovery process progresses, the betweenness values for strategies *recovery time and proximity* and *dynamic recovery* begin to decline, which facilitates a more equitable distribution of traffic. In contrast, strategies *proximity to centre*, *proximity and hierarchy*, and *proximity and recovery time* exhibit a more gradual rise in betweenness centrality, implying that they incorporate nodes that are present on fewer shortest paths, resulting in a less pronounced increase in average betweenness.

The analysis of the betweenness value, as shown in Table E.3, shows significant differences between the strategies. Strategies that integrate recovery mechanisms, such as *recovery time and proximity* and *dynamic recovery*, perform significantly better than strategies that are based solely on proximity.

For example, the comparison between *proximity to centre* and *recovery time and proximity* shows a significant negative effect ($t = -3.03$), implying that *proximity to centre* is inferior in terms of betweenness. Similarly, *proximity to centre* performs significantly worse than *dynamic recovery* ($t = -3.05$), again demonstrating the advantage of recovery strategies.

In addition, *proximity and hierarchy* is found to perform significantly better than *proximity to centre* ($t = 3.82$), demonstrating a clear advantage of adding hierarchy to the network for betweenness.

In summary, strategies employing **recovery time** or **dynamic recovery** are found to perform significantly better in terms of betweenness than strategies focusing solely on proximity, with *proximity and hierarchy* being the exception for betweenness.

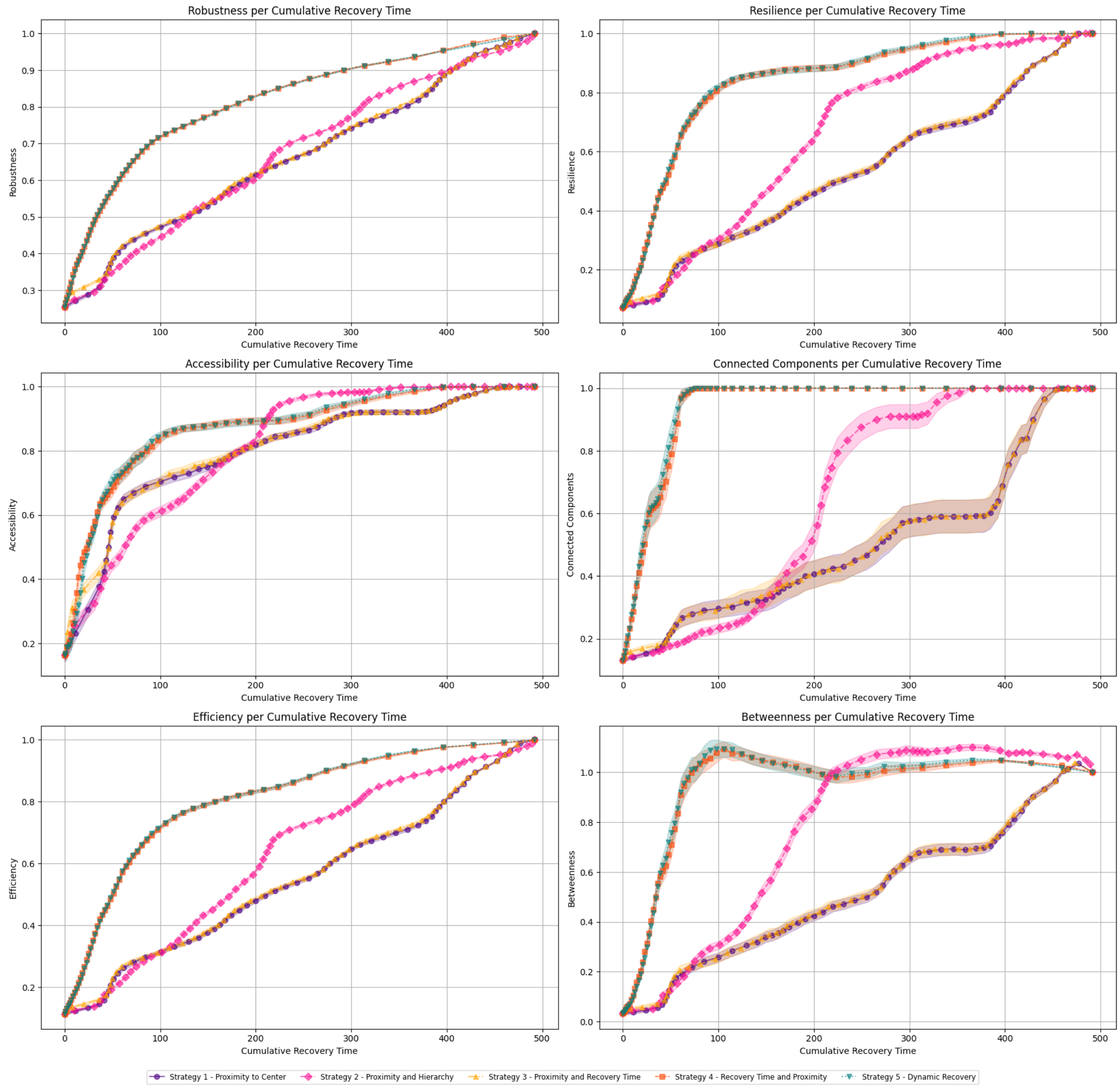

Figure C.1: Impact of 75% edge removal on Sioux Falls network metrics

C.2. Eastern Massachusetts 75% edges removed

In addition to removing 25% and 50% of the edges in the Eastern Massachusetts network, the effect of removing 75% of the edges can also be considered. This means that 193 edges are removed, leaving only 65 edges. This scenario represents a severe disruption to the network and provides insight into how different recovery strategies perform under extreme conditions. The results of this scenario are shown in Figure C.2.

Robustness

In terms of robustness, strategies *recovery time and proximity* and *dynamic recovery* consistently outperform the other strategies. Strategy *proximity and hierarchy*demonstrates superior performance compared to strategies *proximity* and *proximity and recovery time*, which exhibit the least effectiveness. This indicates that strategies *recovery time and proximity* and *dynamic recovery* are more adept at reinforcing the primary and most resilient connections within the network.

Analysis of Table E.3 shows that the strategy *proximity and hierarchy* performs statistically significantly better than the strategies *proximity to centre* and *proximity and recovery time*, both with a t-value of 4.58. In addition, it can be seen that the strategies *recovery time and proximity* and *dynamic recovery* perform statistically significantly better than *proximity to centre* and *proximity and recovery time* in parallel, with a t-value of 2.82.

Based on this, it can be concluded that, with respect to robustness and the removal of 75% of the connections in the Eastern Massachusetts network, the strategies based on *proximity and hierarchy*, *recovery time and proximity* and *dynamic recovery* perform best.

Resilience
In the context of resilience, strategies *recovery time and proximity* and *dynamic recovery* demonstrate the highest performance. Strategies *proximity* and *proximity and recovery time* exhibit slightly better outcomes than strategy *proximity and hierarchy*during the initial phase of the recovery process; however, in the latter half, they perform worse than all other strategies. This indicates that if the objective is to restore the original OD pairs as swiftly as possible, strategies *recovery time and proximity* and *dynamic recovery* are the most effective options.

Based on the results in Table E.3, it appears that the strategy *proximity to centre* performs significantly better than the strategies *recovery time and proximity* and *dynamic recovery*, with t-values of both 3.52. It is also visible that *proximity and hierarchy* performs significantly better than these two strategies, with t-values of 4.08. In addition, *proximity and recovery time* performs statistically significantly better than both *recovery time and proximity* and *dynamic recovery*, both with a t-value of 3.46.

In contrast, no significant differences were found between the strategies *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time*. There is also no significant difference between *recovery time and proximity* and *dynamic recovery* ($t = 0.00$).

Based on these results, it can be concluded that, in terms of robustness, the strategies that rely solely on proximity or proximity in combination with hierarchy or recovery time (*proximity to centre*, *proximity and hierarchy*, and *proximity and recovery time*) outperform strategies that rely heavily on recovery time (*recovery time and proximity* and *dynamic recovery*). This suggests that at high levels of perturbation (such as removing 75% of connections), proximity strategies yield more robust network results.

Accessibility
When looking at accessibility, or the number of nodes that are reachable from the centre node, it appears that strategies *proximity* and *proximity and recovery time* perform slightly better than strategies *recovery time and proximity* and *dynamic recovery* at the beginning of the recovery process. This means that these strategies initially restore connections that provide direct access to a large number of nodes more quickly. What is striking here is that this effect is mainly visible at the beginning of the process, while later the differences become smaller. Strategy *proximity and hierarchy* clearly performs worse here than the other strategies, which indicates that the recovery process with this strategy starts more slowly and that few connections remain reachable from the centre node for a longer period of time.

The analysis of statistical significance reveals that the strategies labelled as *proximity to centre* and *proximity and recovery time* demonstrate a markedly superior performance compared to the strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery*. The t-values for *proximity and recovery time* in relation to *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* are recorded at 4.75, 6.76, and 6.76, respectively. In a similar vein, the t-values for *proximity to centre* against these strategies are 4.72, 6.73, and 6.73, respectively.

These findings suggest that, with respect to accessibility, the strategies *proximity to centre* and *proximity and recovery time* significantly surpass the other three strategies evaluated in this study.

Connected components
The network in this scenario is initially characterized by significant fragmentation, which is understandable given the substantial number of removed edges. This condition results in the presence of numerous isolated clusters, leading to segments of the network being disconnected from one another. Strategies *recovery time and proximity* and *dynamic recovery* are found to be the most effective in rapidly mitigating this fragmentation, as they facilitate a swift reduction in the number of isolated clusters. This outcome is advantageous, as it allows the network to regain functionality more quickly. Following the implementation of strategies *recovery time and proximity* and *dynamic recovery*, strategies *proximity*

and *proximity and recovery time* demonstrate the next best performance, while strategy *proximity and hierarchy*continues to lag in terms of the speed at which the network is restored.

The results for connected components show that the *proximity to centre* strategy performs significantly better than *proximity and hierarchy* (t = 4.25), as well as compared to *recovery time and proximity* and *dynamic recovery* (both t = 2.24).

Furthermore, *proximity and recovery time* performs significantly better than *proximity and hierarchy* (t = -4.28), as well as compared to *recovery time and proximity* and *dynamic recovery* (both t = 2.27). Finally, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.00).

Based on these results, it can be concluded that strategies that are strongly based on proximity (*proximity to centre* and *proximity and recovery time*) are more effective in terms of *connected components*. This suggests that these strategies are better able to preserve network structure under disturbances.

Efficiency

In terms of efficiency, it is evident that strategies *recovery time and proximity* and *dynamic recovery* demonstrate a significant improvement from the outset of the recovery process, consistently outperforming the other strategies throughout the entire duration. This indicates that these strategies are more effective in reducing the average shortest distances between nodes at a faster rate. Initially, strategies *proximity* and *proximity and recovery time* exhibit superior performance compared to strategy *proximity and hierarchy*; however, in the latter half of the recovery process, strategy *proximity and hierarchy*begins to catch up, resulting in a reduction of the performance gap among these three strategies.

For efficiency, the results in Table E.3, show that *proximity to centre* performs significantly better than both *recovery time and proximity* and *dynamic recovery* (both t = 2.39). In addition, *proximity and recovery time* performs significantly better than *recovery time and proximity* and *dynamic recovery* (both t = 2.37).

No significant difference was found between the strategies *proximity to centre* and *proximity and hierarchy* (t = 0.80), as well as between *proximity and hierarchy* and *proximity and recovery time* (t = -0.78). Nor is there a significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.00).

These results indicate that strategies that rely heavily on proximity (*proximity to centre*) or a combination of proximity and recovery time (*proximity and recovery time*) maintain network efficiency better under disruptions than strategies that focus primarily on recovery time (*recovery time and proximity* and *dynamic recovery*).

Betweenness

The betweenness metric reveals that strategies *recovery time and proximity* and *dynamic recovery* exhibit a rapid increase, characterized by a distinct peak. This observation indicates that the restored nodes within these strategies are positioned on numerous shortest paths early in the process. However, this concentration can also represent a vulnerability, as a network with a few critical nodes is more susceptible to disruptions if any of these nodes fail. In contrast, strategy *proximity and hierarchy* demonstrates a less pronounced peak and a more gradual increase, while strategies *proximity* and *proximity and recovery time* display a much flatter progression. This suggests that the shortest paths in the latter two strategies are more evenly distributed across various nodes, potentially contributing to a more resilient network.

The results show that the strategy *proximity to centre* performs significantly worse than *proximity and hierarchy* (t = -2.89), as well as compared to *recovery time and proximity* and *dynamic recovery* (both t = -2.07). This means that *proximity and hierarchy* outperforms *proximity to centre*, as well as the other two strategies.

Furthermore, it turns out that *proximity and recovery time* performs significantly worse than both *proximity and hierarchy* (t = 2.90) and *recovery time and proximity* and *dynamic recovery* (both t = -2.08). No significant difference was found between *recovery time and proximity* and *dynamic recovery* (t = 0.00), as well as between *proximity and hierarchy* and the other strategies *recovery time and proximity* and *dynamic recovery* (both t = 0.67, not significant).

Based on these results, it can be concluded that the strategies containing *proximity and hierarchy* and *recovery time and proximity*, as well as *dynamic recovery*, significantly outperform the strategies based on proximity only, such as *proximity to centre* and *proximity and recovery time*. This suggests that using hierarchy or recovery time is more beneficial for betweenness centrality in the network.

