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Resilience in road networks

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Summary

This thesis aims to answer the question *What are the properties of a resilient road network?* The resilience of a road network indicates the magnitude and consequences of a disruption, which can be events such as a traffic accident or a flood. The literature is not in agreement about the exact definition of road network resilience, and the way to quantify it. A literature search is done to look for definitions and resilience metrics. Eleven metrics are found that quantify resilience in road networks to accidents. These eleven metrics are compared based on whether they are on a network level, and how many variables are used. Two metrics are chosen, one based on travel time, and one based on space-mean flow. Another metric, based on the outflow of the network is added.

The three chosen metrics are then compared in small networks to see if they give the same results. The small network consist of five nodes with different link configurations. The conclusion about which network is the most resilient changes with the resilience metrics. The metric based on travel time is deemed the best for this type of research. The metric based on network outflow can have distorted results due to high peaks, and the metric based on space-mean flow is better suited for a different experiment design.

To see how network parameters such as link density influence the resilience, a simulation with random networks is done. 266 networks with nine nodes in random locations, and random links between them are simulated. It is concluded that networks with a lower link density have a higher resilience. This is not only illustrated by the relation between resilience and link density, but also by several other network parameters which are related to link density such as average number of lanes and connectivity. A reason that these networks are more resilient could be that there is less spillback, the links in the high density networks are longer and have more lanes, so congestion will not spread to other links as fast.

Contents

1 Introduction

1.1 Motivation

The national road network is an essential part of most people's daily lives. It is used by cyclist and drivers to travel to work and leisure activities, it is used by trucks to transport goods, and it is used by buses to transport people. In the Netherlands there is a complex road network of 140.000 kilometers (CBS (2019)), 5458 km of that is national roads, on which the average flow is 2283 vehicles per hour (CBS (2018)). Traffic accidents happen on the road everyday, which cause injuries and deaths, but they also have an impact on the traffic flow. There are also other situations that can occur to disrupt the traffic flow, such as natural disasters or road works. The magnitude and consequences of a disruption depends on many things, such as the number of lanes and roads impacted by the disruption, the traffic flow at the time of the disruption, the resources available to resolve the situation and more.

The resilience of a road network is an indicator for the magnitude and consequences caused by a disruption. In the dictionary resilience is defined as "the ability of a substance to return to its usual shape after being bent, stretched, or pressed" (CambridgeDictionary (2023)). On a road being bent, stretched or pressed could apply to a disruption, and the resilience would then be the ability to return to the previous situation. Although there is no overall agreement in the literature about the exact definition of resilience in road networks. Both the network performance during the disruption and the network performance during the recovery can be considered when calculating the resilience. For example Bhavathrathan and Patil (2015b) only consider the disruption period, they state that the resilience of a system is indicated by the maximum agitation it can take before a state change happens, i.e. when uncongested roads become congested roads. However, Pan *et al.* (2021) consider both the disruption and the recovery phase, they define resilience as the ability of the system to cope with a disturbance, and to quickly return to a normal service level afterwards.

A resilient system, according to Pan *et al.* (2021) is not impacted too much by the disruption, and will recover quickly. For instance, when an accident happens on a motorway in a system with a high resilience, the congestion due to the accident will be little, and the congestion will be cleared up quickly. In a system with a lower resilience the same incident will cause more congestion, and will be cleared up less quickly. Since disruptions such as accidents and road works happen every day, it is important that the road network is resilient, such that people and goods can arrive at their destination on time.

To make road networks resilient, it is important to know what makes roads and road networks resilient. For that, resilience needs to be measured, and factors influencing it need to be found. The literature is not in agreement about the definition and the way to measure resilience. In a literature synthesis by Zhou and Wang (2019) some methods are listed, such as topological metrics which focus on the structure of the transport system, but not on the dynamic features. An example of this is the shortest path lengths in the network, which is based on graphical properties, and not on dynamic features like traffic flow. On the other hand there are performance-based metrics, which focus on the performance of the system during the disruption and recovery period. This performance is usually measured with dynamic features such as traffic flow or travel time.

All in all, there are many different definitions for resilience in the literature and many different ways to measure it. It is unclear which measurement method is the best, and if it matters which one is used.

1.2 Research objective

The purpose of the research proposed in this thesis is to find a clear definition of resilience in road networks and to find the best resilience indicators to quantify resilience in road networks. With these metrics the influence of the network structure on resilience will be researched. The main research question is presented in the following section, together with the sub-questions which are used to get to the answer of the main question.

1.2.1 Research questions

The main research question the proposed research aims to answer is: *What are the properties of a resilient road network?* This question will be answered by answering the following sub-questions:

1. *Which aspects of resilience should be considered in this research?*
   There are many aspects of resilience and not all of them can be taken into account. Some aspects, such as disruption types, will be discussed and it will be considered whether they should be used in this research.

2. *Which resilience indicators are used in the literature?*
   There are many different resilience indicators in the literature. Indicators that have the aspects considered in the first question will be discussed.

3. *Is there a relationship between road network parameters and resilience to accidents in networks with different network capacity?*
   The resilience of networks with different network capacity will be measured, and then the resilience of these networks will be compared with their network parameters. Network capacity refers to the number of lane kilometers in the network.

4. *Is there a relationship between road network parameters and resilience to accidents in networks with comparable network capacity?*
   This question is similar to question 4, but instead networks that have a similar network capacity will be used.

5. *What is the impact of incident start time and duration on the resilience?*
   Incidents are simulated to measure the resilience of networks, but the incident can have different aspects. With this question the impact of a different incident start time and a different incident duration will be studied.

1.3 Report structure

This thesis is split into four parts. The first part is the literature review, in which the first two research questions are answered. To answer the first research question, resilience definitions that are used in the literature are described, as well as disruption types and related terms. Next, a systematic literature search is done to answer the second research question. Chapter 4 explains how disruptions are modelled in the literature, and chapter is 5 about which factors have been found to influence the resilience. Lastly chapter 6 is about resilience in other types of networks.

The second part of this thesis contains an experiment with five small networks, which all have five nodes, but different topologies. This part is structured with an introduction section, a methods section, a results section, a discussion section and a conclusion section. The third part follows the same structure, and contains an experiment with random networks, which all have nine nodes with random locations and random links between them. The last part contains the conclusions and recommendations of the thesis.

Part I

Literature review

2 Definition of resilience

This chapter will describe some of the definitions for resilience used in the literature, and the definition of resilience that will be used in this thesis will be explained.

Resilience is defined by the Cambridge dictionary as “the ability of a substance to return to its usual shape after being bent, stretched, or pressed” (CambridgeDictionary (2023)). The word stems from the Latin verb *resilire*, which means to recoil or to jump back (Merriam-Webster (2023)).

Murray-Tuite (2006) is one of the first to define resilience in the context of transportation. The author states that the ten properties of a resilient transport system are redundancy, diversity, efficiency, autonomous components, strength, adaptability, collaboration, mobility, safety, and the ability to recover quickly. The first six terms were actually defined by Godschalk (2003) in the context of resilient cities and hazard mitigation. The definitions of all ten terms are as follows:

- Redundancy: the system has a number of functionally similar components.
- Diversity: the system has a number of functionally different components.
- Efficiency: the input-output ratio of energy in the system is positive.
- Autonomous components: the system is able to operate independent of outside control.
- Strength: the system has the power to resist outside force.
- Adaptability: the system has the flexibility to change.
- Collaboration: information and resources in the system are shared among stakeholders.
- Mobility: users of the system are able to reach their destination at an acceptable service level.
- Safety: users are not harmed by the system or exposed to hazards.
- The ability to recover quickly: an acceptable service level is restored quickly and with minimal outside assistance after a disruption.

Murray-Tuite studied the influence of system optimal and user equilibrium traffic assignments on the last four of the dimensions listed above. After application in a test network, it was found that user equilibrium results in better adaptability and safety, but system optimum yields better mobility and recovery. The author states that there is no widely accepted measurement for resilience at that time, thus the four contributing factors are studied, to aid future development of a single resilience measurement.

A distinction between static and dynamic resilience can be made. Rose (2007) distinguished between the two types of resilience in the context of economic systems. Static economic resilience refers to the efficient allocation of resources, and dynamic economic resilience refers to the restoration through repair and recovery of the capital stock. Both types of resilience relate to reducing the consequences of a disaster, but the former deals with pre-disaster strategies, while the latter deals with post-disaster strategies.

Pan *et al.* (2021) defined dynamic and static resilience in the context of transport systems: dynamic resilience represents the speed with which the system returns to a normal state after a disruption, while static resilience represents the ability of the system to maintain its function during a disruption.

This relates to the concept of the resilience triangle, which is plotted in figure 2.1. As explained by Tierney and Bruneau (2007) measures to enhance resilience aim to reduce the size of the triangle, which can be done in two ways, along the horizontal or the vertical axis in the figure. Along the vertical axis the functionality and performance of the infrastructure can be improved, which relates to the static resilience. Along the horizontal axis the time to full recovery can be improved, which relates to the dynamic resilience.

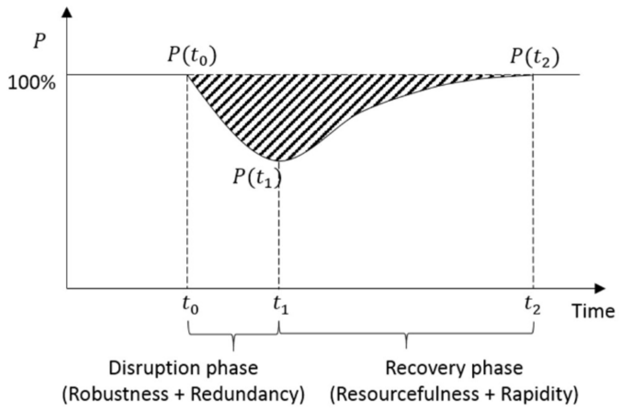


Figure 2.1 – The resilience triangle with two phases of resilience measurement. P indicates the performance of the system. (From Zhou and Wang (2019))

In the literature described above, both the time during the disruption and the recovery period (disruption and recovery phase in figure 2.1, as explained by Zhou and Wang (2019)) are considered in the definition of resilience. This is not always the case, Bhavathrathan and Patil (2015b) state that resilience is a measure of the maximum agitation a system can take before it changes state, for example going from an uncongested state to a congested state. A similar definition is used by Amini *et al.* (2018), who define resilience as the ability of the road network to retain the same level of travel production after a disruption has occurred.