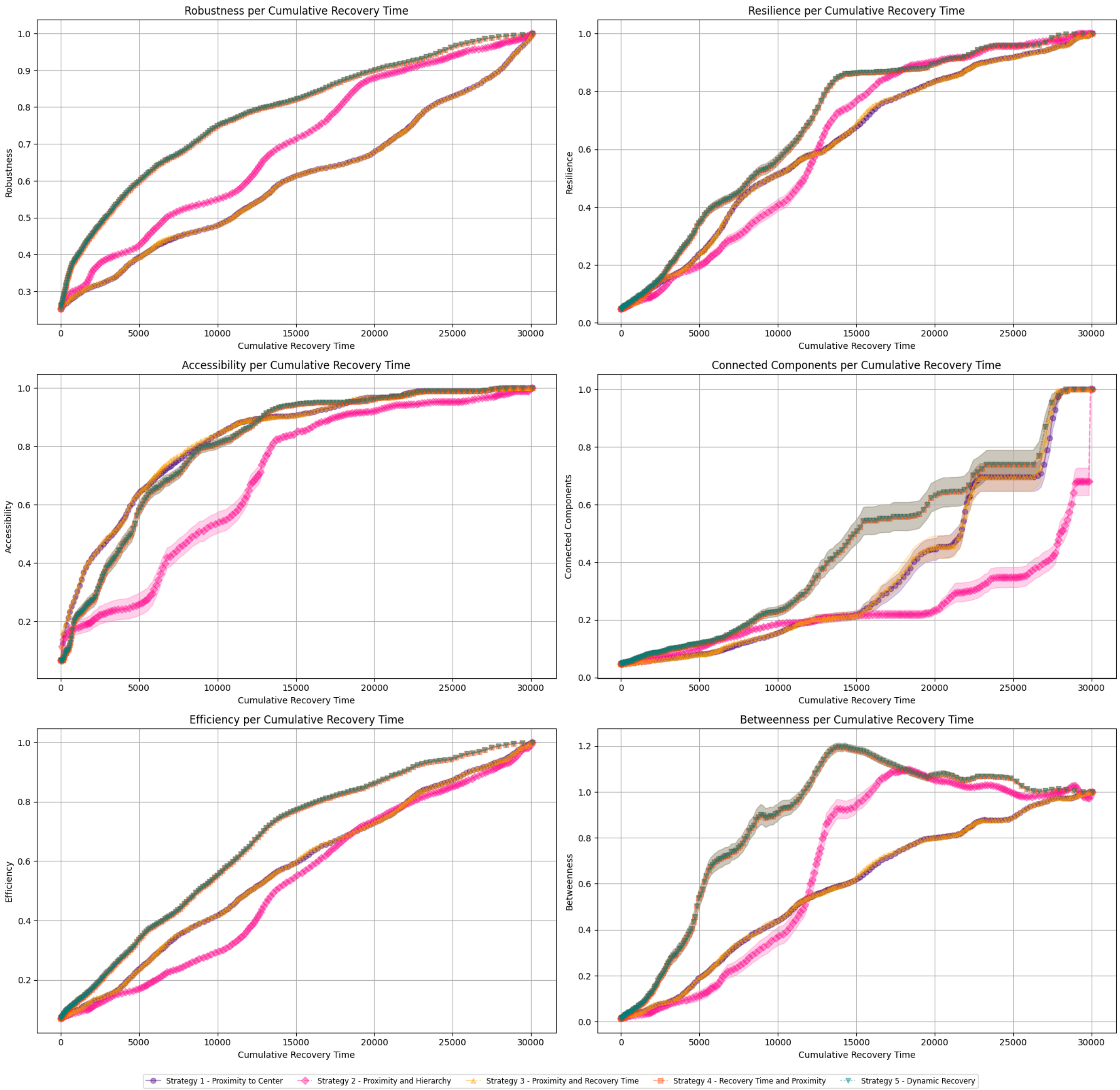

Figure C.2: Impact of 75% edge removal on Eastern Massachusetts network metrics

C.3. Anaheim 75% edges removed

The effect of the different strategies can also be seen when looking at removing 75% of the edges. This is shown in Figure C.3 and can be seen as a severe flood.

Robustness

When examining robustness, it is evident that strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* demonstrate superior performance, while strategies *proximity to centre* and *proximity and recovery time* significantly underperform. Strategy *proximity and hierarchy* exhibits a strong initial performance, showcasing the best results at the outset. As the process progresses, strategy *dynamic recovery* matches this level of performance; however, strategy *proximity and hierarchy* remains the most effective option for robust network recovery overall. This indicates that strategy *proximity and hierarchy* prioritizes the restoration of the more critical connections within the network.

Finally, on robustness, strategy *proximity and hierarchy* is found to significantly outperform strategy *proximity to centre*, strategy *proximity and recovery time*, strategy *recovery time and proximity* and strategy *dynamic recovery*, with t-values of 12.25, 12.26, 17.64 and 17.56, respectively. Strategy *proximity to centre* and strategy *proximity and recovery time* also significantly outperform strategy *recovery time and proximity* and strategy *dynamic recovery*, with t-values of 4.81 and 4.80 for strategy *recovery time and proximity*, and 4.72 and 4.71 for strategy *dynamic recovery*, respectively. This suggests that strategy *proximity and hierarchy*, together with strategy *proximity to centre* and strategy *proximity and recovery time*, produces more robust networks that are more resilient to disruptions and loss of connections.

Resilience
As for the resilience, it can be seen that all five strategies perform about equally well. This means that the amount of OD pairs is recovered at about the same rate across all strategies.

In terms of resilience, Table E.3 shows that strategy *proximity and hierarchy* significantly outperforms strategy *proximity to centre*, strategy *proximity and recovery time*, strategy *recovery time and proximity* and strategy *dynamic recovery*, with respective t-values of 3.53, 3.53, 7.92 and 7.64. Furthermore, strategy *proximity to centre* outperforms strategy *recovery time and proximity* (t-value 4.69) and strategy *dynamic recovery* (t-value 4.43), and strategy *proximity and recovery time* does the same, with t-values of 4.68 and 4.43, respectively. This emphasizes the resilience of the strategies that exploit the combination of proximity and hierarchy, which create more robust networks under disturbances.

Accessibility
For accessibility, it is clear that strategies *proximity to centre* and *proximity and recovery time* perform better at the beginning of the recovery process. But over time, strategies *proximity and hierarchy*, *recovery time and proximity* and *dynamic recovery* show a significant increase and thus make a catch-up leap. So if the intention is to increase accessibility and thus the number of nodes that can be reached from the centre node as quickly as possible, then strategies *proximity to centre* or *proximity and recovery time* should be chosen, but if the goal is to reach as many nodes as possible as quickly as possible, then it would be better to look at strategies *proximity and hierarchy*, *recovery time and proximity* or *dynamic recovery*.

For accessibility, strategy *proximity and hierarchy* performs significantly better than strategy *recovery time and proximity* and strategy *dynamic recovery*, with t-values of 10.63 and 11.30, respectively. Also, strategy *proximity to centre* and strategy *proximity and recovery time* outperform strategy *recovery time and proximity* and strategy *dynamic recovery*, with strategy *proximity to centre* achieving better t-values of 10.85 and 11.61, and strategy *proximity and recovery time* achieving similar performances with t-values of 10.85 and 11.61, respectively. This indicates that the combination of proximity and hierarchy is more effective in maintaining network accessibility when removing a large percentage of edges.

Connected components
The initial approach to all strategies is largely consistent; however, the final results reveal that strategy *dynamic recovery* yields the highest performance, succeeded by strategy *recovery time and proximity*, then strategy *proximity and hierarchy*, with strategies *proximity to centre* and *proximity and recovery time* trailing behind. This outcome suggests that strategy *dynamic recovery* is the most proficient in minimizing network islands and enhancing overall network connectivity.

Regarding connected components, strategy *proximity and hierarchy* significantly outperforms strategy *proximity to centre* and strategy *proximity and recovery time*, with t-values of 3.99. Furthermore, strategy *recovery time and proximity* outperforms strategy *proximity to centre* (t-value 2.23) and strategy *proximity and recovery time* (t-value 2.24), while strategy *dynamic recovery* outperforms strategy *proximity to centre* (t-value 2.53) and strategy *proximity and recovery time* (t-value 2.53). This suggests that strategies combining both proximity and recovery are more effective in preserving network components after edge removal.

Efficiency
In this context, strategies *recovery time and proximity* and *dynamic recovery* exhibit the highest levels of efficiency. Following them, strategy *proximity and hierarchy* occupies the next position, though there is a clear disparity in effectiveness. Meanwhile, strategies *proximity to centre* and *proximity and recovery time* fall considerably short in comparison. Therefore, it can be inferred that Strategies *recovery time*

and proximity and *dynamic recovery* are the most effective options for a network that emphasizes swift recovery in travel speed and overall efficiency.

In terms of efficiency, Table E.3 shows that *proximity and hierarchy* significantly outperforms strategy *recovery time and proximity* and strategy *dynamic recovery*, with t-values of 9.24 and 9.40, respectively. Furthermore, strategy *proximity to centre* outperforms strategy *recovery time and proximity* (t-value 8.82) and strategy *dynamic recovery* (t-value 8.99), and strategy *proximity and recovery time* also achieves better results than strategy *recovery time and proximity* (t-value 8.82) and strategy *dynamic recovery* (t-value 8.99). These results indicate that combining proximity and hierarchy leads to a more efficient use of network resources, especially when removing a large percentage of edges.

Betweenness

The implementation of strategy *proximity and hierarchy* leads to a significant increase in this metric, indicating the restoration of certain pathways that are crucial for many of the shortest routes. Nevertheless, this approach may also create a potential weakness, as an increased dependence on particular nodes renders the network more vulnerable to interruptions. In contrast, strategies *recovery time and proximity* and *dynamic recovery* demonstrate a more gradual improvement and achieve recovery at a faster pace compared to strategies *proximity to centre* and *proximity and recovery time*. Notably, Strategy *dynamic recovery* stands out as the most effective among these options, suggesting that it provides a more balanced recovery mechanism while minimizing reliance on specific nodes.

For betweenness, strategy *proximity and hierarchy* shows significantly better performance than strategy *proximity to centre* and strategy *proximity and recovery time*, both with t-values of 18.33. Strategy *proximity and hierarchy* also outperforms strategy *recovery time and proximity* and strategy *dynamic recovery*, with t-values of 19.15 and 18.71, respectively. The remaining effects do not show statistically significant differences, suggesting that the advantages of strategy *proximity and hierarchy* in terms of betweenness are significant.

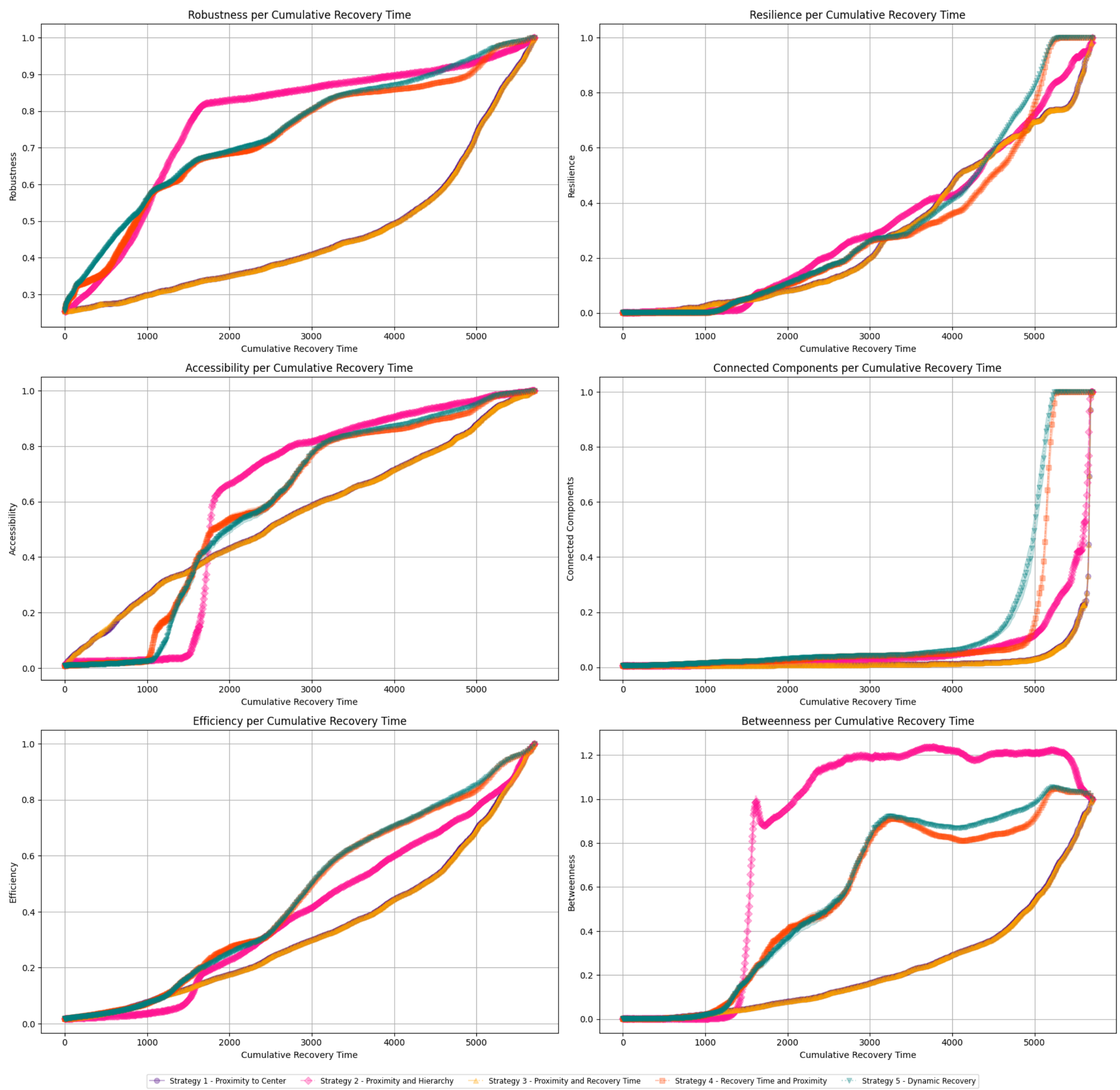

Figure C.3: Impact of 75% edge removal on Anaheim network metrics

C.4. Munich 75% edges removed

When 75% of the connections in the Munich network are removed, different recovery strategies are compared based on their impact on various network metrics. Below is an analysis by metric following from Figure C.4, discussing the performance of the strategies in relation to their impact on the network.

Robustness

When removing 75% of the edges in the Munich network, the *recovery time and proximity* and *dynamic recovery* strategies perform best, indicating that these strategies make the network more resilient to large-scale disruptions. In contrast, the *proximity to centre* and *proximity and recovery time* strategies perform worst, indicating that the network fragments faster with these strategies. The *proximity and hierarchy* strategy performs between these two groups and shows moderate robustness.

The results shown in Table E.3 show a clear pattern in which *proximity and hierarchy* significantly outperforms *proximity to centre*, with a t-value of 17.19. This suggests that a hierarchical structure allows for a more efficient allocation of resources, which in turn better manages bottlenecks in the network.

In addition, both *recovery time and proximity* and *dynamic recovery* significantly outperform *proximity to* *centre* and *proximity and recovery time*. Specifically, *recovery time and proximity* is better than *proximity to centre* (t = 3.47) and better than *proximity and recovery time* (t = 3.48). Strategy *dynamic recovery* outperforms *proximity to centre* (t = 3.51) and *proximity and recovery time* (t = 3.52). This emphasizes the importance of recovery mechanisms in reducing vulnerability and improving network stability.

Interestingly, *proximity and hierarchy* not only clearly outperforms *proximity to centre* and *proximity and recovery time*, but also *recovery time and proximity* (t = 13.47) and *dynamic recovery* (t = 13.45). This confirms that hierarchical ordering within the network plays a decisive role in the efficiency of distribution processes.

In summary, it appears that *proximity and hierarchy* is the most effective strategy to distribute the network load evenly, while *proximity to centre* leads to a less efficient structure. Recovery mechanisms provide a clear improvement, but are less powerful than a hierarchical approach.

Resilience
When 100% of the edges in the Munich network are removed and the recovery process is analysed, it is found that the strategies *recovery time and proximity* and *dynamic recovery* perform best. These strategies ensure that the network recovers relatively quickly and efficiently.

In contrast, the strategies *proximity to centre* and *proximity and recovery time* perform the least well, indicating that these methods are less effective in restoring the network structure. The strategy *proximity and hierarchy* is in between the previously mentioned groups in terms of performance. This suggests that although the network recovers partially under these strategies, the recovery process is less efficient and less robust.

The results show that *proximity to centre* and *proximity and recovery time* perform significantly better in terms of resilience than *proximity and hierarchy*, with a t-value of 13.64 for both strategies. This suggests that a focus on proximity and recovery time is more beneficial for network resilience than a hierarchical structure.

In addition, *proximity to centre* outperforms both *recovery time and proximity* (t = 15.19) and *dynamic recovery* (t = 15.19). This implies that a strategy that is primarily based on proximity without recovery mechanisms can still provide strong resilience.

Furthermore, *proximity and hierarchy* is also shown to outperform *recovery time and proximity* (t = 2.28) and *dynamic recovery* (t = 2.28). This means that although hierarchy is inferior to strategies that rely solely on proximity, it still contributes to better resilience compared to recovery-oriented methods.

Finally, *proximity and recovery time* is shown to outperform both *recovery time and proximity* (t = 15.19) and *dynamic recovery* (t = 15.19), underlining that a combination of proximity and recovery time is more effective than strategies that rely primarily on recovery mechanisms.

In summary, *proximity to centre* and *proximity and recovery time* are the most effective strategies for improving network resilience, while recovery-oriented approaches underperform compared to proximity-based methods.

Accessibility
Regarding network accessibility, the strategies *recovery time and proximity* and *dynamic recovery* again show the best results. The strategies *proximity to centre* and *proximity and recovery time* perform slightly worse, while *proximity and hierarchy* is the least effective. Interestingly, this last strategy only starts to improve from about two-thirds of the recovery process. This indicates that the accessibility of *proximity and hierarchy* is significantly more limited early in the recovery process than the other strategies.

Table E.3 shows that *proximity to centre* and *proximity and recovery time* perform significantly better in terms of accessibility than *proximity and hierarchy*, with a t-value of 9.93 for both strategies. This suggests that proximity and recovery time play a larger role in accessibility than hierarchical ordering.

In addition, *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time* all perform better than both *recovery time and proximity* and *dynamic recovery*. Specifically, *proximity to centre* is better than *recovery time and proximity* (t = 17.42) and *dynamic recovery* (t = 17.44). Similarly, *proximity and hierarchy* outperforms *recovery time and proximity* and *dynamic recovery*, with t-values of respectively 5.47 and 5.49.

Finally, *proximity and recovery time* also outperforms *recovery time and proximity* (t = 17.42) and *dynamic recovery* (t = 17.44).

In summary, strategies that primarily rely on proximity – with or without recovery time – are most effective for accessibility, while strategies that emphasize recovery time show less favourable results.

Connected components

When analysing the connected components in the network, the results for all strategies are relatively close to each other. The strategies *recovery time and proximity* and *dynamic recovery* perform slightly better than the other three: *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time*. What is striking is that all strategies show a significant increase in the number of connected components only quite late in the recovery process. This suggests that the network remains fragmented for a large part of the recovery process before a sudden improvement occurs.

Table E.3 shows that *proximity and hierarchy* outperforms both *proximity to centre* (t = 2.92) and *proximity and recovery time* (t = 2.83) in terms of connected components. This suggests that a hierarchical structure contributes to a more robust network connection compared to strategies based on proximity alone.

In addition, both *recovery time and proximity* and *dynamic recovery* outperform *proximity to centre*, with t-values of 8.25 and 8.26. This implies that recovery mechanisms have a positive impact on network connectivity.

Furthermore, the results show that *recovery time and proximity* and *dynamic recovery* also outperform *proximity and hierarchy* and *proximity and recovery time*. Specifically, *recovery time and proximity* outperforms *proximity and hierarchy* (t = 5.53) and *proximity and recovery time* (t = 8.14).

In summary, recovery-oriented strategies such as *recovery time and proximity* and *dynamic recovery* appear to be the most effective in improving network connectivity, while strategies that primarily rely on proximity perform less well in terms of connected components.

Efficiency

Also, for efficiency, the strategies *recovery time and proximity* and *dynamic recovery* perform best. The strategies *proximity to centre* and *proximity and recovery time* score significantly worse, while *proximity and hierarchy* falls in between. This pattern is similar to what was observed for robustness and suggests that the same strategies that make the network more robust also contribute to more efficient recovery.

Table E.3 shows that *proximity to centre* and *proximity and recovery time* perform significantly better than *proximity and hierarchy*, with t-values of 5.47 and 5.46 respectively. This indicates that proximity and recovery time allow for a more efficient allocation of resources than a hierarchical structure.

In addition, *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time* all perform better than *recovery time and proximity* and *dynamic recovery*. Specifically, *proximity to centre* is better than *recovery time and proximity* (t = 16.17) and *dynamic recovery* (t = 16.17). Similarly, *proximity and hierarchy* outperforms *recovery time and proximity* (t = 10.24) and *dynamic recovery* (t = 10.24). Finally, *proximity and recovery time* outperforms *recovery time and proximity* (t = 16.16) and *dynamic recovery* (t = 16.16).

In summary, it is found that strategies focusing on proximity are the most efficient in allocating resources, while recovery mechanisms are less efficient compared to approaches that place more emphasis on the proximity of the components.

Betweenness

For betweenness, it can be seen that the strategies *recovery time and proximity* and *dynamic recovery* increase strongly at the beginning of the recovery process. It is striking that these strategies even temporarily exceed the final network situation, after which they decrease again in the later phases of the recovery. This indicates that the network initially restructures quickly with these strategies, but that the distribution of connections then stabilizes somewhat.

The strategy *proximity and hierarchy* shows a slightly different pattern: this strategy also increases rapidly initially, experiences a temporary peak, followed by a slight decrease, and then recovers to the final network situation. This indicates a less stable recovery process compared to the other strategies.

The strategies *proximity to centre* and *proximity and recovery time* show a more gradual increase without strong fluctuations. This indicates that these strategies make a more constant contribution to the betweenness of the network during the recovery process.

Regarding betweenness, the results show that *proximity and hierarchy* significantly outperforms both *proximity to centre* and *proximity and recovery time*, with a t-value of 14.16. This indicates that a hierarchical structure allows for a more efficient distribution of network traffic than strategies that focus primarily on proximity.

Furthermore, *proximity and hierarchy* also outperforms *recovery time and proximity* (t = 10.70) and *dynamic recovery* (t = 10.69). These findings support the idea that adding a hierarchical structure improves betweenness, which allows for more efficient route selection within the network.

There are no further significant differences between the other strategies, indicating that, outside of the comparisons mentioned above, no other strategies are statistically distinguished in terms of betweenness.

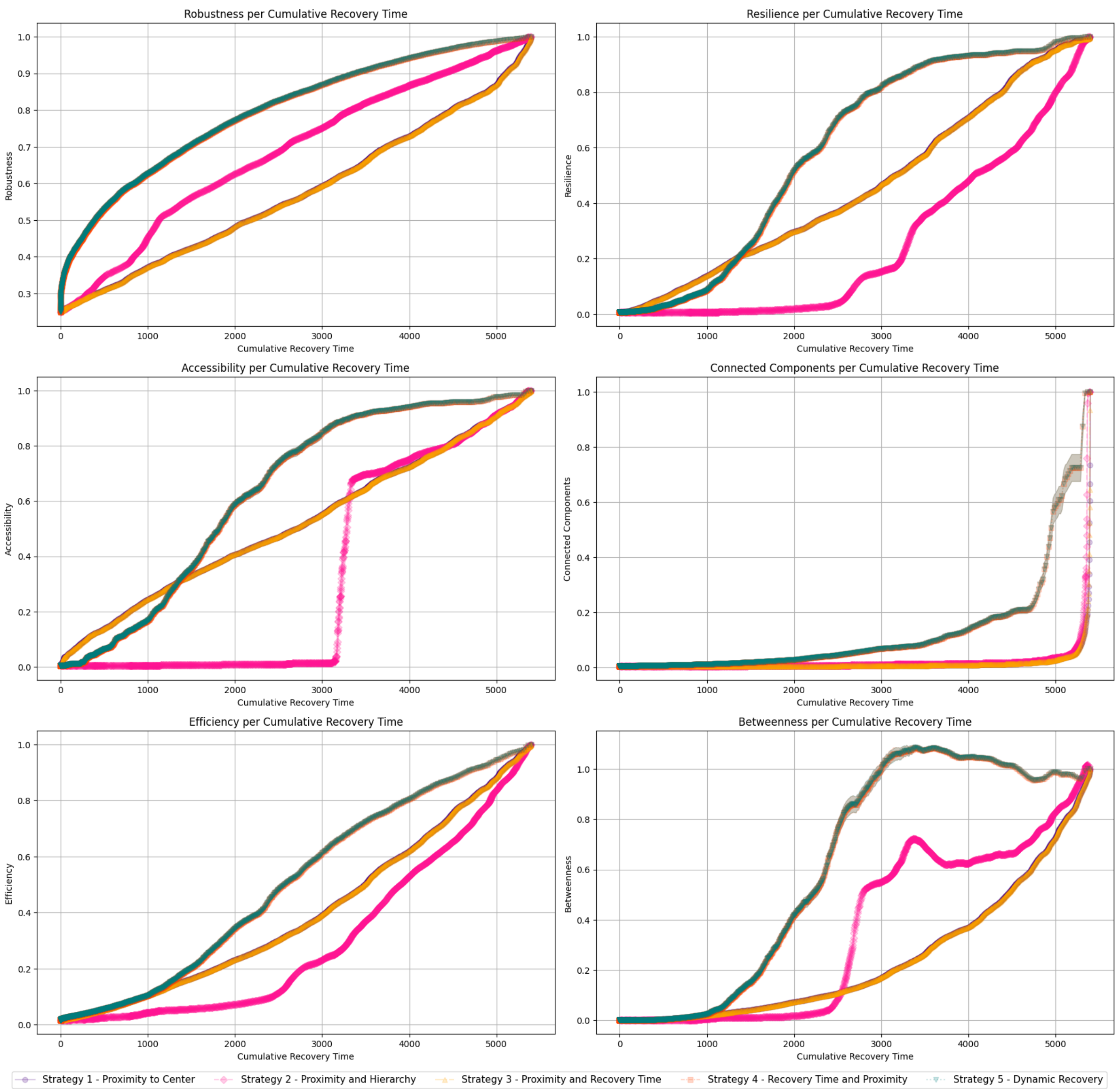

Figure C.4: Impact of 75% edge removal on Munich network metrics

D

Simulation results of 100% edge removal

D.1. Sioux Falls 100% edges removed

Eliminating all edges entirely is distinct from other removal percentages, as it does not involve any simulation. With the complete removal of edges, there are no alternative combinations of edges that can be removed, leading to graphs that lack confidence intervals. The graphs depicting the complete removal of edges in the Sioux Falls network are presented in Figure D.1, where it is evident that confidence intervals are absent.

Robustness

Strategies based on *recovery time and proximity* and *dynamic recovery* exhibit the most rapid increase in robustness, indicating that these strategies facilitate a network that becomes operational more quickly following disruptions. However, it is observed that these strategies plateau midway through the recovery process, suggesting that edges are added at that point which do not contribute to enhancing resilience. In contrast, strategies based on *proximity to centre*, *proximity and hierarchy*, and *proximity and recovery time* demonstrate a slower rate of growth. This implies that the strategies based on *recovery time and proximity* and *dynamic recovery* are the most effective in restoring the network in a manner that maximizes overall capacity and reliability.

When examining robustness, it is evident from Table E.4 that the removal of 100% of the edges in the Sioux Falls network reveals no statistically significant differences. This indicates that the variations observed among the strategies are insufficiently substantial to be deemed reliable or reproducible. In essence, the discrepancies between the strategies may be merely coincidental or influenced by other unconsidered factors, making it impossible to link them to the specific strategies employed. Consequently, the absence of statistically significant differences prevents any definitive conclusions regarding the superior performance of one strategy over another.

Resilience

Resilience grows slower in the 100% version than in the 75% version, which makes sense given the severity of the disruption. However, strategies *recovery time and proximity* and *dynamic recovery* still provide the fastest growth, meaning they better recover the network from structural disruptions. Strategy *proximity and recovery time* performs reasonably well, while strategies *proximity to centre* and *proximity and hierarchy* grow slower. This means that strategies *recovery time and proximity* and *dynamic recovery* are the most effective in creating a resilient network after a major disruption.

The analysis of the resilience value, as shown in Table E.3, shows some significant differences between the strategies. Strategies that integrate recovery mechanisms, such as *proximity and hierarchy*, perform significantly better than strategies that focus solely on proximity, such as *proximity to centre*.