Pan *et al.* (2021) state that resilience is “The abilities of the transportation system to resist and adapt to external disturbance and then quickly return to a normal service level to meet the original travel demand after being disturbed by internal or external factors.”. A comparable definition is used in a chapter about resilience in the Encyclopedia of Transportation by Jenelius and Mattsson (2021), it is defined as “a transport system’s ability to prepare for and to withstand, absorb and adapt to shocks, and to recover from the consequences in a timely and efficient manner.”.

2.1 Disruption types

The resilience of a system is a measure to see how it copes with disruptions, but different types of disruptions exist. There are many ways to classify disruptions, Ge *et al.* (2022) list some examples. Disturbances can be natural or man-made, planned or unplanned, they can have high or low impact, high or low probability and they can be recurrent or non-recurrent. Sullivan *et al.* (2009) state that there are long-term and short-term disruptions. A bridge collapse or a flooding falls into the first category and a lane closure or a road obstruction falls into the second category. The difference lies in the ability to restore the functionality from before the disruption. For short-term disruptions, the same functionality as the base case is never far away, while long-term disruptions may lead to a permanent change and an alternative equilibrium needs to be sought. A graphic representation of the disruption types is in figure 2.2, with some examples at the bottom.

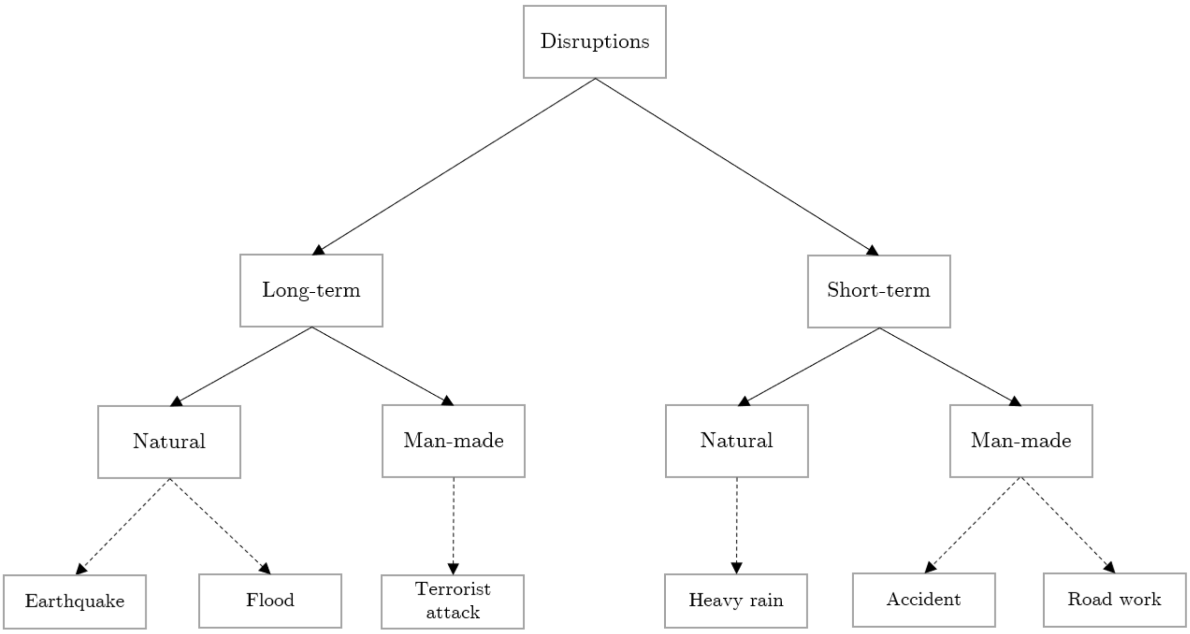


Figure 2.2 – A graphic representation of the disruption types in a road network. The first distinction is made between long and short-term disruptions (as done by Sullivan et al. (2009)), then the distinction is made between natural and man-made disruptions (as done by Ge et al. (2022)). Some examples are listed at the bottom.

2.2 Related terms

In the literature about resilience some other terms are also used, some of them have definitions similar to resilience, in this section some of them will be explained. Similar to the definition of resilience, the literature is not unanimous about the exact definition of these terms. The terms are explained in this section to aid in the understanding of resilience.

Bruneau *et al.* (2003) defined the “4 R” framework for resilience, which consists of robustness, redundancy, resourcefulness and rapidity. The terms are given the following definitions:

- Robustness: the ability of the system to withstand stress without losing function.
- Redundancy: the availability of alternative resources (similar to the definition by Godschalk (2003) in the previous section).
- Resourcefulness: the ability to identify problems and priorities, and the ability to mobilize and use resources.
- Rapidity: the ability to use resources to contain losses and avoid future disruptions.

The writers differentiate between the “ends” (robustness and redundancy) and the “means” (resourcefulness and rapidity). The “means” are the ways in which the resilience can be improved, and the “ends” are the outcomes after applying resilience enhancing measures.

Zhou and Wang (2019) explain robustness and redundancy as the performance loss during the disruption phase, while resourcefulness and rapidity show how well the system is able to restore its functionality during the recovery phase. A graphic representation of the disruption and recovery phase can be seen in figure 2.1. The static resilience is thus measured during the disruption phase, and the dynamic resilience is measured during the recovery phase.

Zhou and Wang (2019) defined the difference between resilience and robustness: a robust system can withstand the impact of a disruption while the original state is maintained, resilience measures how well the system can get back into balance when the disruption is too big and an imbalanced situation occurs.

Another term relating to resilience and starting with an R is reliability. It is used to describe the stability, certainty and predictability of travel conditions in the transport network (Mattsson and Jenelius (2015)).

Vulnerability is another term which is prevalent in the literature about resilience. The definition by Berdica (2002) is commonly accepted: “Vulnerability in the road transportation system is a susceptibility to incidents that can result in considerable reductions in road network serviceability.”

Criticality is used to rank links on their importance, it is described by Kim and Yeo (2017) as the lines or hub nodes which will cause the largest trouble for the network if they are shut down. The authors also introduce the concept of friability: “The friability of an edge or node is defined as the reduction of network resilience resulting from its removal from the network.”

2.3 Conclusion

There are different definitions for resilience in the literature, and there are also many different types of disruptions. The rest of this thesis will focus on one disruption type, and will also be using the same definition of resilience throughout. Short-term instead of long-term disruptions will be considered, both the natural and man-made type. This is chosen because these types are more frequent and more relevant for practical application in the Netherlands.

The definition of resilience that will be used in this thesis should include both the disruption and the recovery phase. This is because for short-term disruptions both these phases are important. Thus the definition by Pan *et al.* will be used. The definitions of resilience and related terms can be found in table 2.1.

Term	**Definition**
Resilience	The ability of the transportation system to resist and adapt to external disturbance and then quickly return to a normal service level to meet the original travel demand after being disturbed by internal or external factors. (Pan *et al.* (2021))
Robustness	The ability of the system to withstand stress without losing function. (Bruneau *et al.* (2003))
Redundancy	The availability of alternative resources. (Bruneau *et al.* (2003))
Resourcefulness	The ability to identify problems and priorities, and the ability to mobilize and use resources. (Bruneau *et al.* (2003))
Rapidity	The ability to use resources to contain losses and avoid future disruptions. (Bruneau *et al.* (2003))
Vulnerability	A susceptibility to incidents that can result in considerable reductions in road network serviceability. (Berdica (2002))
Reliability	Describes the stability, certainty and predictability of travel conditions in the transport network. (Mattsson and Jenelius (2015))
Criticality	The lines or hub nodes which will cause the largest trouble for the network if they are shut down. (Kim and Yeo (2017))
Friability	The friability of an edge or node is defined as the reduction of network resilience resulting from its removal from the network. (Kim and Yeo (2017))

Table 2.1 – Definitions of resilience and related terms.

3 Quantifying resilience in road networks

The next step is to find ways to quantify resilience. To do this a systematic literature search was carried out to find papers with resilience metrics for short-term disruptions in road networks.

The Scopus (Scopus (2023)) database was used, with a search term to include all papers about resilience in road networks or road traffic, and to exclude all the papers which are about big disasters, such attacks, floods and earthquakes. The exact search term was: *TITLE (resilien* AND ("road network*" OR "road traffic")) KEY (resilien* AND NOT attack* AND NOT disaster AND NOT flood* AND NOT earthquake* AND NOT seism*).* The search returned 27 papers, 13 of which were excluded after reading the abstract because of their topics. For example there were some papers about transportation of hazardous materials, and still some papers with a focus on disasters. After further reading another three papers were excluded, because they presented no metrics. In the end the 11 papers in table 3.1 were left. The table list some properties of the metrics:

- Whether they are user focused, road focused or both. User focused metrics can use travel time for example, while road focused methods can have traffic flow in their metrics. The first focuses on the performance from the perspective of the user, the other has a focus on road level performance. Some metrics use a combination of user and road focused methods.

- The range of the metric. Not all metrics have the same range, so it is important to take this into account when comparing them.

- What value of the metric indicates the most resilient system. In addition to not all metrics having the same range, the value of the metric which indicates the highest resilience is not always the same.

- The method they use to evaluate their metric. Some papers use road data for evaluation, and others use simulation. For some papers in the table the type of simulation is specified, for the ones where it is not it was not clear from the paper which method they used. Operations Research (OR) simulation uses the BPR (Bureau of Public Roads) function, a relation between the travel time and the flow on a link (Maerivoet and De Moor (2005)). Traffic flow simulation is based on the fundamental diagram, a relation between the flow and density on a link.