For example, the comparison between *proximity to centre* and *proximity and hierarchy* shows a significant negative effect ($t = -2.01$, $p = 0.046$), implying that *proximity to centre* is inferior in terms of resilience. This emphasizes that the addition of a hierarchical structure within the network is beneficial for the resilience after a disturbance.

In addition, the comparison between *proximity and hierarchy* and *proximity and recovery time* shows that *proximity and hierarchy* performs significantly better ($t = 1.99$), indicating the advantage of integrating a hierarchical structure into the recovery strategy.

However, no significant effects were found between the other strategies, such as *proximity to centre* versus *recovery time and proximity* ($t = -0.65$) and *proximity to centre* versus *dynamic recovery* ($t = -0.68$), suggesting that these strategies do not show a significant difference in terms of resilience.

In summary, the analysis of the resilience results shows that strategies that include *proximity and hierarchy* significantly outperform *proximity to centre*, highlighting the importance of hierarchical structures in the recovery process. However, strategies that focus on recovery, such as *proximity and recovery time* and *dynamic recovery*, did not show significant advantages over the other strategies in terms of resilience.

Accessibility

The first and third strategies exhibit the most rapid growth, with the second strategy following closely behind. In contrast, the fourth and fifth strategies demonstrate a slower restoration of accessibility, suggesting that they yield less efficient pathways during the initial phases of recovery. This observation implies that strategies one and three enable a significant proportion of nodes to be accessed from the central node, thereby ensuring a relatively high level of network connectivity. Conversely, strategies four and five display a sudden and substantial increase in accessibility, indicating the addition of specific edges that subsequently allow for a greater number of nodes to become reachable within the network.

The analysis of the accessibility value, as shown in Table E.3, shows significant differences between the strategies, especially in terms of the effectiveness of recovery mechanisms. Strategies that include recovery principles such as *recovery time and proximity* and *dynamic recovery* perform significantly better than strategies that focus solely on proximity.

For example, the comparison between *proximity to centre* and *recovery time and proximity* shows that *proximity to centre* performs significantly worse ($t = -4.61$), suggesting that the recovery mechanism in *recovery time and proximity* significantly improves network accessibility after disruptions. Similarly, *proximity to centre* performs significantly worse than *dynamic recovery* ($t = -4.66$), again demonstrating the benefit of recovery-oriented strategies.

Furthermore, the comparison between *proximity and hierarchy* and *recovery time and proximity* shows that *proximity and hierarchy* also performs significantly better ($t = 4.34$). This points to the added value of integrating a hierarchical structure into the recovery mechanism for improving network accessibility.

The comparison between *proximity and hierarchy* and *dynamic recovery* also shows a significant difference ($t = 4.40$), which emphasizes the effectiveness of recovery strategies that integrate dynamic recovery in improving accessibility.

In summary, the analysis of the accessibility results shows that strategies that integrate recovery mechanisms such as *recovery time and proximity* and *dynamic recovery* significantly outperform strategies that focus on proximity alone. Furthermore, *proximity and hierarchy* plays an important role in improving accessibility, especially when it comes to restoring network capacity after disruptions.

Connected Components

The graph depicting connected components indicates that the network begins in a state of significant fragmentation. Strategies *recovery time and proximity* and *dynamic recovery* lead to a more rapid increase in the number of connected components approaching unity, signifying their greater efficacy in re-establishing network connectivity. In contrast, strategies *proximity to centre*, *proximity and hierarchy*, and *proximity and recovery time* require a longer duration to achieve complete network recovery. This observation implies that strategies *recovery time and proximity* and *dynamic recovery* facilitate the quicker recovery of highly connected nodes, thereby enabling the network to operate cohesively at an earlier phase.

The analysis of the connected components shows that strategies with recovery mechanisms, such as *recovery time and proximity* and *dynamic recovery*, perform significantly better in maintaining network connectivity after disruptions. For example, *proximity to centre* performs significantly worse than *recovery time and proximity* ($t = -5.65$) and *dynamic recovery* ($t = -5.82$), indicating that recovery-oriented strategies are more effective in maintaining network structure.

In addition, the comparison between *proximity and hierarchy* and *recovery time and proximity* shows that *proximity and hierarchy* performs worse in terms of connected components ($t = -2.64$). Similarly, *proximity and hierarchy* also performs worse than *dynamic recovery* ($t = -2.77$).

In summary, the recovery strategies with *recovery time and proximity* and *dynamic recovery* are more effective in maintaining network connectivity.

Efficiency

Efficiency demonstrates a consistent upward trend across all strategies, albeit with notable distinctions. Strategies*recovery time and proximity* and *dynamic recovery* exhibit the most rapid improvement, indicating their effectiveness in restoring shorter routes more swiftly. Strategies *proximity to centre* and *proximity and recovery time* show a marginally delayed response, while strategy *proximity and hierarchy* remains the least effective. This observation reinforces the earlier findings that strategies *recovery time and proximity* and *dynamic recovery* focus on the most significant connections, thereby enhancing the overall efficiency of network recovery.

Betweenness

Betweenness centrality exhibits a significant peak during the initial phase, particularly for strategies *recovery time and proximity* and *dynamic recovery*. This observation indicates that certain nodes temporarily assume a disproportionately influential position within the network traffic. Additionally, it is evident that these strategies experience fluctuations in betweenness, suggesting that a limited number of nodes are critical to network traffic dynamics. In contrast, strategies *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time* demonstrate a more gradual trajectory, devoid of such peaks and troughs, which implies a more evenly distributed recovery approach.

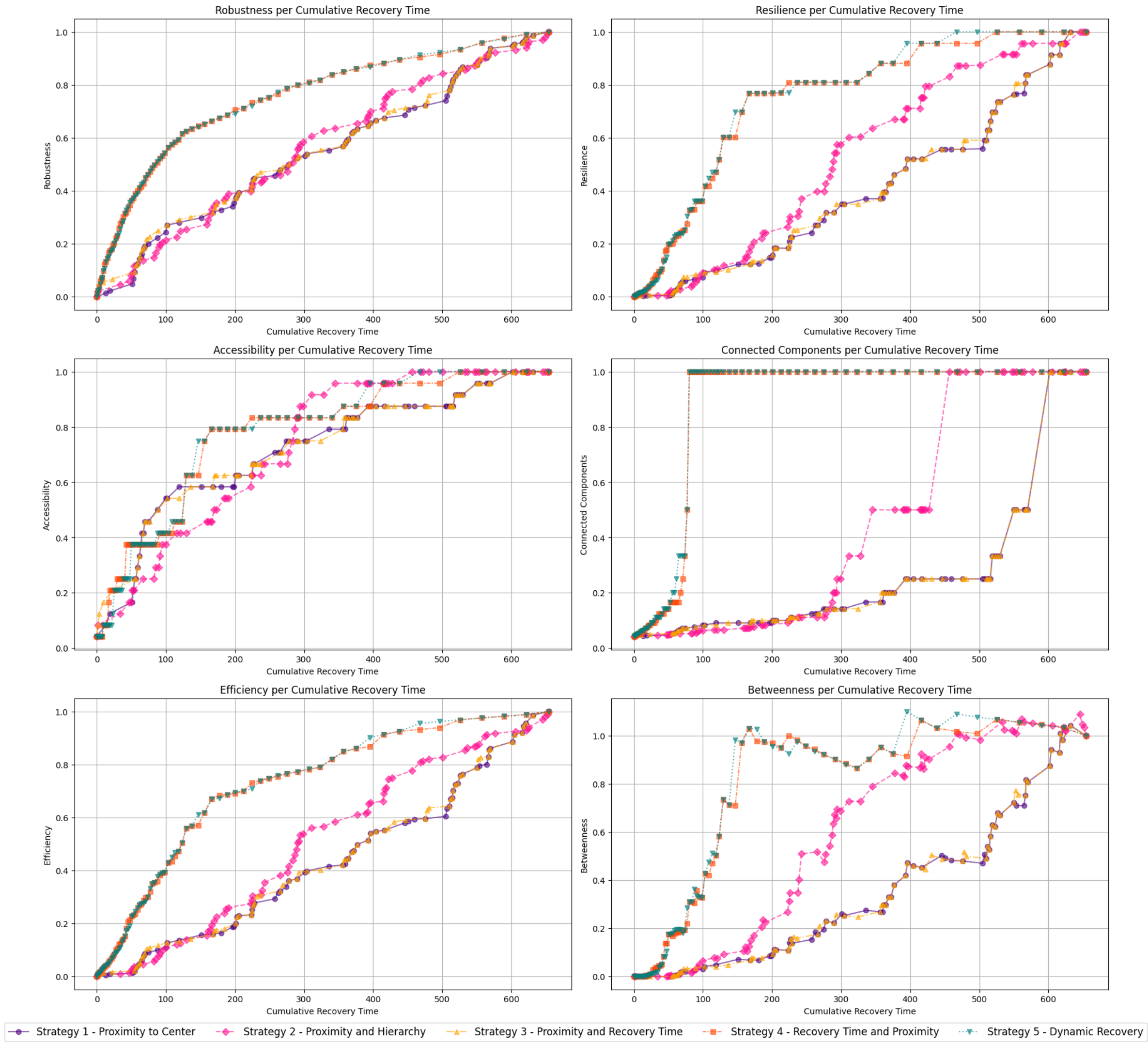

Figure D.1: Impact of 100% edge removal on Sioux Falls network metrics

D.2. Eastern Massachusetts 100% edges removed

The final scenario under analysis involves the complete removal of 100% of the edges within the Eastern Massachusetts network. This action results in the total disintegration of the network, leaving no connections intact initially. This can be interpreted as an extreme disruption, such as a very severe flood that paralyses all transportation infrastructure. The results of this scenario are illustrated in Figure D.2. Given that all edges are eliminated in each iteration, there is no variation across different runs, and consequently, no confidence interval is presented.

Robustness

In terms of robustness, strategies *recovery time and proximity* and *dynamic recovery* once again outperform the other strategies. Notably, strategy *proximity and hierarchy*achieves better results than strategies *proximity* and *proximity and recovery time*, which perform the least effectively. This suggests that strategies *recovery time and proximity* and *dynamic recovery* are more focused on reinforcing the most robust connections, whereas strategy *proximity and hierarchy*may concentrate on enhancing specific nodes that play a critical role in the network structure.

Looking at the statistical significance of the effects, as shown in Table E.4, it appears that strategy *proximity and hierarchy* performs statistically significantly better than strategies *proximity to centre* and *proximity and recovery time*, both with a t-value of 5.29. Furthermore, it appears that *proximity and* *hierarchy* also performs better than *recovery time and proximity* and *dynamic recovery*, both with a t-value of 2.08. However, these two strategies do perform better than *proximity to centre* and *proximity and recovery time*, each with a t-value of 3.31.

Based on this, it can be concluded that, under a scenario of 100% edge removal in the Eastern Massachusetts network, strategy *proximity and hierarchy* performs statistically significantly better than the other strategies.

Resilience

In terms of resilience, strategies *recovery time and proximity* and *dynamic recovery* achieve the highest scores, indicating that these strategies are the most effective in restoring the original OD pairs. Strategies *proximity* and *proximity and recovery time* perform better than strategy *proximity and hierarchy*during the initial phase of the recovery process; however, in the latter half, they lag behind the other strategies, with strategy *proximity and hierarchy*demonstrating superior performance compared to all others. This implies that while strategies *proximity* and *proximity and recovery time* provide rapid recovery in the early stages, strategies *recovery time and proximity* and *dynamic recovery* ultimately facilitate a more sustainable recovery.

Regarding resilience, in Table E.4, no statistically significant difference can be found between strategies *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time*. However, what may not have been expected based on Figure D.2, can be seen that strategies *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time* with t values of 5.16, 6.14 and 5.08 respectively perform better than strategies *recovery time and proximity* and *dynamic recovery*.

Thus, it can be said that when looking at the Eastern Massachusetts network, where 100% of the edges are removed, then strategies *proximity to centre*, *proximity and hierarchy* or *proximity and recovery time* perform the most favourably.

Accessibility

In terms of accessibility, strategies *proximity to centre* and *proximity and recovery time* perform the best, with strategy *proximity and recovery time* slightly outperforming strategy *proximity to centre*. This indicates that these strategies are more effective in re-establishing connectivity for a greater number of nodes from the central node. Strategies *recovery time and proximity* and *dynamic recovery* closely follow, while strategy *proximity and hierarchy*lags behind. This suggests that strategies *proximity* and *proximity and recovery time* are preferred when rapid network accessibility is of utmost importance.

The results for accessibility shown in Table E.4, show that proximity to centre performs significantly better than proximity and hierarchy (t = 7.08), and also better than both recovery time and proximity and dynamic recovery (both t = 9.96). This means that proximity to centre has the best performance in terms of accessibility.

In contrast, proximity and hierarchy performs worse than proximity to centre (t = -7.09), but proximity and hierarchy performs better than recovery time and proximity (t = 2.07) and dynamic recovery (t = 2.07). There is no significant difference between recovery time and proximity and dynamic recovery (t = 0.00), which means that these two strategies perform equally in terms of accessibility.

In summary, *proximity to centre* and *proximity and recovery time* are the best strategies for accessibility, out of the examined strategies, followed by *proximity and hierarchy*, and then *recovery time and proximity* and *dynamic recovery*, which perform equally.

Connected components

At the beginning of the recovery process, all strategies show a similar development, with the network completely fragmented. Subsequently, strategies *proximity*, *proximity and recovery time*, *recovery time and proximity*, and *dynamic recovery* demonstrate a rapid increase in connectivity, effectively reassembling the network at a comparable rate. In contrast, strategy *proximity and hierarchy* lag significantly behind, indicating that it takes a longer duration for the network to operate as a cohesive entity under this particular strategy.

Looking at the statistical significance of the connected components results as shown in the data, it is found that strategy *proximity to centre* performs statistically significantly better than strategy *proximity* *and hierarchy* (t = 5.18) and strategy *recovery time and proximity* (t = 4.75), as well as strategy *dynamic recovery* (t = 4.75).

However, there is no significant difference between strategy *proximity to centre* and strategy *proximity and recovery time* (t = -0.11), which means that these two strategies perform equally in this respect. This implies that both proximity to centre and proximity and recovery time have strong performances in terms of connected components.

In addition, strategy *proximity and hierarchy* is found to perform significantly worse than strategy *proximity and recovery time* (t = -5.28), while proximity and hierarchy also shows no significant difference compared to recovery time and proximity and dynamic recovery (both t = -0.06).

In summary, *proximity to centre* and *proximity and recovery time* perform best for connected components, while *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* are less effective, with *proximity and hierarchy* performing the worst of the three.

Efficiency

In terms of efficiency, specifically the shortest travel time between nodes, strategies *recovery time and proximity* and *dynamic recovery* demonstrate the highest performance. This indicates that these strategies achieve the most significant improvements in network connections, resulting in reduced travel times. During the first half of the recovery process, strategies *proximity* and *proximity and recovery time* follow, while strategy *proximity and hierarchy*ranks the lowest. However, in the second half, the recovery of strategy *proximity and hierarchy*aligns more closely with that of strategies *proximity* and *proximity and recovery time*. Consequently, strategies *recovery time and proximity* and *dynamic recovery* are the optimal choices when a rapid increase in efficiency and enhanced accessibility are desired.

Looking at the statistical significance of the efficiency results as shown in the data, it appears that strategy *proximity to centre* does not show significant differences compared to strategy *proximity and hierarchy* (t = 0.40) and strategy *proximity and recovery time* (t = 0.03). This means that proximity to centre does not perform significantly better or worse than these two strategies.

However, strategy *proximity to centre* does perform significantly better than strategy *recovery time and proximity* (t = 2.84) and strategy *dynamic recovery* (t = 2.84), indicating that proximity to centre has a clear advantage over these two strategies in terms of efficiency.

Furthermore, the comparison between strategy *proximity and hierarchy* and strategy *proximity and recovery time* (t = -0.37) shows that there is no significant difference between these two strategies. However, *proximity and hierarchy* performs significantly better than recovery time and proximity (t = 2.30) and *dynamic recovery* (t = 2.30), suggesting that *proximity and hierarchy* is more efficient than these two strategies.

It also shows that *proximity and recovery time* performs significantly better than recovery time and proximity (t = 2.80) and dynamic recovery (t = 2.80), indicating the effectiveness of *proximity and recovery time* in terms of efficiency.

In summary, *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time* performs best in terms of efficiency, while *recovery time and proximity* and *dynamic recovery* show the least effectiveness in this regard.

Betweenness

In terms of betweenness, strategies *proximity* and *proximity and recovery time* exhibit a relatively linear and stable recovery, indicating that the network is being restored gradually and consistently. In contrast, strategies *recovery time and proximity* and *dynamic recovery* demonstrate a more pronounced increase after approximately one-third of the recovery process, followed by fluctuations characterized by peaks and troughs. This suggests that these strategies temporarily assign a significantly high centrality to certain nodes within the shortest paths. Strategy *proximity and hierarchy*initiates with a slower recovery but later shows a substantial increase, stabilizing around a fixed value there after. This implies that in a later phase, strategy *proximity and hierarchy*restores nodes that are strategically important for the shortest paths.

Regarding betweenness, proximity to centre is found to perform worse than proximity and hierarchy (t = -3.08), indicating that proximity and hierarchy is better at improving betweenness centrality. Furthermore, proximity and hierarchy is found to perform significantly better than both recovery time and proximity and dynamic recovery (both t = 2.23). This indicates that proximity and hierarchy provides a better distribution of intermediate connections in the network.

However, there is no significant difference between proximity and recovery time and the other strategies recovery time and proximity and dynamic recovery (t = -0.57 and t = 0.00), indicating that these two strategies perform equally in terms of betweenness.

In summary, the betweenness analysis shows that *proximity and hierarchy* is the best strategy for betweenness out of the incorporated strategies.

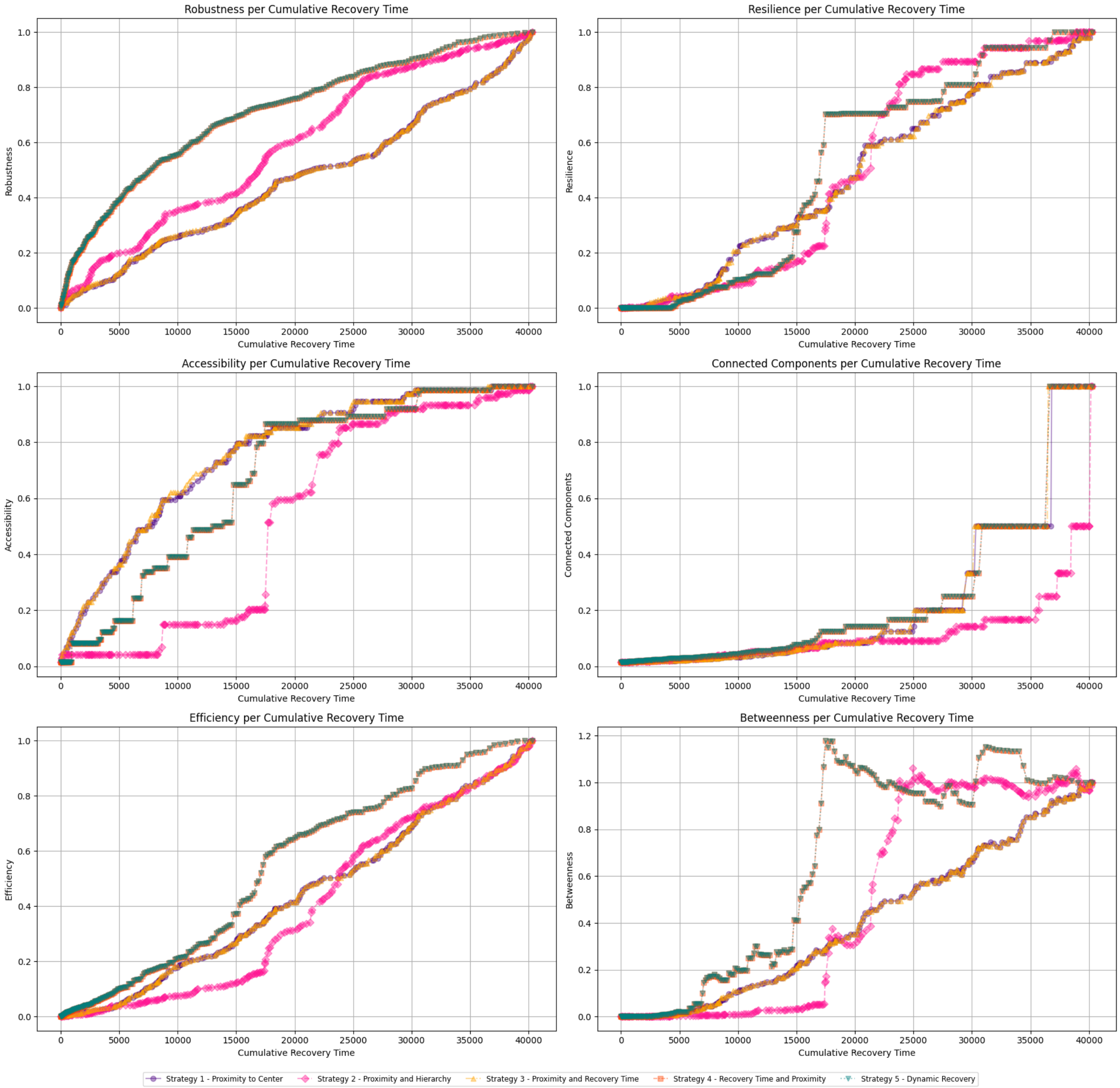

Figure D.2: Impact of 100% edge removal on Eastern Massachusetts network metrics

D.3. Anaheim 100% edges removed

An analysis can also be conducted for the Anaheim network under a scenario where 100% of the edges are removed. This implies that all 914 connections within the network are eliminated, leading to a complete disintegration of the network. The outcomes of this extreme disruption are illustrated in

Figure D.3 and will be further examined below.

Robustness
Strategy *proximity and hierarchy* demonstrates a very rapid initial increase, followed closely by strategies *recovery time and proximity* and *dynamic recovery*, with strategy *dynamic recovery* slightly outperforming strategy *recovery time and proximity*. Strategies *proximity to centre* and *proximity and recovery time* exhibit the slowest growth and lag behind the other strategies. This indicates that strategy *proximity and hierarchy* is preferred for a swift increase in robustness, followed by strategy *dynamic recovery*, then strategy *recovery time and proximity*, and finally strategies *proximity to centre* and *proximity and recovery time*.

When looking at Table E.4, in terms of robustness, *proximity and hierarchy* is significantly better than the other strategies, with t-values of 14.17, 14.17, 20.50 and 20.38 for *proximity to centre*, *proximity and recovery time*, *recovery time and proximity* and *dynamic recovery* respectively. This emphasizes that the combination of proximity and hierarchy best protects the network against connection loss. Furthermore, both *proximity to centre* and *proximity and recovery time* outperform *recovery time and proximity* and *dynamic recovery*, with t-values of 5.64 for *proximity to centre* and 5.49 for *proximity and recovery time* compared to *recovery time and proximity* and *dynamic recovery*, respectively. This indicates that strategies emphasizing maintaining both proximity and recovery capabilities are more robust in terms of structural stability after connection loss.

Resilience
In terms of resilience, all strategies show a comparable increase, with one strategy performing better at certain times and another excelling at different intervals. Consequently, it is not possible to assign a clear preference to any specific strategy based on this metric.

In terms of resilience, in Table E.4, it has been shown that *proximity and hierarchy* significantly outperforms all other strategies, with t-values of 2.81, 2.81, 9.34, and 8.77 for *proximity to centre*, *proximity and recovery time*, *recovery time and proximity*, and *dynamic recovery*, respectively. This suggests that the combination of proximity and hierarchy increases the network strength against perturbations, making the network more robust. Furthermore, *proximity to centre* outperforms *recovery time and proximity* and *dynamic recovery*, with t-values of 6.96 and 6.39, respectively. *Proximity and recovery time* also outperforms the other two strategies, with t-values of 6.97 for *recovery time and proximity* and 6.41 for *dynamic recovery*, indicating higher resilience of the network structure in recovering from disturbances.

Accessibility
In terms of accessibility, strategies *proximity to centre* and *proximity and recovery time* exhibit a relatively linear progression throughout the recovery process. Conversely, strategy *proximity and hierarchy* begins with a notably low value but subsequently experiences a sudden increase, ultimately performing the best regarding accessibility. Strategies *recovery time and proximity* and *dynamic recovery* demonstrate a more gradual recovery, eventually reaching a level comparable to that of strategy *proximity and hierarchy*. This indicates that Strategies *proximity to centre* and *proximity and recovery time* provide a stable and predictable recovery, while strategies *proximity and hierarchy*, *recovery time and proximity*, and *dynamic recovery* lead to a fully restored network more rapidly, although with a less gradual build-up.

In terms of accessibility, the *proximity and hierarchy* strategy significantly outperforms the *recovery time and proximity* and *dynamic recovery* strategies, with respective t-values of 15.87 and 15.94. This suggests that the combination of proximity and hierarchy provides a more robust approach to improving accessibility within the network, resulting in a more efficient network for reaching nodes after removing edges. The *proximity to centre* and *proximity and recovery time* strategies also outperform *recovery time and proximity* and *dynamic recovery*, with t-values of 17.81 and 17.84 for *proximity to centre*, and 17.82 and 17.85 for *proximity and recovery time*, respectively. This suggests that these strategies provide a more effective approach than the other strategies in terms of accessibility, although they do not outperform the *proximity and hierarchy* strategy.

Connected components
All strategies commence with a limited number of interconnected components and remain fragmented for a significant portion of the recovery process. Subsequently, they exhibit a sharp increase, with strategy *dynamic recovery* being the first to re-establish network connectivity, followed by strategy *recovery*

time and proximity, then strategy *proximity and hierarchy*, and finally strategies *proximity to centre* and *proximity and recovery time*. This indicates that strategy *dynamic recovery* is preferred when the objective is to restore the network to a fully functioning state as quickly as possible.

Regarding connected components, Table E.4 shows that *proximity and hierarchy* significantly outperforms both *proximity to centre* and *proximity and recovery time*, with t-values of 1.98 for both. This shows that *proximity and hierarchy* contributes to a more connected network, with stronger internal connectivity. The *recovery time and proximity* strategy outperforms *proximity to centre* by a t-value of 2.11 and *proximity and recovery time* by a t-value of 2.24, suggesting that this strategy has a more beneficial impact on the network topology, especially on preserving connected components after removing edges. Similarly, *dynamic recovery* outperforms *proximity to centre* with a t-value of 2.19 and outperforms *proximity and recovery time* with a t-value of 2.19, indicating that the dynamic recovery factors play an important role in maintaining network integrity after disruptions.

Efficiency

Initially, all strategies demonstrate a similar increase in efficiency during the recovery process. Subsequently, strategies *recovery time and proximity* and *dynamic recovery* exhibit a more rapid improvement compared to the other three, indicating that these strategies facilitate a more effective network recovery. Strategies *proximity to centre*, *proximity and hierarchy*, and *proximity and recovery time* then increase at a comparable rate, yet they lag behind strategies *recovery time and proximity* and *dynamic recovery*. This implies that if a swift enhancement in travel times is desired, strategies *recovery time and proximity* and *dynamic recovery* are the most advantageous options.

In terms of efficiency, *proximity and hierarchy* achieves superior results compared to the other strategies. The differences with *proximity to centre*, *proximity and recovery time*, *recovery time and proximity* and *dynamic recovery* are significant with respective t-values of 13.36 and 13.53, indicating a better utilization of network resources when proximity and hierarchy are combined. Furthermore, both *proximity to centre* and *proximity and recovery time* outperform *recovery time and proximity* and *dynamic recovery*, with t-values of 14.01 for both strategies compared to *recovery time and proximity* and 14.19 for both compared to *dynamic recovery*. This shows that strategies that combine both proximity and recovery generally lead to a more efficient use of network resources after disruptions.