- The region in which they evaluate their metric. All but one paper evaluates their metric with a model or data from a specific region.

The following sections are named after the three types of focuses, and will describe the papers that have this focus and their differences and similarities.

Author(s)	Year	Focus	Range	Most resilient	Method	Test region
Bhavathrathan and Patil	2015b	User	$[0, 1)$	Closest to 1	OR simulation	Sioux Falls, US
Bhavathrathan and Patil	2015a	User	$[0, 1)$	Closest to 1	OR simulation	Sioux Falls, US
Patil and Bhavathrathan	2016	User	$[0, 1)$	Closest to 1	OR simulation	Fake networks
Calvert and Snelder	2018	Road	$[-\infty, \infty]$	≤ 1	Data	A13+A20, Netherlands
Amini *et al.*	2018	Road	$[-\infty, \infty]$?	Highest	Traffic flow simulation	Sioux Falls, US
Nogal and Honfi	2019	Road	$[0, 100\%]$	100%	OR simulation	Luxembourg-Metz
Sohouenou and Neves	2021	User	$[0, 100\%]$	100%	OR simulation	Sioux Falls, US
Serdar and Al-Ghamdi	2021	Road & user	$[0, 1]$	1	Simulation	Doha, Qatar
Mehrabani *et al.*	2022	Road & user	$[1, \infty]$	1	Simulation	Sioux Falls, US
Flores-González *et al.*	2022	Road & user	$[-\infty, 1]$	1	Simulation	Callao, Peru
Yu *et al.*	2022	Road	$[0, 1]$	1	Data	Olympic Park, China

Table 3.1 – Papers from systematic search

3.1 User focused methods

This section will list the user focused papers found in the systematic literature search. The first three papers in table 3.1 (Bhavathrathan and Patil (2015b), Bhavathrathan and Patil (2015a) and Patil and Bhavathrathan (2016)) are all by the same writers.

Bhavathrathan and Patil (2015b) define resilience as “a measure of maximum agitation a system can take in before getting displaced from one state to another”. This fits more with the definition of robustness than the definition of resilience, as described in section 2.2.

The writers propose the following metric for the resilience ρ:

$$\rho = 1 - \frac{\mathrm{ESTT}_0}{\mathrm{ESTT}_{\mathrm{Cr}}} \tag{3.1}$$

ESTT stands for the expected system travel time, ESTT_0 is the minimum possible ESTT in an undisrupted state and $\mathrm{ESTT}_{\mathrm{Cr}}$ is the critical state which is the maximum ESTT the system can have before changing from a demand-meeting state to a demand-not-meeting state, which is the definition of resilience the writers use. The value of ρ is on the $[0, 1)$ interval. $\rho = 0$ when the system can take no disruptions before changing state, as the amount of disruptions a system can take $\mathrm{ESTT}_{\mathrm{Cr}}$ increases, and so does ρ. As the network is able to take more disruptions, ESTT_{Cr} will increase, and so will the resilience. The value can never be 1 on a network with flow, because the ESTT will be a nonzero positive value.

Bhavathrathan and Patil state that each road has different capacity levels that can occur, and will recur, each with a different probability. ESTT_{Cr} is obtained by solving a minmax optimization problem, subject to some constraints:

$$\text{ESTT}_{\text{Cr}} = \min_{x_{ij}} \max_{p_{ij}^k} \sum_{ij} \sum_{k} x_{ij} \cdot t_{ij}^k(x_{ij}, c_{ij}^k) \cdot p_{ij}^k \tag{3.2}$$

The maximization is done by varying the probabilities of the capacity levels (p_{ij}^k), and the minimization is done by varying over the link flows (x_{ij}). The summation is done over the links ij and the disrupted capacity levels k. t_{ij}^k is the travel time function and c_{ij}^k is the capacity level.

The other paper, Bhavathrathan and Patil (2015a) uses a similar metric for the resilience, but the minmax optimization to find the critical state is slightly different. In the paper from 2016 Patil and Bhavathrathan use the metric from Bhavathrathan and Patil (2015a) to study the effect of demand variation on resilience.

Sohouenou and Neves (2021) consider the entire recovery period in their resilience metric. First, they define a road network performance indicator (NP) based on the difference between the disrupted and undisrupted travel times:

$$\text{NP} = \sum_{w} k_w \left(1 + \frac{TT_d^w - TT_0^w}{TT_0^w}\right)^{-1} \tag{3.3}$$

$$= \sum_{w} k_w \left(\frac{TT_0^w}{TT_d^w}\right) \tag{3.4}$$

In these equations w indicates an OD pair, k_w is a weighting factor (the ratio between the demand for w and the total network demand), TT_0^w are the travel times along w in an undisrupted situation and TT_d^w are the travel times along w during a disruption. Equation 3.3 is how it is written by Sohouenou and Neves, but it can be simplified into the fraction in equation 3.4. The authors define a network resilience indicator (RE) as an integral of the network performance:

$$\text{RE} = \frac{\int_0^{\tau_H} \text{NP}(\tau) d\tau}{\tau_H} \tag{3.5}$$

The network performance indicator is integrated over the time elapsed since the start of the recovery, τ, for the duration of the time horizon, from 0 to τ_H. Figure 3.1 shows a resilience triangle, which illustrates the concepts defined by the authors. The resilience index is the part under the curve during the recovery phase. The closer RE is to 100%, the more resilient the network is.

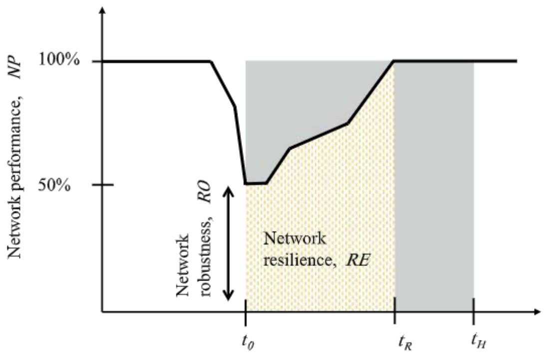


Figure 3.1 – Figure to illustrate the network performance (NP) and resilience (RE) as described by Sohouenou and Neves. (From Sohouenou and Neves (2021))

3.2 Road focused methods

The papers discussed in this section all use road focused methods, such as flow, in their resilience metrics.

Calvert and Snelder (2018) present the link performance indicator for resilience (LPIR), to evaluate the resilience of a road section with respect to the rest of the road network. They consider resilience as "the ability of a road section to resist and to recover from disturbances in traffic flow", and thus the LPIR is also split into a resistance and a recovery part:

$$\text{Resistance} = \frac{\left[\frac{q+\psi^q}{v}\right]}{\left[\frac{q_{cap}(g,h)\cdot f+\psi^{cap}}{v_{crit}}\right]} \tag{3.6}$$

$$\text{Recovery} = \frac{\left[\frac{q+\Delta q}{v_{eq}(q)}\right]}{\left[\frac{q_{cap}(g,h)\cdot f-q_{cd}}{v_{crit}}\right]} \tag{3.7}$$

The equations are valid for a set time interval T, and the time dependencies are left out of the equations for readability. The variables in the equation have the following meanings:

- q: flow
- ψ^q: volatility of flow, defined as $\psi^q = \frac{1}{2}(q_{max} - q_{min})$
- q_{max}: maximum flow in a predefined time period, identical to T
- q_{min}: minimum flow in a predefined time period, identical to T
- v: speed
- q_{cap}: road capacity
- g: road characteristics
- h: traffic characteristics

- f: temporal capacity reductions (incidents)
- ψ^{cap}: volatility of capacity, defined as $\psi^{cap} = \frac{1}{2}\left(q_{cap,max} - q_{cap,min}\right)$
- v_{crit}: critical speed
- Δq: flow volatility, defined as $\Delta q = q_{in} - q_{out}$
- q_{in}: inflow
- q_{out}: outflow
- $v_{eq}(q)$: speed, derived from the fundamental diagram
- q_{cd}: capacity drop

The resistance is before the critical density is reached, so when the network is not in a state of congestion. The recovery part is after the critical density has been reached, so when the system is in a state of congestion. The LPIR is then the average over all time intervals in the considered time period, of either the resistance or the recovery, depending on the density.

$$\mathrm{LPIR} = \sum_{t=0}^{T} \begin{cases} \dfrac{\left[\frac{q+\psi^{q}}{v}\right]}{\left[\frac{q_{cap}(g,h)\cdot f+\psi^{cap}}{v_{crit}}\right]}/T & k \leq k_{crit} \\ \dfrac{\left[\frac{q+\Delta q}{v_{eq}(q)}\right]}{\left[\frac{q_{cap}(g,h)\cdot f-q_{cd}}{v_{crit}}\right]}/T & k > k_{crit} \end{cases} \tag{3.8}$$

The authors state that a value of LPIR ≤ 1 indicates a resilient and robust road section, because it is able to resist a large drop in service level. They also say that value of LPIR > 1 does not always indicate a non-resilient network, because in this case the road section may have recovered quickly. It seems from this that the authors consider resilience a binary variable; that a road section is either resilient or not, which is not completely in accordance with the resilience definition used in this thesis.

The indicator in equation 3.8 is deterministic, the authors also present a stochastic version of the LPIR. This indicator is very similar to equation 3.8, but the flow is replaced by the random variable $\boldsymbol{q}$, and the volatility variables have been removed because they have become obsolete.

Nogal and Honfi (2019) present a stochastic approach to measure the resilience. The approach is similar to Calvert and Snelder, because it is also split into two parts, the resilience of perturbation and the resilience of recovery. The resilience index provided by the authors is the average of both types of resilience:

$$\chi_{\kappa} = \frac{1}{2}\left(\chi_{\kappa}^{p} + \chi_{\kappa}^{r}\right) \tag{3.9}$$

Where χ_{κ}^{p} is the resilience of perturbation, which calculates how far the system is from complete exhaustion, when it can no longer provide the services it needs to provide. χ_{κ}^{r} is the resilience of recovery, which considers the time needed to go back to a new equilibrium stage. The resilience depends on the disruption κ.