Betweenness

The betweenness metric reveals a complex pattern. Strategies *proximity to centre* and *proximity and recovery time* show a slight exponential recovery, while strategy *proximity and hierarchy* experiences a sharp increase, followed by a decline and a subsequent rise. By the end of the process, strategy *proximity and hierarchy* exhibits another peak. Strategies *recovery time and proximity* and *dynamic recovery* initially recover slowly, followed by a significant increase that remains just below the final level. Strategy *dynamic recovery* displays a more stable trend than strategy *recovery time and proximity*, suggesting that it is the most suitable for achieving a balanced distribution of network traffic.

For betweenness, Table E.4 shows that, *proximity and hierarchy* is significantly better than both *proximity to centre* and *proximity and recovery time*, with t-values of 18.29. This strategy is found to provide the most efficient distribution of intermediate connections within the network, meaning that the strategy contributes to a better distribution of network nodes that are most crucial for intra-network communication. Furthermore, *proximity and hierarchy* outperforms the strategies *recovery time and proximity* and *dynamic recovery*, with respective t-values of 25.57 and 23.14, indicating the greater effectiveness of this strategy in improving betweenness compared to the others. Interestingly, both *proximity to centre* and *proximity and recovery time* in turn outperform *recovery time and proximity* and *dynamic recovery*, with t-values of 8.17 for *proximity to centre* and 6.27 for *proximity and recovery time*, respectively. This emphasizes that the combinations of proximity and recovery in the *proximity to centre* and *proximity and recovery time* strategies are more robust in terms of betweenness compared to the other strategies.

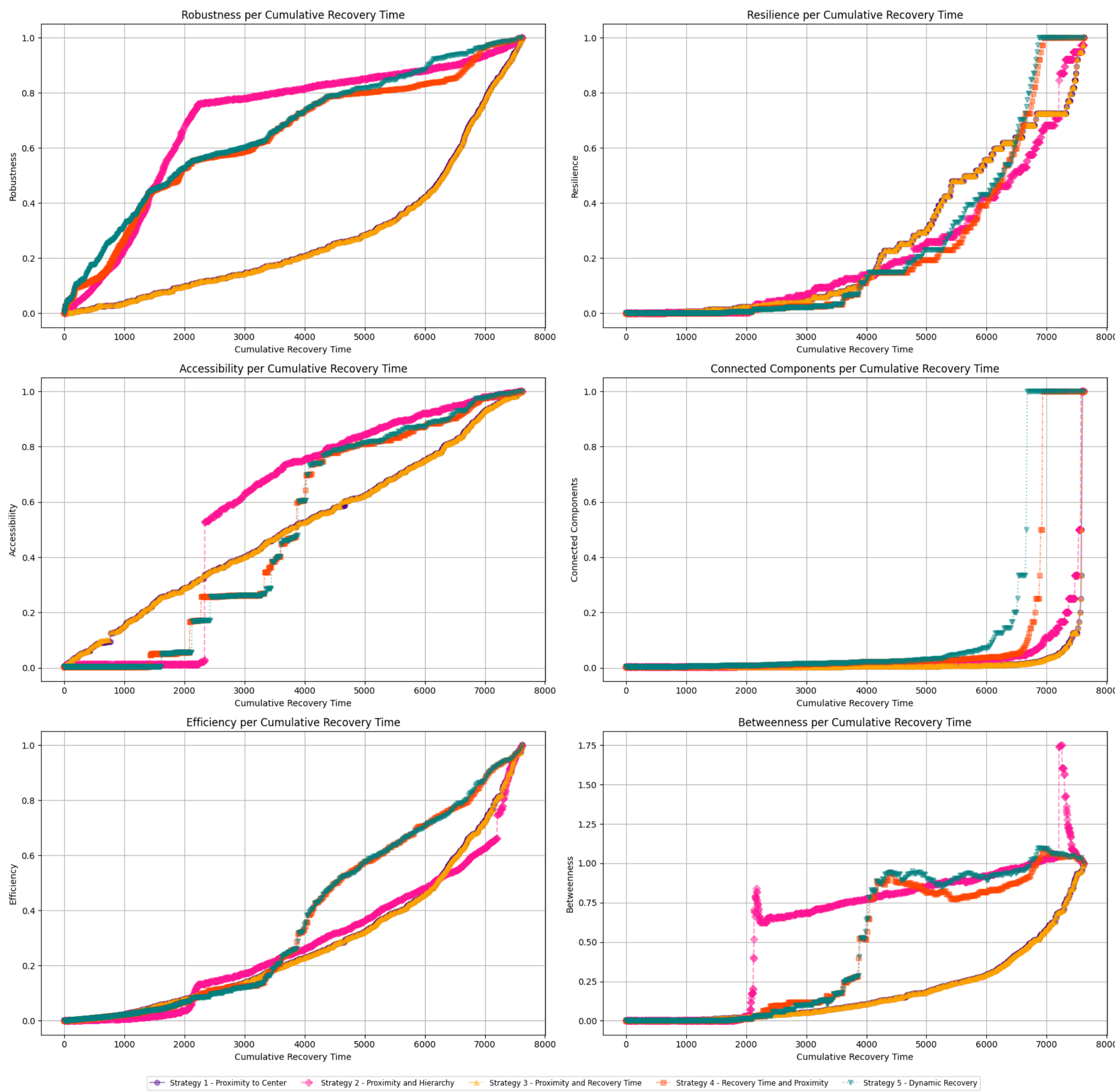

Figure D.3: Impact of 100% edge removal on Anaheim network metrics

D.4. Munich 100% edges removed

When 100% of the connections in the Munich network are removed, different recovery strategies are compared based on their impact on various network metrics. Below is an analysis by metric following from figure D.4, discussing the performance of the strategies in relation to their impact on the network.

Robustness

When 100% of the edges in the Munich network are removed and the recovery process is analysed, it is found that the strategies *recovery time and proximity* and *dynamic recovery* perform best. These strategies ensure that the network recovers relatively quickly and efficiently.

In contrast, the strategies *proximity to centre* and *proximity and recovery time* perform the least well, indicating that these methods are less effective in restoring the network structure. The strategy *proximity and hierarchy* is in between the previously mentioned groups in terms of performance. This suggests that although the network recovers partially under these strategies, the recovery process is less efficient and less robust.

The results show that there are significant differences in robustness between the different strategies.

Proximity to Center performs significantly worse than *Proximity and hierarchy*, as shown by the t-value of -19.86, which means that the difference is large and statistically significant. This suggests that adding a hierarchical structure to the strategy has a positive effect on robustness.

When comparing *Proximity to Center* to *Proximity and Recovery Time*, there is hardly any difference, as the t-value is 0.01 and the effect is not statistically significant. This suggests that adding recovery time does not have a noticeable effect on robustness in this case. In contrast, *Proximity to Center* performs significantly worse than both *Recovery Time and Proximity* (t = -4.04) and *Dynamic Recovery* (t = -4.08), suggesting that strategies that take into account recovery time or dynamic adjustments may be more robust than an approach that only focuses on proximity to the center.

Furthermore, *Proximity and hierarchy* is the best performing strategy, as it significantly outperforms all other strategies. The comparison with *Proximity and Recovery Time* yields a t-value of 19.87, while the differences with *Recovery Time and Proximity* (t = 15.53) and *Dynamic Recovery* (t = 15.51) are also significant. This confirms that the addition of a hierarchical component makes a crucial contribution to robustness.

When comparing *Proximity and Recovery Time* with *Recovery Time and Proximity*, a significant difference is again found, with a t-value of -4.05, as in the comparison with *Dynamic Recovery* (t = -4.09). This indicates that although both strategies take recovery time into account, the way in which this factor is integrated has a noticeable impact on performance. Finally, there is no significant difference between *Recovery Time and Proximity* and *Dynamic Recovery* (t = -0.03), suggesting that both strategies contribute equally to robustness.

In summary, the results show that strategies based solely on *proximity to the centre* are less robust than strategies that also take other factors such as hierarchy or recovery time into account. In particular, *proximity and hierarchy* proves to be clearly superior to the other strategies, while *Recovery Time and Proximity* and *Dynamic Recovery* differ little in their robustness.

Resilience

When analysing the resilience after removing 100% of the edges, the *recovery time and proximity* and *dynamic recovery* strategies again perform best. They are followed by the *proximity to centre* and *proximity and recovery time* strategies, which perform slightly worse but are still relatively close to the former strategies.

Interestingly, *recovery time and proximity* and *dynamic recovery* perform worse than the other strategies in the early stages of the recovery process, but as the recovery progresses, they gain in effectiveness and outperform the other methods. In contrast, the *proximity and hierarchy* strategy lags behind; it takes longer for the resilience to increase, which means that this strategy is less suitable for fast network recovery.

In terms of resilience, *proximity to centre* and *proximity and recovery time* also outperforms the other strategies. The positive t-values in the comparisons with *proximity and hierarchy* (t = 18.78 and t = 18.77), *recovery time and proximity* (t = 23.57 and t = 23.56), and *dynamic recovery* (t = 23.58 and t = 23.57) indicate that these strategies are significantly more resilient than the alternatives. This suggests that a strategy based purely on proximity can maintain a high degree of resilience without the need for recovery mechanisms. Furthermore, *proximity and hierarchy* outperforms both *recovery time and proximity* and *dynamic recovery* (t = 5.28 in both cases). Finally, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.00), indicating that both strategies have a similar impact on resilience.

Accessibility

For the *accessibility* metric, it is noticeable that the *proximity to centre* and *proximity and recovery time* strategies perform better in the early stages of the recovery process. This indicates that these strategies quickly achieve an initial improvement in accessibility.

However, over time, these strategies are overtaken by *recovery time and proximity* and *dynamic recovery*, which ultimately achieve better accessibility for the network. This suggests that these strategies are more effective in restoring access to network connections in the long run.

The *proximity and hierarchy* strategy initially remains low and only shows an increase halfway through the recovery process. Eventually, this strategy reaches a similar level as *proximity to centre* and *proximity and recovery time*, but the slower recovery rate indicates that this method is less suitable for quickly restoring accessibility.

The results in Table E.4 show that *proximity to centre* generally outperforms most other strategies in terms of *accessibility*. The t-value of 12.65 in the comparison with *proximity and hierarchy* indicates that proximity without hierarchy has a significant positive effect on network accessibility. This effect becomes even more evident in the comparisons with *recovery time and proximity* (t = 28.27) and *dynamic recovery* (t = 28.30), which show that recovery mechanisms reduce accessibility.

In addition, *proximity and hierarchy* performs significantly worse than *proximity and recovery time* (t = -12.65), but better than both *recovery time and proximity* (t = 11.60) and *dynamic recovery* (t = 11.61). This suggests that hierarchy does provide some improvement over strategies that rely heavily on recovery processes, but not enough to match the superior accessibility of a pure proximity strategy.

Interestingly, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.01, not significant), suggesting that both strategies have a similar impact on accessibility.

Connected components

In the analysis of the connected components, the strategies *recovery time and proximity* and *dynamic recovery* again perform best. They are followed by the strategies *proximity to centre*, *proximity and hierarchy* and *proximity and recovery time*, which lag slightly behind.

An important point of attention is that all strategies show a significant increase in the number of connected components only late in the recovery process. This implies that the network remains fragmented for a large part of the recovery process, which hinders its functional functioning. Only in a later phase of the recovery process are the components recombined, which indicates a gradual improvement of the network structure.

The results in Table E.4 show that there are significant differences between the strategies in terms of connected components. *Proximity to centre* performs significantly worse than both *recovery time and proximity* (t = -5.88) and *dynamic recovery* (t = -5.88), indicating that strategies that integrate recovery mechanisms are better able to keep the network connected. Furthermore, *proximity and hierarchy* does not significantly differ from *proximity and recovery time* (t = 1.40, not significant), but performs significantly worse than *recovery time and proximity* and *dynamic recovery* (both with t = -4.47). This suggests that hierarchy alone is not sufficient to maintain network connectivity and that dynamic recovery strategies play a crucial role in this. In addition, there appears to be no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.00), indicating that both strategies have a similar impact on network connectivity.

Efficiency

Also in efficiency, the strategies *recovery time and proximity* and *dynamic recovery* show the best performance. This means that the network recovers faster and more efficiently after complete edge removal under these strategies.

On the other hand, the strategies *proximity to centre* and *proximity and recovery time* perform the least well. This suggests that although these methods can provide some improvement in the short term, they are less efficient in recovering the network in the long term. The strategy *proximity and hierarchy* is again in between these two groups, indicating moderate efficiency in the recovery process.

In terms of efficiency, it turns out that strategies *proximity to centre* and *proximity and recovery time* are the most effective strategies. The t-values of 8.24 and 8.23 compared to *proximity and hierarchy* indicate that adding hierarchy leads to a significant decrease in efficiency. Furthermore, the differences between *proximity to centre* and both *recovery time and proximity* (t = 23.26) and *dynamic recovery* (t = 23.27) are highly significant, indicating that strategies that include recovery processes are much less able to ensure efficiency. Interestingly, *proximity and hierarchy* significantly outperforms *recovery time and proximity* and *dynamic recovery* both with a t-value of 4.27. This suggests that while hierarchy has a positive effect, the addition of recovery mechanisms is even more important. Finally, the comparison between *recovery* *time and proximity* and *dynamic recovery* shows no significant difference (t = 0.00), indicating that these strategies are equally effective in optimising efficiency.

Betweenness

When analysing the betweenness, it turns out that the strategies *recovery time and proximity* and *dynamic recovery* are distinguished by a rapid increase in the initial phase of the recovery process. It is striking that these strategies even outperform the final network situation, meaning that an excessive number of connections are initially restored, followed by a slight decrease as the network stabilizes.

The strategy *proximity and hierarchy* also shows a rapid increase in betweenness, but with a less stable course. After an initial peak, a decrease follows, after which the betweenness stabilizes at a final value. This indicates that this strategy has a less consistent recovery process compared to the other methods.

For the strategies *proximity to centre* and *proximity and recovery time* there is a gradually increasing betweenness, without strong fluctuations. This means that these strategies show a more even recovery, without excessive peaks or valleys.

For betweenness, *proximity and hierarchy* actually outperforms *proximity to centre*. This is evident from the negative t-value of -12.80 in the comparison between these two strategies, suggesting that hierarchy leads to a network in which crucial nodes carry less load.