The resilience of recovery depends on the ratio between the time to recover an equilibrium and the largest time acceptable to recover from a perturbation:

$$\chi_{\kappa}^{r} = \max\left\{\left(1 - \frac{t_{rec}}{T_{th}}\right) \cdot 100; 0\right\} \tag{3.10}$$

Where t_{rec} is the time required to get to another equilibrium state, and T_{th} is a temporal threshold for the largest acceptable time required to recover an equilibrium.

The resilience of perturbation index is defined as the area of the exhaustion curve, during the time the disruption is occurring (from t_0 to t_1).

$$\chi_{\kappa}^{p} = \frac{\int_{t_0}^{t_1} (1 - \psi_{\kappa}(t))dt}{t_1 - t_0} \cdot 100 \tag{3.11}$$

$\psi_{\kappa}(t)$ is the exhaustion level of the traffic network, given the perturbation κ. It is a weighted sum of the stress and cost level, and it ranges between 0 and 1.

$$\psi_{\kappa}(t) = (1 - w)\sigma_{\kappa}(t) + w\ \tau_{\kappa}(t) \tag{3.12}$$

w is a weighting factor, between 0 and 1. $\sigma_{\kappa}(t)$ and $\tau_{\kappa}(t)$ are the stress level and cost level respectively.

$$\sigma_{\kappa}(t) = \max_{pq \in D}\left(\frac{1}{\alpha}\frac{\sum_{r \in R_{pq}} |\rho_r(t) - 1|}{n_{pq}}\right) \tag{3.13}$$

$$\tau_{\kappa}(t) = \frac{C_T(t) - C_0}{C_{th} - C_0} \tag{3.14}$$

In the stress level equation pq are OD pairs in D, the subset of OD pairs of nodes, α is the system impedance, R_{pq} is the set of routes with OD pair pq, $\rho_r(t)$ is the net flow variation among routes within the same OD pair in two consecutive time intervals and n_{pq} is the number of routes with OD pair pq. The stress level ranges between 0 and 1. In the equation for the cost level $C_T(t)$ is the actual cost level, calculated as the sum of travel times along all links in each time interval. C_0 is the initial total cost ($C_0 = C_T(t = 0)$), C_{th} is a cost threshold for the largest acceptable cost in the traffic network during a perturbation. The cost level is non-negative.

The resilience index, the resilience of recovery and the resilience of perturbation are all between 0 and 100 (%). The higher the resilience index, the more resilient the system is. The resilience of recovery is 0%, when the time to recover equilibrium is 0, and when the time to recover equilibrium is equal to or larger than the temporal threshold, the resilience of recovery is 100%. The resilience of perturbation is 0% when the exhaustion level is 1, which is when the system is no longer able to provide the services it needs to, the resilience of perturbation is 100% when the exhaustion level is 0.

Yu *et al.* (2022) use the same definition for resilience as Calvert and Snelder (2018), but instead of time steps they consider time a continuous function in their metric for the resilience of a road section. The writers represent the resilience with an indicator for the remaining resilience (RR), the resilience remaining after being affected by the events, which corresponds to the area under the resilience triangle. The remaining resilience of road section i is as follows:

$$\mathrm{RR}_i = \frac{\int_{t_0}^{t} \frac{v_{it}}{v_{ff,i}} dt}{t - t_0} \tag{3.15}$$

The integral goes over time t from the start time of the event t_0 to the current time t. v_{it} indicates the average vehicle speed in road section i at time t, and $v_{ff,i}$ is the free flow speed in road section i. The remaining resilience is 1 when there is no disruption, the closer RR_i is to 0, the less resilient the road section is.

Amini *et al.* (2018) use the difference in performance between normal conditions and disrupted conditions. They define the resilience of a road network as "its ability to retain the same level of travel production after occurrence of a disruption". The performance indicator (PI) they use is based on the flow[1]:

$$\mathrm{PI} = \frac{q^w \times L}{\mathcal{L}} \tag{3.16}$$

q^w is the weighted space-mean flow, L is the total network length and $\mathcal{L}$ is the average trip length in the road network. The resilience is then represented by the vehicles that could not complete their trip in a certain time, which is written in the resilience index (RI) as:

$$\mathrm{RI} = \mathrm{PI}_n - \mathrm{PI}_a \tag{3.17}$$

The subscript n indicates normal conditions, and the subscript a represents anomaly conditions, when an incident has occurred. The RI can take any value, a negative sign indicates a loss of performance, and the higher the RI, the better the resilience.

3.3 Road and user focused methods

This section presents some papers that have resilience metrics that can be classified as both road focused and user focused.

Flores-González *et al.* (2022) calculate resilience in port network with a resilience metric based on the total network cost, which is based on both the flow and the travel time:

$$C = \sum_{a \in A} x_a t_a \tag{3.18}$$

Where a is a link, A is the influence area, x_a is the flow in link a and t_a is the travel time in link a. The resilience metric is then based on the ratio between the total network cost in regular conditions and the network costs when a link is removed:

$$R(a) = 1 + \frac{C - C_a}{C} \tag{3.19}$$

[1]In the paper (Amini *et al.* (2018)) the performance indicator is written as $\mathrm{PI} = \frac{q^w}{L \times \mathcal{L}}$, this was revealed to be a mistake after emailing the authors.

C_a is the cost of the network without link a. Assuming that the total network cost will not get lower upon removing a link, $R \leq 1$. When removing the link has no impact on the total cost ($C_a = C$), the resilience is 1. In all other cases, the resilience will be below 1, as the network cost after removing a link gets higher, the resilience gets lower. If the network cost after removal is twice as high as the network cost in regular conditions, the resilience is 0. An even higher C_a will result in a negative resilience.

Serdar and Al-Ghamdi (2021) evaluated the road resilience during mega sport events, such as the football world cup in Qatar. They calculate the resilience of the road network based on a weighted sum of the resilience of the network to three different disruption types, natural hazards, intentional attacks and accidents. Resilience to accidents is within the scope of this research, so only that indicator will be discussed here. The road network is represented as a complex network, consisting of edges and nodes which represent roads and intersections respectively. The writers present a resilience index based on the betweenness centrality of nodes:

$$C_B(i) = \sum_{s \neq t \neq i \in N} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{3.20}$$

Where $C_B(i)$ is the betweenness centrality of node i, σ_{st} is the number of shortest paths from node s to node t, and $\sigma_{st}(i)$ is the number of these shortest paths through node i.

The mega sport event road resilience index (MSERRI) for accidents is then:

$$MSERRI_A = \alpha_G \cdot \frac{\sum_{i \in N} C_{BA}}{\sum_{i \in N} C_{B0}} + \alpha_L \cdot \frac{T_0}{T_A} \tag{3.21}$$

T_0 is the average trip time in normal conditions, and T_A is the average trip time during the accident scenario. C_{BA} is the betweenness centrality during the accident scenario, and C_{B0} is the betweenness centrality in the baseline case. It is not entirely clear from the paper what the sum before C_{BA} and C_{B0} is calculated over, but $\sum C_{B0}$ is described in the paper as the betweenness centrality of all nodes, so the sum is assumed to be over all nodes i.

Mehrabani *et al.* (2022) studied how the amount of polluted emissions will change after a disruption occurs. The authors define four resilience metrics, two are traffic related (based on travel time and mean speed) and two are environmental (based on emitted NO_X and CO_2). The travel time resiliency is:

$$\mathrm{R_T} = \frac{\text{Travel time (in abnormal conditions)}}{\text{Travel time (in normal conditions)}} \tag{3.22}$$

The travel time is the travel time of the entire network. Under normal conditions $\mathrm{R_T} = 1$, but a disruptive event may make the travel times longer, thus $\mathrm{R_T}$ will increase. The closer $\mathrm{R_T}$ is to one, the more resilient the network is. Assuming travel time in abnormal conditions is never lower than in normal conditions, $\mathrm{R_T} \geq 1$.

The writers also present a resilience index based on the mean speed:

$$\mathrm{R_S} = \frac{\text{Mean speed (in normal conditions)}}{\text{Mean speed (in abnormal conditions)}} \tag{3.23}$$

The mean speed resiliency has the same range as the travel time resiliency. Assuming that the mean speed only decreases in abnormal conditions, $R_S \geq 1$, and the closer R_S is to 1, the more resilient the network is. The resilience indices based on the emissions are omitted from this thesis, because they are not relevant.

Even though the writers include the recovery in their definition of resilience, this metric only considers one point in time, in the simulations this is a time when the disruptions are still active.

3.4 Conclusion

Some metrics from to papers described in this section will be used in the rest of the thesis. The metrics will firstly be evaluated on two criteria:

1. whether they are on a network level. The metrics will be used to evaluate resilience in road networks.
2. the amount of variables used (the index itself and subscripts were not counted). This will be used as a measure for how easy it will be to implement the variable.

The evaluation can be found in table 3.2.

With the criteria to only consider metrics on a road level, and papers that use five variables or less, four papers are left. One road focused metric, Amini *et al.* (2018), one user focused metric, Sohouenou and Neves (2021), and two road and user focused metrics, Mehrabani *et al.* (2022) and Flores-González *et al.* (2022). It would be interesting to compare the resilience result of two different metrics, to see how the resilience results compare. A user and a road focused metric differ the most, and therefore it would be best to do the comparison of resilience metric with the Sohouenou and Neves (2021) metric and the Amini *et al.* (2018) metric.