Despite this finding, *proximity to centre* still significantly outperforms *recovery time and proximity* (t = 6.07) and *dynamic recovery* (t = 6.09), implying that strategies that employ recovery mechanisms create a larger spread of *betweenness*, possibly due to an increased reliance on specific recovery pathways.

In addition, *proximity and hierarchy* significantly outperforms *proximity and recovery time* (t = 12.80) and even better than *recovery time and proximity* (t = 16.88) and *dynamic recovery* (t = 16.90). This confirms that a hierarchical structure can improve the efficiency of the network by distributing the load across multiple nodes.

Finally, there is no significant difference between *recovery time and proximity* and *dynamic recovery* (t = 0.02), indicating that both strategies have similar effects on the distribution of *betweenness* within the network.

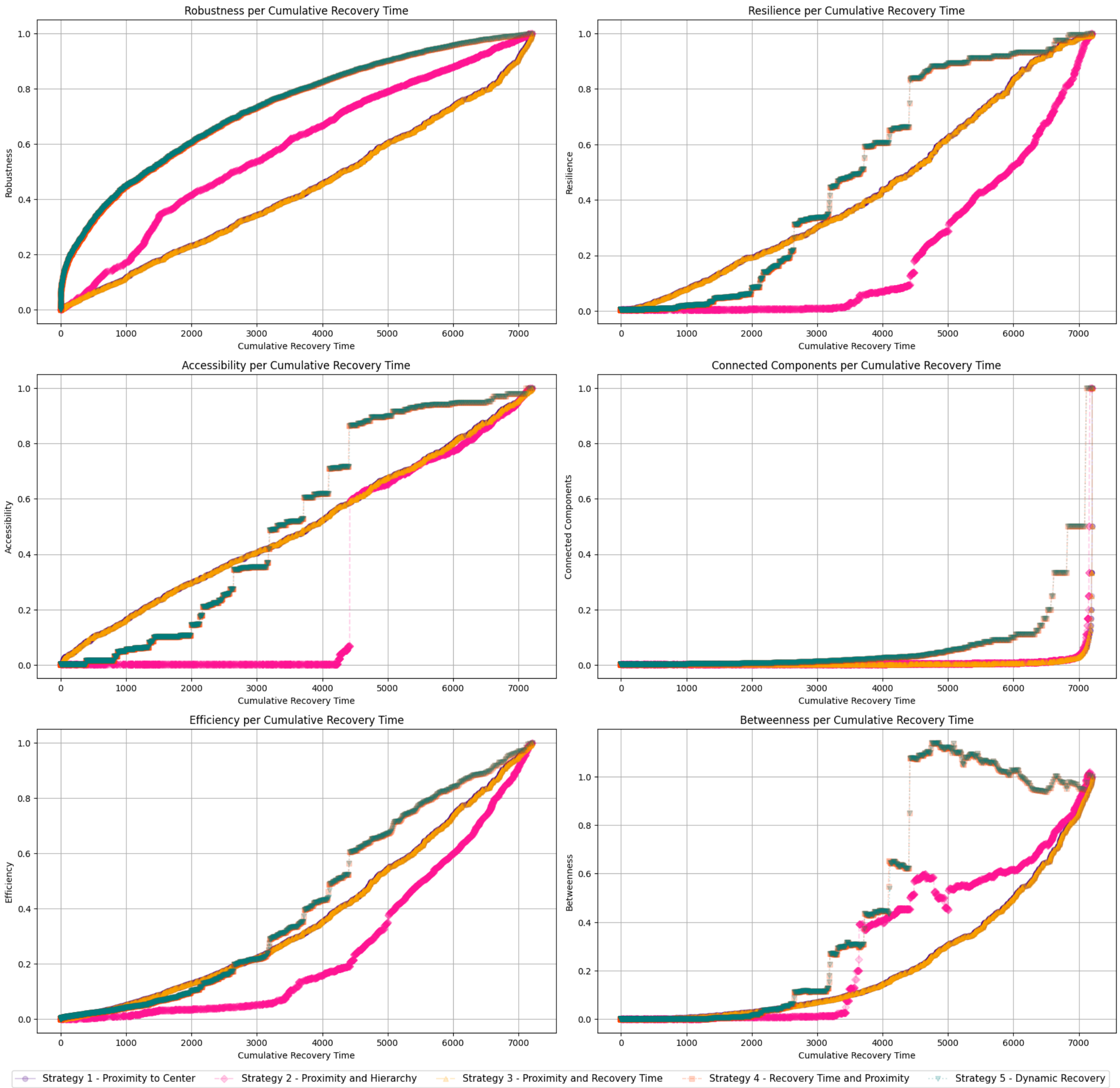

Figure D.4: Impact of 100% edge removal on Munich network metrics

E

Results statistical tests

This appendix presents the results of the statistical t-tests performed to analyse the significant differences between strategies per metric and per network. The analyses were performed for four different scenarios of network disruption: 25%, 50%, 75%, and 100% edge removal.

For each pair of strategies, the following statistical values were calculated:

- **t-statistic**: The t-value of the test, which indicates how large the difference is relative to the spread of the data.
- **Sig.?**: An indication of whether the difference is statistically significant based on a significance level of 0.05.

To facilitate the interpretation of the results, colour coding has been applied:

- **Red (×)**: Not statistically significant ($p > 0.05$).
- **Green (✓)**: Statistically significant ($p \leq 0.05$).

The tables show how the different strategies compare within the Sioux Falls, EMA, Anaheim, and Munich networks. This comparison allows for the identification of patterns and differences between strategies, contributing to a better understanding of the impact of disruptions and strategy choices on network performance.

Table E.1: Comparison of strategies by metric with a 25% removal across four networks.

		Sioux Falls		EMA		Anaheim		Munich	
Comparison	Metric	t-stat	Sig.?	t-stat	Sig.?	t-stat	Sig.?	t-stat	Sig.?
Proximity vs Proximity and hierarchy	Accessibility	-1.07	×	0.67	×	-7.86	✓	-14.34	✓
	Betweenness	-0.16	×	-8.87	✓	-18.21	✓	-35.28	✓
	Connected components	-3.22	✓	1.01	×	-12.21	✓	-11.18	✓
	Efficiency	-0.75	×	1.26	×	-2.95	✓	-5.77	✓
	Resilience	-2.13	×	0.43	×	-5.99	✓	-5.53	✓
	Robustness	0.02	×	-2.59	×	-7.09	✓	-9.79	✓
Proximity vs Proximity and recovery time	Accessibility	0.04	×	-0.02	×	0.00	×	0.00	×
	Betweenness	0.02	×	-0.12	×	0.00	×	-0.01	×
	Connected components	0.18	×	-0.07	×	0.01	×	-0.01	×
	Efficiency	0.00	×	0.02	×	0.00	×	0.01	×
	Resilience	0.01	×	0.04	×	0.00	×	0.00	×
	Robustness	0.00	×	-0.01	×	0.00	×	0.01	×
Proximity vs Recovery time and proximity	Accessibility	-0.02	×	1.63	×	-0.77	×	-5.91	✓
	Betweenness	-0.82	×	-12.78	✓	-6.88	✓	-20.09	✓
	Connected components	-4.91	✓	0.30	×	-1.43	×	-16.14	✓
	Efficiency	-0.57	×	-1.69	×	0.77	×	-0.08	×
	Resilience	-2.58	✓	1.89	×	-0.25	×	-5.54	✓
	Robustness	0.39	×	-1.61	×	2.83	✓	-1.96	✓
Proximity vs Dynamic recovery	Accessibility	-0.08	×	1.63	×	-0.84	×	-5.90	✓
	Betweenness	-0.88	×	-12.78	✓	-7.59	✓	-20.08	✓
	Connected components	-5.43	✓	0.30	×	-1.76	×	-16.14	✓
	Efficiency	-0.57	×	1.69	×	0.83	×	-0.08	×
	Resilience	-2.72	×	1.89	×	-0.41	×	-5.53	✓
	Robustness	-0.41	×	-1.61	×	2.78	✓	-1.99	✓
Proximity and hierarchy vs Proximity and recovery time	Accessibility	1.12	×	-0.69	×	7.86	✓	14.34	✓
	Betweenness	0.17	✓	8.76	✓	18.21	✓	35.29	✓
	Connected components	3.57	✓	-1.09	×	12.22	✓	11.17	✓
	Efficiency	0.75	×	-1.23	×	2.95	✓	5.77	✓
	Resilience	2.15	✓	-0.39	×	5.99	✓	5.53	✓
	Robustness	-0.02	×	2.58	✓	7.09	✓	9.79	✓
Proximity and hierarchy vs Recovery time and proximity	Accessibility	1.18	×	1.15	×	7.79	✓	6.89	✓
	Betweenness	-0.67	×	-3.41	✓	15.02	✓	8.57	✓
	Connected components	-1.93	×	-0.66	×	11.58	✓	-6.89	✓
	Efficiency	0.20	×	0.52	×	3.97	✓	5.53	✓
	Resilience	-0.09	×	1.57	×	6.13	✓	-0.67	×
	Robustness	0.37	×	1.03	×	10.25	✓	7.67	✓
Proximity and hierarchy vs Dynamic recovery	Accessibility	1.13	×	1.15	×	7.75	✓	6.90	✓
	Betweenness	-0.73	×	-3.41	✓	14.70	✓	8.57	✓
	Connected components	-2.37	✓	-0.66	×	11.18	✓	-6.90	✓
	Efficiency	0.19	×	0.51	×	4.03	✓	5.53	✓
	Resilience	-0.19	×	1.57	×	6.02	✓	-0.67	×
	Robustness	0.38	×	1.03	×	10.21	✓	7.67	✓
Proximity and recovery time vs Recovery time and proximity	Accessibility	-0.07	×	1.65	×	-0.77	×	-5.91	✓
	Betweenness	-0.84	×	-12.66	✓	-6.88	✓	-20.09	✓
	Connected components	-5.35	✓	0.37	×	-1.44	×	-16.12	✓
	Efficiency	-0.56	×	1.67	×	0.77	×	-0.08	×
	Resilience	-2.61	×	1.84	×	-0.26	×	-5.54	✓
	Robustness	0.38	×	-1.60	×	2.83	✓	-1.97	✓
Proximity and recovery time vs Dynamic recovery	Accessibility	-0.13	×	1.65	×	-0.84	×	-5.89	✓
	Betweenness	-0.90	×	-12.66	✓	-7.59	✓	-20.08	✓
	Connected components	-5.94	✓	0.37	×	-1.77	×	-16.13	✓
	Efficiency	-0.57	×	1.67	×	0.83	×	-0.08	×
	Resilience	-2.75	✓	1.84	×	-0.41	×	-5.53	✓
	Robustness	0.40	×	-1.60	×	2.78	✓	-1.99	✓
Recovery time and proximity vs Dynamic recovery	Accessibility	-0.07	×	0.00	×	-0.07	×	0.01	×
	Betweenness	-0.07	×	0.00	×	-0.79	×	0.00	×
	Connected components	-0.27	×	0.00	×	-0.38	×	0.00	×
	Efficiency	-0.01	×	0.00	×	0.06	×	0.00	×
	Resilience	-0.11	×	0.00	×	-0.16	×	0.01	×
	Robustness	0.02	×	0.00	×	-0.06	×	-0.02	×

Table E.2: Comparison of strategies by metric with a 50% removal across four networks.

		Sioux Falls		EMA		Anaheim		Munich	
Comparison	Metric	t-stat	Sig.?	t-stat	Sig.?	t-stat	Sig.?	t-stat	Sig.?
Proximity vs Proximity and hierarchy	Accessibility	-0.58	×	1.60	×	-5.80	✓	2.85	✓
	Betweenness	-3.94	✓	-7.89	✓	-19.66	✓	-16.81	✓
	Connected components	-2.02	✓	2.36	✓	-8.34	✓	-5.51	✓
	Efficiency	-1.11	×	0.87	×	-2.74	✓	1.15	×
	Resilience	-1.88	×	-0.80	×	-7.05	✓	6.05	✓
	Robustness	0.01	×	-3.75	✓	-10.02	✓	-13.97	✓
Proximity vs Proximity and recovery time	Accessibility	0.00	×	0.08	×	0.00	×	0.00	×
	Betweenness	-0.07	×	0.06	×	0.00	×	0.00	×
	Connected components	0.02	×	-0.02	×	0.01	×	0.00	×
	Efficiency	-0.01	×	0.03	×	0.00	×	0.01	×
	Resilience	-0.03	×	0.07	×	0.01	×	0.00	×
	Robustness	0.00	×	0.00	×	0.00	×	0.01	×
Proximity vs Recovery time and proximity	Accessibility	-0.99	×	3.98	✓	3.07	✓	7.80	✓
	Betweenness	-5.64	✓	-6.72	✓	-5.82	✓	-7.17	✓
	Connected components	-4.84	✓	1.34	×	-2.14	✓	-11.66	✓
	Efficiency	-0.68	×	2.06	✓	3.32	✓	8.59	✓
	Resilience	-1.73	×	2.50	✓	0.80	×	6.80	✓
	Robustness	0.60	×	-2.37	✓	3.96	✓	-2.77	✓
Proximity vs Dynamic recovery	Accessibility	1.15	×	3.98	✓	3.63	✓	7.81	✓
	Betweenness	-5.59	✓	-6.73	✓	-5.72	✓	-7.17	✓
	Connected components	-5.21	✓	1.34	×	-2.52	✓	-11.66	✓
	Efficiency	-0.66	×	2.06	✓	3.51	✓	8.59	✓
	Resilience	-1.71	×	2.50	✓	0.70	×	6.80	✓
	Robustness	0.63	×	-2.37	✓	3.89	✓	-2.80	✓
Proximity and hierarchy vs Proximity and recovery time	Accessibility	0.58	×	-1.50	×	5.81	✓	-2.85	✓
	Betweenness	3.91	✓	7.90	✓	19.66	✓	16.81	✓
	Connected components	2.04	✓	-2.39	✓	8.35	✓	5.51	✓
	Efficiency	1.09	×	-0.84	×	2.74	✓	-1.15	×
	Resilience	1.87	×	0.86	×	7.06	✓	-6.05	✓
	Robustness	-0.01	×	3.75	✓	10.02	✓	13.98	✓
Proximity and hierarchy vs Recovery time and proximity	Accessibility	1.48	×	2.56	✓	8.32	✓	4.25	✓
	Betweenness	-1.09	×	0.58	×	15.15	✓	7.25	✓
	Connected components	-1.94	×	-0.87	×	6.15	✓	-6.69	✓
	Efficiency	0.42	×	1.22	×	6.07	✓	7.19	✓
	Resilience	0.22	×	3.27	✓	7.81	✓	1.18	×
	Robustness	0.58	×	1.46	×	14.45	✓	11.00	✓
Proximity and hierarchy vs Dynamic recovery	Accessibility	1.62	×	2.56	✓	8.77	✓	4.27	✓
	Betweenness	-1.15	×	0.58	×	15.06	✓	7.24	✓
	Connected components	-2.17	✓	-0.87	×	5.63	✓	-6.70	✓
	Efficiency	0.43	×	1.22	×	6.24	✓	7.19	✓
	Resilience	0.23	×	3.27	✓	7.68	✓	1.18	×
	Robustness	0.61	×	1.46	×	14.39	✓	10.98	✓
Proximity and recovery time vs Recovery time and proximity	Accessibility	1.00	×	3.88	✓	3.07	✓	7.80	✓
	Betweenness	-5.62	✓	-6.73	✓	-7.17	✓	-19.54	✓
	Connected components	-4.85	✓	1.36	×	-2.15	✓	-11.66	✓
	Efficiency	-0.67	×	2.03	✓	3.32	✓	8.58	✓
	Resilience	-1.71	×	2.42	✓	0.79	×	6.80	✓
	Robustness	0.60	×	-2.37	✓	3.95	✓	-2.78	✓
Proximity and recovery time vs Dynamic recovery	Accessibility	1.15	×	3.88	✓	3.62	✓	7.81	✓
	Betweenness	-5.57	✓	-6.74	✓	-5.72	✓	-7.17	✓
	Connected components	-5.22	✓	1.36	×	-2.53	✓	-11.66	✓
	Efficiency	-0.65	×	2.03	✓	3.51	✓	8.58	✓
	Resilience	-1.69	×	2.42	✓	0.70	×	6.80	✓
	Robustness	0.63	×	-2.37	✓	3.88	✓	-2.81	✓
Recovery time and proximity vs Dynamic recovery	Accessibility	0.17	×	0.00	×	0.56	×	0.01	×
	Betweenness	-0.08	×	0.00	×	0.03	×	0.00	×
	Connected components	-0.25	×	0.00	×	-0.42	×	0.00	×
	Efficiency	0.02	×	0.00	×	0.21	×	0.00	×
	Resilience	0.01	×	0.00	×	-0.09	×	0.00	×
	Robustness	0.03	×	0.00	×	-0.08	×	-0.02	×