Author(s)	Year	Network level	Number of variables
Bhavathrathan and Patil	2015b	Yes	9
Bhavathrathan and Patil	2015a	Yes	9
Patil and Bhavathrathan	2016	Yes	9
Calvert and Snelder	2018	No	19
Amini *et al.*	2018	Yes	3
Nogal and Honfi	2019	Yes	18
Sohouenou and Neves	2021	Yes	5
Serdar and Al-Ghamdi	2021	Yes	9
Mehrabani *et al.*	2022	Yes	2
Flores-González *et al.*	2022	Yes	4
Yu *et al.*	2022	No	4

Table 3.2 – Papers from systematic search with criteria

4 Modelling disruptions in road networks

Five of the papers discussed in the previous chapters use the Sioux Falls network, the other papers use different regions to model their resilience indices. See table 3.1 for the region modelled in each paper. Although some models use the same region for modelling, they all have different ways to model disruptions. There are a few papers that model a network and then close some links to see how this affects the resilience. Flores-González *et al.* (2022) consider the closing of different links in the port road network in Callao, Peru, and study how the resilience is affected.

Sohouenou and Neves (2021) distinguish between three damage types (localised, random and targeted) and four damage extensions (1, 2, 3 and 4 affected links). When links are affected by a disruption they are considered closed. Localised damage considers the failure of links adjacent to each other, random damage considers the failure of randomly selected links and targeted damage considers the failure of links with a maximum impact on the performance of the network.

Amini *et al.* (2018) use a simulation of the Sioux Falls network to get the resilience. They use three scenarios, the first is the base scenario where no incidents occurs. Then there are two scenarios with an incident, in both a central link is closed (the same in each scenario) for 25 minutes. In one of the incident scenarios no vehicle is informed about the closure of the link, route choice is the same as the base scenario and vehicles which have a route including the closed link will remain in a standstill. In the other incident scenario 15% of the vehicles have smart navigation devices which recommend an alternative route.

In the paper by Serdar and Al-Ghamdi (2021) the accidents are modelled as a removal of nodes and links in a 500 meter radius in 10 random points.

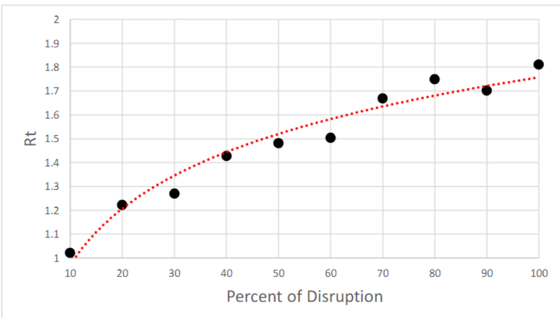


Figure 4.1 – Relation between travel time resiliency (R_T or Rt in the figure and the percentage of disrupted links in the Sioux Falls network. (From Mehrabani et al. (2022))

Mehrabani *et al.* (2022) use ten different scenarios to study the resilience, the scenarios have 50% speed reduction on 10%/20%/.../100% of the links. The links which have the speed reduction are chosen randomly. The researchers found that as the number of affected links increases, so does the travel time and the travel time resiliency. As can be seen in figure 4.1, the increase is non-linear, the rate of change in scenarios with 10% to 70% disruptions is higher than the rate of change with 70% to 100% disruptions.

Nogal and Honfi (2019) use the example of asphalting to test their resilience index. Half of the lanes are closed on some of the roads in the Luxembourg-Metz network, for 20 days. Additionally speed is reduced from 130 km/h to 80 km/h.

In the model by Bhavathrathan and Patil (2015b) it is not needed to model disruptions, but the probability levels for all capacity levels in the links are needed to find the critical expected system travel time. The writers did this for 0%, 50% and 100% capacity on all links. Calvert and Snelder (2018) and Yu *et al.* (2022) do not use scenario's to measure the resilience, instead they use traffic data. Calvert and Snelder use traffic loop data from two major motorways (A13 and A20) near Rotterdam, and Yu *et al.* use traffic speed data from the Olympic Park in Chaoyang, Beijing.

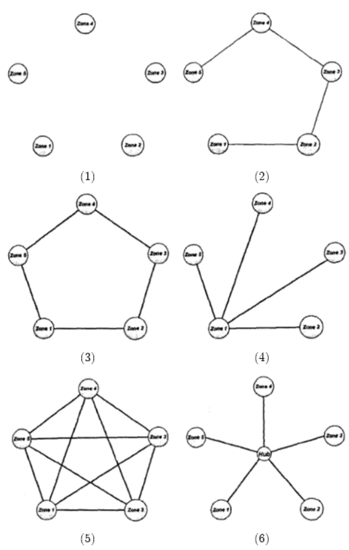
4.1 Conclusion

Most papers described in this chapter model scenarios in a network, with the exception of three data-based resilience metrics. The number and type of scenario differs across the papers, but most papers model different incidents with different impact, and then compare the resilience of the scenarios. Most papers model resilience in only one network, many of them use the Sioux Falls network. None of the papers compare the resilience of different networks.

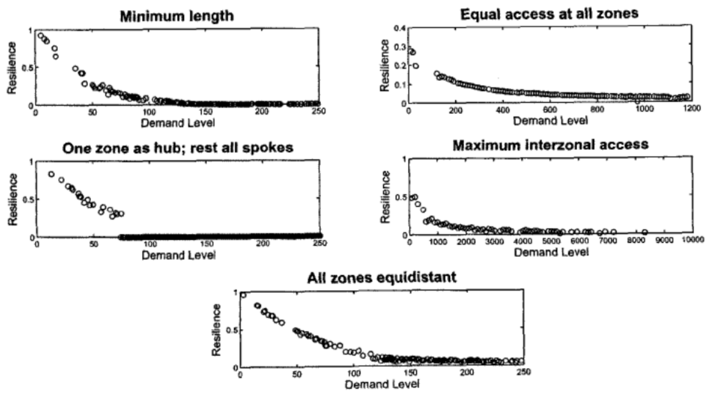
5 Factors influencing resilience in road networks

Some of the papers found in the systematic literature search (table 3.1) just present a resilience metric, while others present a resilience metric to research a factor influencing resilience. The latter type of papers will be discussed in this chapter.

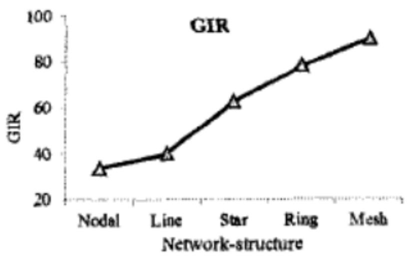
Patil and Bhavathrathan (2016) researched the influence of traffic demand on network resilience. The writers studied the resilience metric by Bhavathrathan and Patil (2015a) (equation 3.1) in different test networks for different demand levels. In all networks, resilience decreased as demand increased, usually as an exponential distribution. The results for five networks with the same size but different topology (figure 5.1a) are in figure 5.1b. The writers then defined the GIR (Generalized Index of Resilience) as the area under the resilience-demand curves (figure 5.1b). They used this to compare the resilience of the different network topologies, see figure 5.1c. It can be seen that as the number of links increases, so does the resilience.



(a) Five networks of the same size with different topologies. (1) five zones in an urban area (2) minimum length/line (3) equal access at all zones/ring (4) one zones as hub, rest all spokes/nodal (5) maximum inter-zonal access/mesh (6) all zones equidistant/star (From Patil and Bhavathrathan (2016))



(b) Resilience-demand curves for the five different networks. (From Patil and Bhavathrathan (2016))



(c) GIR for the five different networks. (From Patil and Bhavathrathan (2016))

Figure 5.1

Amini *et al.* (2018) use the resilience metric in formula 3.17 to evaluate the impact of re-routing during a disruption. They compare three different scenarios (already described in chapter 4), the base scenario where there is no disruption, the incident scenario without re-routing and the incident scenario with re-routing where 15% of vehicles will take an alternative route. The results are in figure 5.2, plotted as the performance indicator (PI) over time. The resilience is defined by the authors as the difference between the performance in normal condition and the performance in disrupted conditions (equation 3.17). In the scenario without re-routing the system gets into a gridlock state, while the performance with rerouting is very similar to the performance in normal conditions.

Figure 5.2 – Performance (PI) of the road network over time, for three different scenarios. (From Amini et al. (2018))

Sohouenou and Neves (2021) presented the resilience metric in equation 3.5 and used it to evaluate the impact of different link-repair strategies on resilience. The authors tested four different strategies:

- Optimal: the links are repaired in a way that minimizes the consequences of the disruption during the recovery time
- Average: the links are repaired in a random order
- Flow-based: the links with the highest traffic flow in the normal state are repaired first
- Criticality-based: the most critical links are repaired first

Firstly, all possible repair strategies were compared during a scenario where four links have failed, to find the optimal repair strategy. Then, the optimal strategy is compared with the other strategies. In this case the optimal strategy was the same as the link-criticality strategy, both having the highest resilience. The link-flow based recovery was still better than the average recovery strategy. The authors conclude that it is more crucial to identify the optimal recovery strategy when more links are affected, otherwise the criticality-based repair strategy is close to optimal.

5.1 Conclusion

Amini *et al.* (2018) and Sohouenou and Neves (2021) compare the impact of different scenarios on the resilience. The conclusion of the paper by Amini *et al.* (2018) is that the system performs much better during an incident if 15% of vehicles take a different route. Sohouenou and Neves (2021) draw conclusions about strategies to repair links, the most critical links can be repaired first if only a few links are impacted, but when more links are impacted links should be repaired in an order such that the consequences of the disruption are minimized.

Patil and Bhavathrathan (2016) compare the resilience of different networks. Five networks were compared, and it was concluded that the resilience increases with the number of links in the network.

6 Quantifying resilience in other transport networks

This chapter will list some resilience metrics used in other transport networks, to show how they compare to resilience metrics in road networks.

Zhou and Wang (2019) distinguish resilience measurement metrics into three categories: topological metrics, attribute-based metrics and performance-based metrics.