Table E.3: Comparison of strategies by metric with a 75% removal across four networks.

		Sioux Falls		EMA		Anaheim		Munich	
Comparison	Metric	t-stat	Sig.?	t-stat	Sig.?	t-stat	Sig.?	t-stat	Sig.?
Proximity vs Proximity and hierarchy	Accessibility	-0.28	×	4.75	✓	-1.36	×	9.93	✓
	Betweenness	-3.82	✓	-2.89	✓	-18.33	✓	-14.16	✓
	Connected components	2.34	✓	4.25	✓	-3.99	✓	-2.92	✓
	Efficiency	-1.31	×	0.80	×	-0.75	×	5.47	✓
	Resilience	-2.81	✓	-0.81	×	-3.53	✓	13.64	✓
	Robustness	-0.02	×	-4.58	✓	-12.25	✓	-17.19	✓
Proximity vs Proximity and recovery time	Accessibility	0.03	×	0.01	×	0.00	×	0.00	×
	Betweenness	-0.01	×	0.01	×	0.00	×	0.00	×
	Connected components	0.01	×	-0.03	×	0.00	×	-0.07	×
	Efficiency	-0.01	×	0.02	×	0.00	×	0.00	×
	Resilience	-0.01	×	0.05	×	0.00	×	0.00	×
	Robustness	-0.01	×	0.00	×	0.01	×	0.01	×
Proximity vs Recovery time and proximity	Accessibility	2.52	✓	6.76	✓	10.85	✓	17.42	✓
	Betweenness	-3.03	✓	-2.07	✓	1.42	×	-1.20	×
	Connected components	-5.03	✓	2.24	✓	-2.23	✓	-8.25	✓
	Efficiency	-0.50	×	2.39	✓	8.82	✓	16.17	✓
	Resilience	-1.28	×	3.52	✓	4.69	✓	15.19	✓
	Robustness	0.70	×	-2.82	✓	4.81	✓	-3.47	✓
Proximity vs Dynamic recovery	Accessibility	2.60	✓	6.76	✓	11.61	✓	17.44	✓
	Betweenness	-3.05	✓	-2.07	✓	1.19	×	-1.20	×
	Connected components	-5.24	✓	2.24	✓	-2.53	✓	-8.26	✓
	Efficiency	-0.49	×	2.39	✓	8.99	✓	16.17	✓
	Resilience	-1.28	×	3.52	✓	4.43	✓	15.19	✓
	Robustness	0.73	×	-2.82	✓	4.72	✓	-3.51	✓
Proximity and hierarchy vs Proximity and recovery time	Accessibility	0.31	×	-4.72	✓	1.37	×	-9.93	✓
	Betweenness	3.80	✓	2.90	✓	18.33	✓	14.16	✓
	Connected components	2.35	✓	-4.28	✓	3.99	✓	2.83	✓
	Efficiency	1.30	×	-0.78	×	0.75	×	-5.46	✓
	Resilience	-2.18	✓	0.85	×	3.53	✓	-13.64	✓
	Robustness	0.01	×	4.58	✓	12.26	✓	17.20	✓
Proximity and hierarchy vs Recovery time and proximity	Accessibility	2.64	✓	1.94	×	10.63	✓	5.47	✓
	Betweenness	0.69	×	0.67	×	19.15	✓	10.24	✓
	Connected components	-2.14	×	-1.88	×	1.50	×	-5.53	✓
	Efficiency	0.77	×	1.53	×	9.24	✓	10.24	✓
	Resilience	-0.84	×	4.08	✓	7.92	✓	2.28	✓
	Robustness	0.72	×	1.83	×	17.64	✓	13.47	✓
Proximity and hierarchy vs Dynamic recovery	Accessibility	2.72	✓	1.94	×	11.30	✓	5.49	✓
	Betweenness	0.64	×	0.67	×	18.71	✓	10.69	✓
	Connected components	-2.31	×	-1.88	×	1.19	×	-5.54	✓
	Efficiency	0.78	×	1.53	×	9.40	✓	10.24	✓
	Resilience	0.83	×	4.08	✓	7.64	✓	2.28	✓
	Robustness	0.74	×	1.83	×	17.56	✓	13.45	✓
Proximity and recovery time vs Recovery time and proximity	Accessibility	2.49	✓	6.73	✓	10.85	✓	17.42	✓
	Betweenness	-3.02	✓	-2.08	✓	-1.20	×	1.29	×
	Connected components	-5.04	✓	2.27	✓	-2.24	✓	-8.14	✓
	Efficiency	-0.50	×	2.37	✓	8.82	✓	16.16	✓
	Resilience	-1.27	×	3.46	✓	4.68	×	15.19	✓
	Robustness	0.71	×	-2.82	✓	4.80	✓	-3.48	✓
Proximity and recovery time vs Dynamic recovery	Accessibility	2.57	×	6.73	✓	11.61	✓	17.44	✓
	Betweenness	-3.04	✓	-2.08	✓	1.19	×	-1.20	×
	Connected components	-5.26	✓	2.37	✓	-2.53	✓	-8.14	✓
	Efficiency	-0.49	×	2.37	✓	8.99	✓	16.16	✓
	Resilience	-1.27	×	3.46	✓	4.43	✓	15.19	✓
	Robustness	0.74	×	-2.82	✓	4.71	✓	-3.52	✓
Recovery time and proximity vs Dynamic recovery	Accessibility	0.14	×	0.00	×	0.81	×	0.01	×
	Betweenness	0-.04	×	0.00	×	-0.19	×	0.00	×
	Connected components	-0.17	×	0.00	×	-0.29	×	0.00	×
	Efficiency	0.01	×	0.00	×	0.19	×	0.00	×
	Resilience	0.00	×	0.00	×	-0.20	×	0.00	×
	Robustness	0.03	×	0.00	×	-0.10	×	-0.03	×

Table E.4: Comparison of strategies by metric with a 100% removal across four networks.

		Sioux Falls		EMA		Anaheim		Munich	
Comparison	Metric	t-stat	Sig.?	t-stat	Sig.?	t-stat	Sig.?	t-stat	Sig.?
Proximity vs Proximity and hierarchy	Accessibility	-0.10	×	7.08	✓	-0.54	×	12.65	✓
	Betweenness	-3.83	✓	-3.08	✓	-18.29	✓	-12.80	✓
	Connected components	-2.87	✓	5.18	✓	-1.98	✓	-1.43	×
	Efficiency	-1.14	×	0.40	×	0.13	×	8.24	✓
	Resilience	-2.01	✓	-1.50	×	-2.81	✓	18.78	✓
	Robustness	-0.08	×	-5.29	✓	-14.17	✓	-19.86	✓
Proximity vs Proximity and recovery time	Accessibility	0.04	×	-0.02	×	0.00	×	-0.01	×
	Betweenness	-0.02	×	0.03	×	0.01	×	0.00	×
	Connected components	0.01	×	-0.11	×	0.00	×	-0.02	×
	Efficiency	-0.02	×	0.03	×	0.00	×	0.00	×
	Resilience	-0.02	×	0.08	×	-0.01	×	0.01	×
	Robustness	-0.03	×	0.00	×	0.00	×	0.01	×
Proximity vs Recovery time and proximity	Accessibility	4.61	✓	9.96	✓	17.81	✓	28.27	✓
	Betweenness	-1.97	×	-0.55	×	8.17	✓	6.07	✓
	Connected components	-5.65	✓	4.75	✓	-2.11	✓	-5.88	✓
	Efficiency	-0.06	×	2.84	✓	14.01	✓	23.26	✓
	Resilience	-0.65	×	5.16	✓	6.96	✓	23.57	✓
	Robustness	0.77	×	-3.31	✓	5.64	✓	-4.04	✓
Proximity vs Dynamic recovery	Accessibility	4.66	✓	9.96	✓	17.84	✓	28.30	✓
	Betweenness	-2.07	✓	-0.55	×	6.27	✓	6.09	✓
	Connected components	-5.82	✓	4.75	✓	-2.19	✓	-5.88	✓
	Efficiency	-0.07	✓	2.84	✓	14.19	✓	23.27	✓
	Resilience	-0.68	×	5.16	✓	6.39	✓	23.58	✓
	Robustness	0.80	×	-3.31	✓	5.49	✓	-4.08	✓
Proximity and hierarchy vs Proximity and recovery time	Accessibility	0.13	×	-7.09	✓	0.54	×	-12.56	✓
	Betweenness	3.80	✓	3.10	✓	18.29	✓	12.80	✓
	Connected components	2.87	✓	-5.28	✓	1.98	✓	1.40	×
	Efficiency	1.13	×	-0.37	×	-0.13	×	-8.23	✓
	Resilience	1.99	✓	1.57	×	2.80	✓	-18.77	✓
	Robustness	0.05	×	5.29	✓	14.17	✓	19.87	✓
Proximity and hierarchy vs Recovery time and proximity	Accessibility	4.34	✓	2.07	✓	41.17	✓	11.60	✓
	Betweenness	1.59	×	2.23	✓	25.57	✓	16.88	✓
	Connected components	-2.64	✓	-0.06	×	-0.31	×	-4.49	✓
	Efficiency	1.04	×	2.30	✓	13.36	✓	14.27	✓
	Resilience	1.26	×	6.14	✓	9.34	✓	5.28	✓
	Robustness	0.84	×	2.08	✓	20.50	✓	15.53	✓
Proximity and hierarchy vs Dynamic recovery	Accessibility	4.40	✓	2.07	✓	15.94	✓	11.61	✓
	Betweenness	1.46	✓	2.23	✓	23.14	✓	16.90	✓
	Connected components	-2.77	✓	-0.06	×	-0.35	×	-4.47	✓
	Efficiency	1.03	×	2.30	✓	13.53	✓	14.27	✓
	Resilience	1.21	×	6.14	✓	8.77	✓	5.28	✓
	Robustness	0.88	×	2.08	✓	20.38	✓	15.51	✓
Proximity and recovery time vs Recovery time and proximity	Accessibility	4.56	✓	9.96	✓	17.82	✓	28.28	✓
	Betweenness	-1.95	×	-0.57	×	8.17	✓	6.07	✓
	Connected components	-5.66	✓	4.84	✓	-2.11	✓	-5.85	✓
	Efficiency	-0.05	✓	2.80	✓	14.01	✓	23.26	✓
	Resilience	-0.63	×	5.08	✓	6.97	✓	23.56	✓
	Robustness	0.80	×	-3.31	✓	5.64	✓	-4.05	✓
Proximity and recovery time vs Dynamic recovery	Accessibility	4.62	✓	9.96	✓	17.85	✓	28.31	✓
	Betweenness	-2.05	✓	-0.57	×	6.27	✓	6.09	✓
	Connected components	-5.83	✓	4.84	✓	-2.19	✓	6.09	✓
	Efficiency	-0.05	×	2.80	✓	14.19	✓	23.26	✓
	Resilience	-0.67	×	5.08	✓	6.41	✓	23.57	✓
	Robustness	0.84	×	-3.31	✓	5.49	✓	-4.09	✓
Recovery time and proximity vs Dynamic recovery	Accessibility	0.16	×	0.00	×	0.22	×	0.01	×
	Betweenness	-0.11	×	0.00	×	-1.42	×	0.02	×
	Connected components	-0.10	×	0.00	×	-0.04	×	0.00	×
	Efficiency	-0.01	×	0.00	×	0.19	×	0.00	×
	Resilience	-0.04	×	0.00	×	-0.40	×	0.00	×
	Robustness	0.04	×	0.00	×	-0.17	×	-0.03	×