Topological metrics focus on the structure of the transport system but ignore the dynamic features, they are often based on graph properties. One example is the resilience metric proposed by Ip and Wang (2011) to quantify the resilience of the main railway system on the Chinese mainland. The authors made a graph to represent the transportation network, where cities are represented as nodes and rail roads as edges. The resilience of a city (or node) is evaluated by the weighted average of the number of reliable passageways, and the network resilience is then calculated as the weighted sum of the resilience of all nodes.

$$R(G) = \sum_{i=1}^{n} w_i r_i \tag{6.1}$$

$$r_i = \sum_{j=1, j \neq i} v_j \sum_{\forall k \ link \ (i,j)} P_k(i,j) \tag{6.2}$$

$R(G)$ is the network resilience, based on the graph G representing the network, w_i is the weight of node i based on the population of the city represented by the node. r_i is the resilience of a node, calculated as the self-exhausted weight of a node v_j (based on the difference between the population of the current node and other nodes) multiplied by the number of reliable passageways between nodes i and j, $P_k(i,j)$.

The attribute-based metrics distinguished by Zhou and Wang (2019) are based on the theory by Bruneau *et al.* (2003) that resilience has four properties: robustness, redundancy, resourcefulness and rapidity, as described in section 2.2. Attribute-based metrics focus on these properties and measure the resilience of the system based on the performance at specific periods. Two important examples of metrics are recovery speed (the time required for the system to return to equilibrium) and recovery efficiency (the resources required for recovery).

Instead of the performance at specific periods, performance-based metrics measure the resilience of the system based on the performance during the entire time the system is affected by the disruption. According to Zhou and Wang (2019) the metrics most used in the literature are degradation of system quality over time, time-dependent ratio of recovery to loss and the expected demand that is satisfied in the post-disaster network based on recovery costs. Bruneau *et al.* (2003) were the first to use a metric based on system quality over time, they used it to measure seismic resilience. They calculated the resilience as the expected drop in infrastructure quality over time with an integral, similar to the shaded space in figure 2.1.

6.1 Conclusion

There are also many different metrics to measure resilience in other transport networks, this chapter discussed a few of them. Resilience metrics in all types of transport networks are categorised into three categories by Zhou and Wang (2019), topological metrics, attribute-based metrics and performance-based metrics. These categories are different from the categories used for road networks metrics in chapter 3, where metrics were categorised based on whether they are user focused, road focused or both. The metrics in other transport networks will not be considered in the rest of this thesis, because the metrics discussed in chapter 3 already provide a wide range of resilience metrics.

7 Literature Review - Conclusion

This part started with finding a definition of resilience to use in this thesis. The definition of resilience is not the same in all literature, and there are also some terms used that are similar to resilience, such as robustness and vulnerability. The resilience definition should include all of the resilience triangle, which describes the network performance during the disruption phase and the recovery phase. The definition that will be used is described by Pan *et al.* (2021): resilience is the ability of a transport system to resist and adapt to a disruption, and to quickly return to a normal service level afterwards. The type of disruption is also an important part of the resilience. Disruptions can be classified into short-term and long-term disruptions, for short-term disruptions it is easier to return to the normal service level, while for long-term disruptions to system may be permanently changed. In this research the focus will be on short-term disruptions, because they are more frequent and more relevant for practical applications in the Netherlands.

After defining the resilience, ways to quantify resilience were researched with a systematic literature search. Eleven papers were found which consider resilience for road traffic or road networks, with short-term disruptions. The metrics differed, they were classified into three categories: road focused metrics, user focused metrics and metrics that are both user and road focused. There are four papers which have user focused methods, which look at the performance of the system from the perspective of the users. There are three papers with road focused metrics, which look at the performance at a road level. Then there are three metrics that have both user focused and road focused aspects. The metrics were evaluated on how many variables they used and whether they are on a network level, after which a road focused metric and a user focused metric are deemed the most interesting to compare in further research.

Most of the literature used here uses one network to compare different disruption scenarios, and some papers only present a resilience metric. Patil and Bhavathrathan (2016) did compare different networks, five small networks with five nodes and different topologies. They found that networks with more links have a higher resilience. In the part II, these experiments will be recreated with the resilience metrics by Sohouenou and Neves (2021) and Amini *et al.* (2018).

Part II

Five node networks

8 Five node networks - Introduction

This part contains a reproduction of the experiment by Patil and Bhavathrathan (2016), where five nodes are connected with links in five different ways (see chapter 5 and figure 5.1). The way resilience is measured will be done in a different way, with the metrics chosen in chapter 7. With the results the third research question can be answered: *Is there a relationship between road network parameters and resilience to accidents in networks with different network capacity?* The results will also be used when designing the larger experiments, for this different incident start times will be compared and different resilience metrics will be compared.

8.1 Networks

The networks in this experiment all consist of five nodes in a pentagon shape, connected differently, as shown in figure 8.1. The center of the pentagon is in (0,0) and the nodes are placed evenly on a circle with a radius of 4.5 kilometers. The line network and the ring network are similar, but the ring network has one more link. The nodal and star network are also very similar, there is one node that connects to all other nodes, but in the star network this an extra node (without demand). In the mesh network all nodes are directly connected to each other.

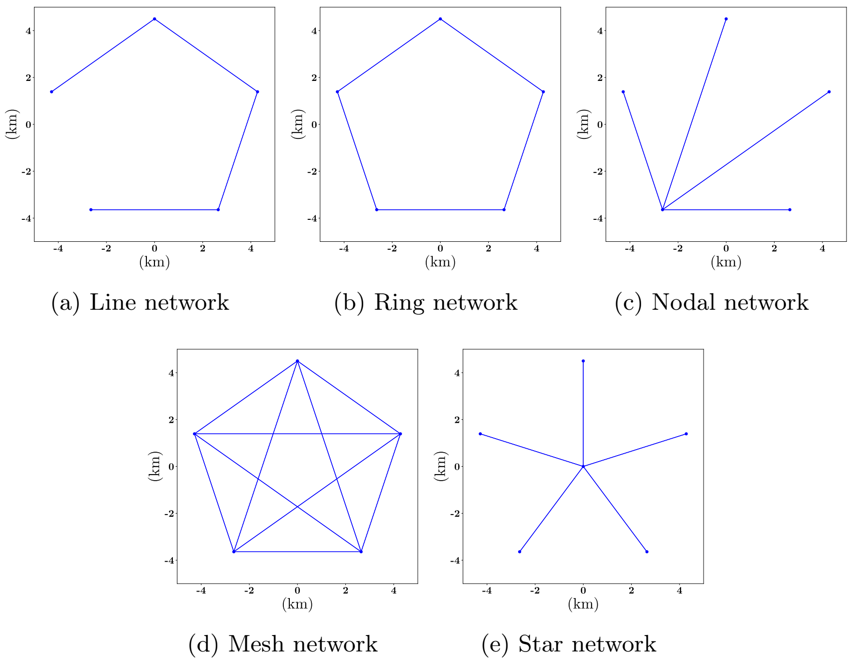


Figure 8.1 – The five node networks.

In table 8.1 some graphical information about the networks is presented. The table starts with information about the nodes, the number of nodes and the average, minimum and maximum degree of the nodes. The degree of a node is the number of links it connects to. The number of nodes is the same for all networks, except the star network, which has one node which is just used for connecting links. All networks have an average degree between one and two, except the mesh networks, in which all nodes have a degree of four.

Next, some link information is presented, the number of links, the length of all links added together, and the average, minimum and maximum link length. The nodes are evenly placed on a circle, so there are only two possible link lengths. The distance between adjacent nodes is 5.29 km, and the distance between other nodes is 8.56 km. The star network is an exception, because links connect to a node located in the origin, all links in that network are 4.5 km long. In the line network and the ring network, there are only connections between adjacent nodes, so all nodes are 5.29 km long. In the mesh network and the nodal network, there are the same number of links between adjacent nodes, as there are links between non-adjacent nodes, so they have the same average link length.

Lastly, there is some general graph information in the table, the connectivity and the link density of the graphs. The connectivity of a graph is the minimum number of links that need to be removed before the graph becomes disconnected (two separate graphs). The link density of a graph with n nodes and m links is $d = \frac{2m}{n(n-1)}$, which corresponds to the number of links divided by the maximum number of links. The connectivity is the highest for the mesh network, and the lowest for the line network, the nodal network, and the star network. The mesh network, in which all possible links exist (it is fully connected), has a link density of 1. The link density is the lowest in the star network, the connection node is taken into account for these calculations. The line network and the nodal network have the same link density, and the link density of the ring network is a little higher.

	Line	Ring	Nodal	Mesh	Star (OD)
Number of nodes	5	5	5	5	6
Average degree	1.6	2	1.6	4	1.67
Minimum degree	1	2	1	4	1
Maximum degree	2	2	4	4	5
Number of links	4	5	4	10	5
Total link length (km)	21.16	26.45	27.70	69.25	22.50
Av. link length (km)	5.29	5.29	6.92	6.92	4.5
Min. link length (km)	5.29	5.29	5.29	5.29	4.5
Max. link length (km)	5.29	5.29	8.56	8.56	4.5
Connectivity	1	2	1	4	1
Link density	0.4	0.5	0.4	1	0.33

Table 8.1 – Graph information for the five node networks.

9 Five node networks - Methods

This chapter describes the methods that are used in the experiments with the five node networks, starting with the simulation model.

9.1 Simulation model

Most resilience metrics compare the traffic situation in a normal state with the traffic situation when there is an incident, which can be done with traffic data or simulation.

The goal of this research is to find the properties of resilient road networks, which will be done by comparing resilience in different road networks. Because of this, simulation is chosen as a method. The state of the art of simulation models is clearly explained in Calvert *et al.* (2016), two important types of simulation models are macroscopic and microscopic models. Macroscopic traffic models focus on the relationship between aggregate traffic characteristics, such as traffic flow and mean speed. Microscopic models simulate individual vehicles which results in a higher level of detail, because of this these models have a higher computation time. To be able to simulate many different networks, a macroscopic simulation model will be used in this thesis.

There are two types of macroscopic models, static and dynamic (Calvert *et al.* (2016)). Static models do not consider time-dependency, thus the impact of spill-back due to congestion is disregarded, or solved with a vertical queue. Dynamic models use a time dimension in their prediction, spill-back due to congestion is taken into account with mathematical relations. Congestion is an important part of this study, therefore a dynamic model is chosen, which will model it more realistically.

In the end, MARPLE (Taale (2008)) is used in this research, a dynamic macroscopic model, based on flow-travel time relations. This model is because it is free to use, there is a simple way of adding incidents, it is easy to design networks and it can be used in combination with Python programming.

9.2 Simulation

The five networks in figure 8.1 are simulated with MARPLE (TrafficQuest (2023)). The links in the networks all have the same properties (only their length differs): they all have two lanes, a maximum speed of 100 km/h and a saturation flow of 2100 veh/h/lane. The nodes also all have the same properties, they are origin-destination (OD) nodes of the same size, with the same demand. The node in the middle of the star network is an exception, it is only used to change links.

A Python script was written to run the simulations of the networks and calculate the resilience. The Python script first creates MARPLE input files with the network data explained before. Since origin and destination nodes are separate in MARPLE, every OD node has an origin node and a destination node one kilometer away, as can be seen in figure 9.1. These origin and destination nodes are connected to the OD by links with 2 lanes, a saturation flow of 9999 veh/h/lane and maximum speed of 100 km/h. The saturation flow in these links is a high value to avoid it being the cause of congestion.

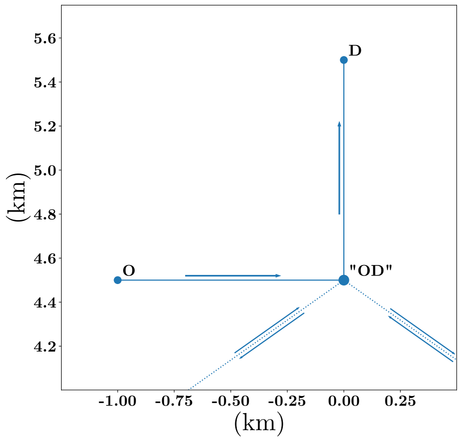


Figure 9.1 – The five node networks all consist of five origin-destination (OD) nodes connected with links. In MARPLE origin (O) and destination (D) nodes are separate, so the "OD" nodes are connected to O and D links one kilometer away.

Next, the script runs the MARPLE simulations. A stochastic dynamic user equilibrium (SDUE) assignment is chosen, because it is faster and results in a more stable assignment (Mathew and Rao, 2007, chapter 10). The simulation runs for 15 time periods, 9 minutes each, for a total of 2 hours and 15 minutes. The simulation has time steps of 10 seconds. The demand is uniform between nodes, but is not uniform over time. The total demand from one node to another is shown in figure 9.2. The last six time periods have no demand, because these are needed for all vehicles to arrive at their destination.

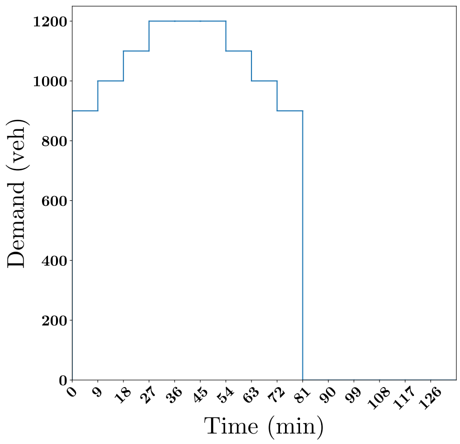


Figure 9.2 – Demand curve of demand between nodes in the five node networks.

At some point in the simulation there is an incident, which lasts 27 minutes (three time periods) and affects one link. In this link one lane is closed, and in the other lane the saturation flow is reduced by 12% to 1848 veh/h/lane, and the free flow speed is reduced to 52.4 km/h. These numbers are shown in the fundamental diagram in figure 9.3.

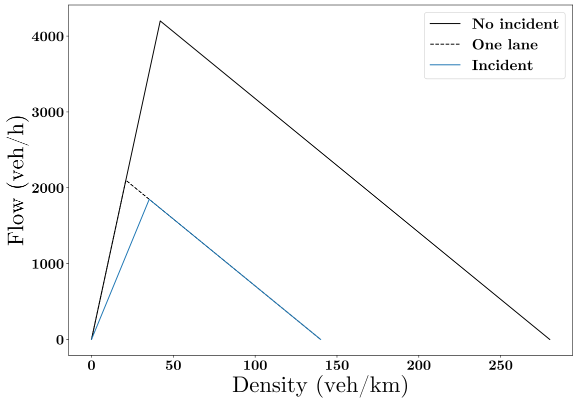


Figure 9.3 – Fundamental diagram of the links with the normal situation in black and the incident in blue.

The links are different in all networks, and so are the flows on these links. If an incident happens in a link with a higher flow, this would have a bigger impact. To correct for this, each network was simulated with the incident in a different link. Thus, each network was simulated as many times as it has links, resulting in 56 simulations.

To study the impact of the time period these 56 simulations were done nine times. First with the incident starting in the first time period, then with the incident starting in the second , and so on until the ninth time period (time periods after that have no demand).

Lastly the Python script calculates the network performance and resilience of the networks.

9.3 Resilience and network performance metrics

The resilience is calculated in three ways, with a user focused metric and two road focused metrics. The user focused metric is the resilience metric from Sohouenou and Neves (2021), which is in equation 3.4. It is the area under the travel time (TT) network performance curve.

One of the road focused metrics is the one by Amini *et al.* (2018) (see equation 3.17), based on the space-mean flow. The other road focused metric is the area of the network performance based on the outflow of the network, see equation 9.2. This metric is added to look at the network performance more globally.

$$\mathrm{NP}_{q^{\mathrm{out}}} = \frac{q_I^{\mathrm{out}}}{q_0^{\mathrm{out}}} \tag{9.1}$$

$$\mathrm{RE}_{q^{\mathrm{out}}} = \frac{\sum^T |\mathrm{NP}_{\mathrm{q}^{\mathrm{out}}} - 1|}{T} \tag{9.2}$$

In these equations $\mathrm{NP}_{q^{\mathrm{out}}}$ is the network performance based on the outflow of the network (q^{out}), which is the difference between the outflow during the incident q_I^{out} and the outflow during the normal situation q_0^{out}. The resilience ($\mathrm{RE}_{q^{\mathrm{out}}}$) is then the sum of the network performance in all time periods (T) divided by the number of time periods. This resilience is the area of the resilience triangle, instead of the area under the resilience triangle, which is used by Sohouenou and Neves (2021).

For each simulation the network performance was calculated in five ways:

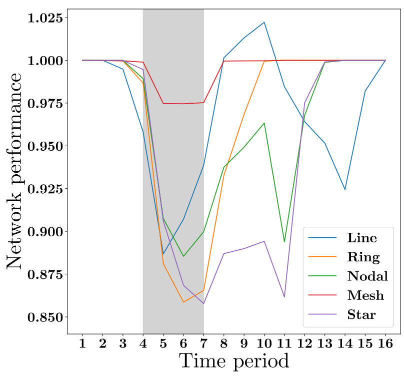
- Based on the ratio of the travel time between OD pairs in normal situation and the incident situation, as described by Sohouenou and Neves (2021) (equation 3.3).
- Based on the ratio between the outflow of the network in the incident situation and the outflow of the network in the normal situation (equation 9.1).
- Based on the outflow of the network.
- Based on the queue length.
- Based on the vehicles that are still in the origin.

10 Five node networks - Results

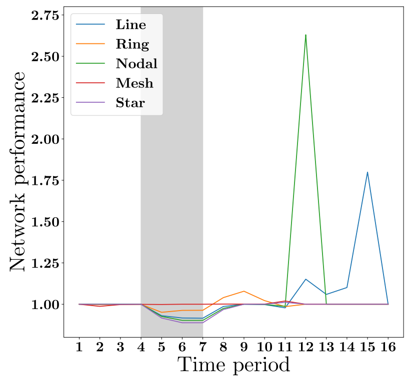
In this chapter results are presented which were obtained using the methods discussed in the previous chapter. The results for different incident start times are presented in section 10.4, before that all results are for an incident in time period 4, 5 and 6.

10.1 Network performance

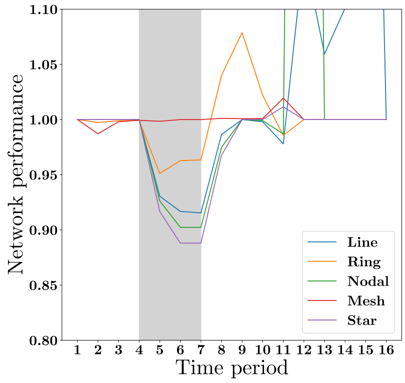
The network performance was measured in different ways, all of them are presented in figure 10.1. The network performances were calculated for an incident in each link, the figures presented here are the average of that.



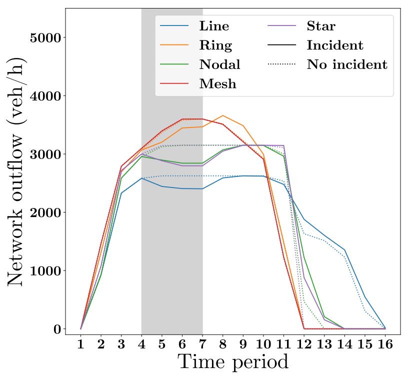
(a) Travel time network performance



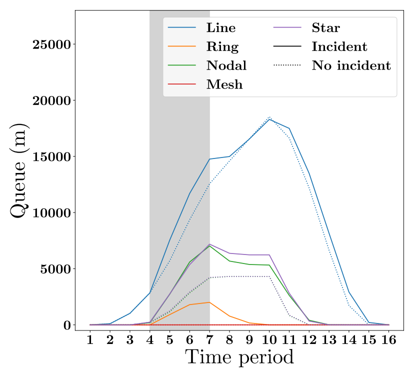
(b) Network performance based on outflow



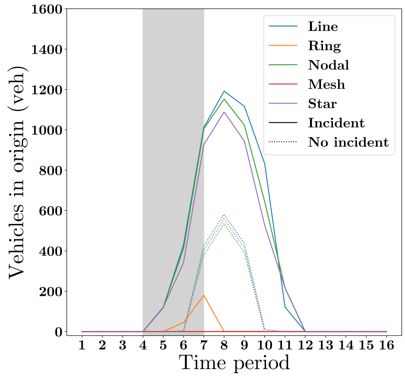
(c) Network performance based on outflow, zoomed in



(d) Outflow of the network



(e) Total queue length in the network



(f) Total number of vehicles in the origin

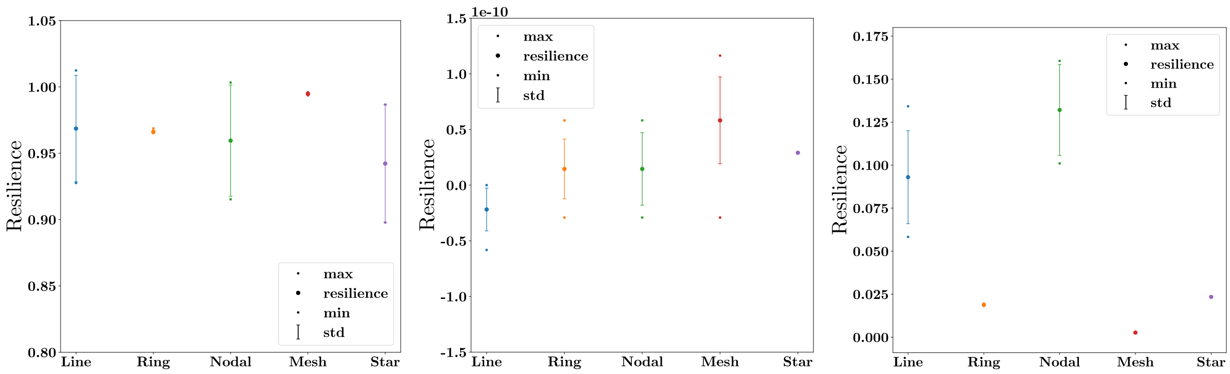
Figure 10.1 – Different network performance measures. The grey area represents the time when the incident is happening. In figure d, e and f the continuous line represents the incident situation, and the dotted line indicates the normal situation. In figure a,b and c the ratio between the incident and normal situation is used.

The TT network performance is in figure 10.1a. Figure 10.1b and 10.1c are the same figure, with a different scale. This is the network performance calculated based on the outflow (equation 9.1). The outflow of the network is in figure 10.1d, the normal situation is indicated with the dotted line and the incident situation with the continuous line. The total queue length is shown in figure 10.1e. Lastly, in figure 10.1f is the number of vehicles that are still in the origin, this picture was added because vehicles left in the origin might affect the results.

10.2 Resilience

For each incident start time, the number of times the simulation was run is the same as the number of links in the network, each time for the incident in a different link. The average of this is considered as the resilience of the network. Figure 10.2 shows the average, the standard deviation and the maximum and the minimum for all three resilience metrics. The exact values of the average resilience are in appendix C.

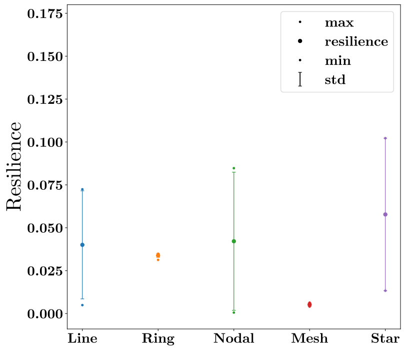
In figure 10.2a is the TT resilience (equation 3.5), the network is more resilient when the value is closer to one. In figure 10.2b is the flow resilience (equation 3.17), the closer to zero the resilience value, the more resilient the network. In figure 10.2c is the outflow resilience (equation 9.2), values closer to zero mean a more resilient network.



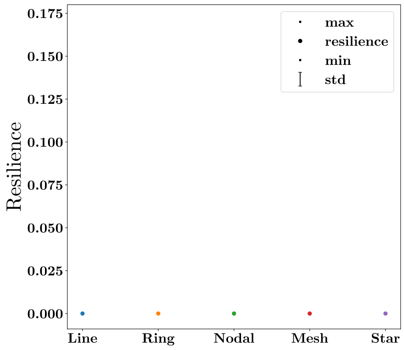
(a) Travel time resilience (b) Flow resilience (c) Outflow resilience

Figure 10.2 – The resilience from different resilience metrics. In figure a the highest value represents the most resilient network, and in figure b this is the value closest to zero (but not all values are positive), in figure c the most resilient network is the one with the value closest to zero (and all values are positive).

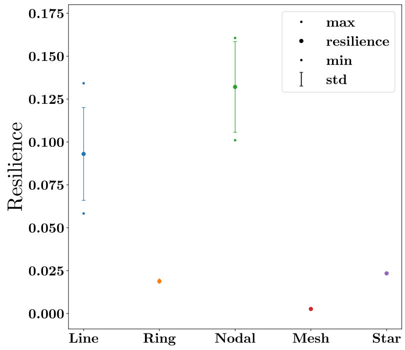
To make it easier to compare the resilience metrics the plots in figure 10.3 are added. Figure 10.3a and 10.3b are again the TT and flow resiliences, but with a change such that all resilience metrics use the same scale. In figure 10.3, all values are positive, and the network is more resilient when the value is closer to zero. For the TT resilience this is done by using $|1 - R|$ instead of the resilience R and for the flow resilience $|R|$ is used instead of R, the outflow resilience is already on this scale. The transformation of the resilience values is done before taking the average, which might cause changes in which network is the most resilient.



(a) Travel time resilience (transformed)



(b) Flow resilience (transformed)

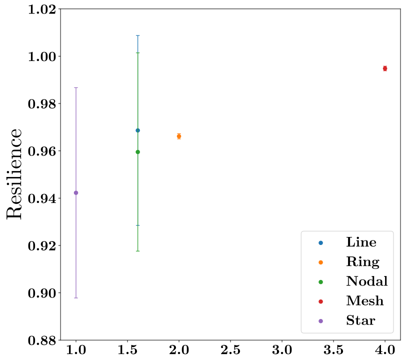


(c) Outflow resilience

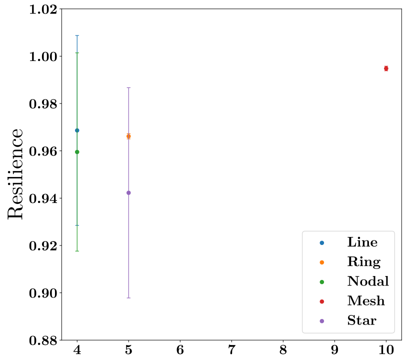
Figure 10.3 – The resilience from different resilience metrics. The same values were used to in this figure as in figure 10.2, but here all values are positive, and the most resilient network is the one with the value closest to zero.

10.3 Network parameters

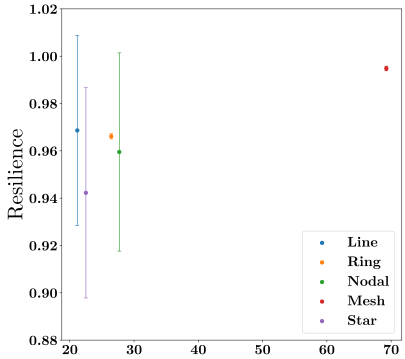
The values of the TT resilience was also plotted with some of the network parameters presented in table 8.1. These plots are presented in figure 10.4.



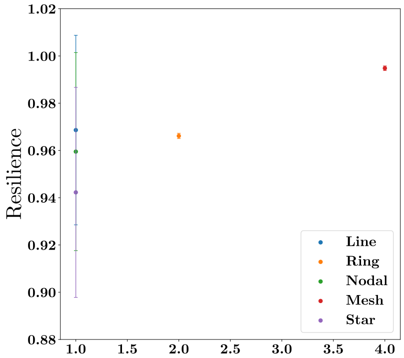
(a) Average degree



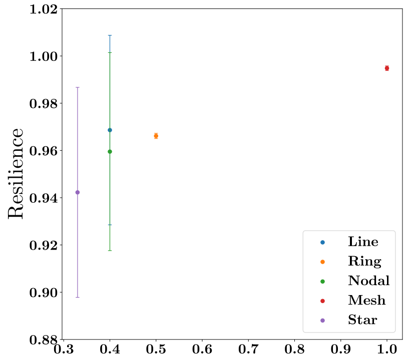
(b) Number of links



(c) Link length



(d) Connectivity



(e) Link density

Figure 10.4 – Travel time resilience plotted with network parameters.

10.4 Incident time

To study whether the start time of the incident influences the resilience and performance, the simulation was carried out nine times, for an incident start time in the first to the ninth time period. The results for all performance and resilience metrics with all different start times are in appendix B. In this section only the network performance and resilience from Sohouenou and Neves (2021) is used. To show the difference between the incident times, the network performance plots were shifted to make the incident times align. These plots were made for every network type separately, in figure 10.5. The average of all lines is also plotted.

The difference between the average network performance (NP_t^{av}) and the network performance (NP_t) for different incident timings was also calculated, the result of this is in appendix C. This was done per time period t: $\sum_t |NP_t^{av} - NP_t|$.

The TT resilience for all time periods and all networks is in figure 10.6, including the average. The figure is plotted like this to show how the networks compare to each other. The difference between the average and the resilience for each time period is in table C.3. This was calculated similar to the difference in network performance, by taking the absolute value of the difference between the average resilience (RE_t^{av}) and the resilience per time period (RE_t): $\sum_t |RE_t^{av} - RE_t|$.

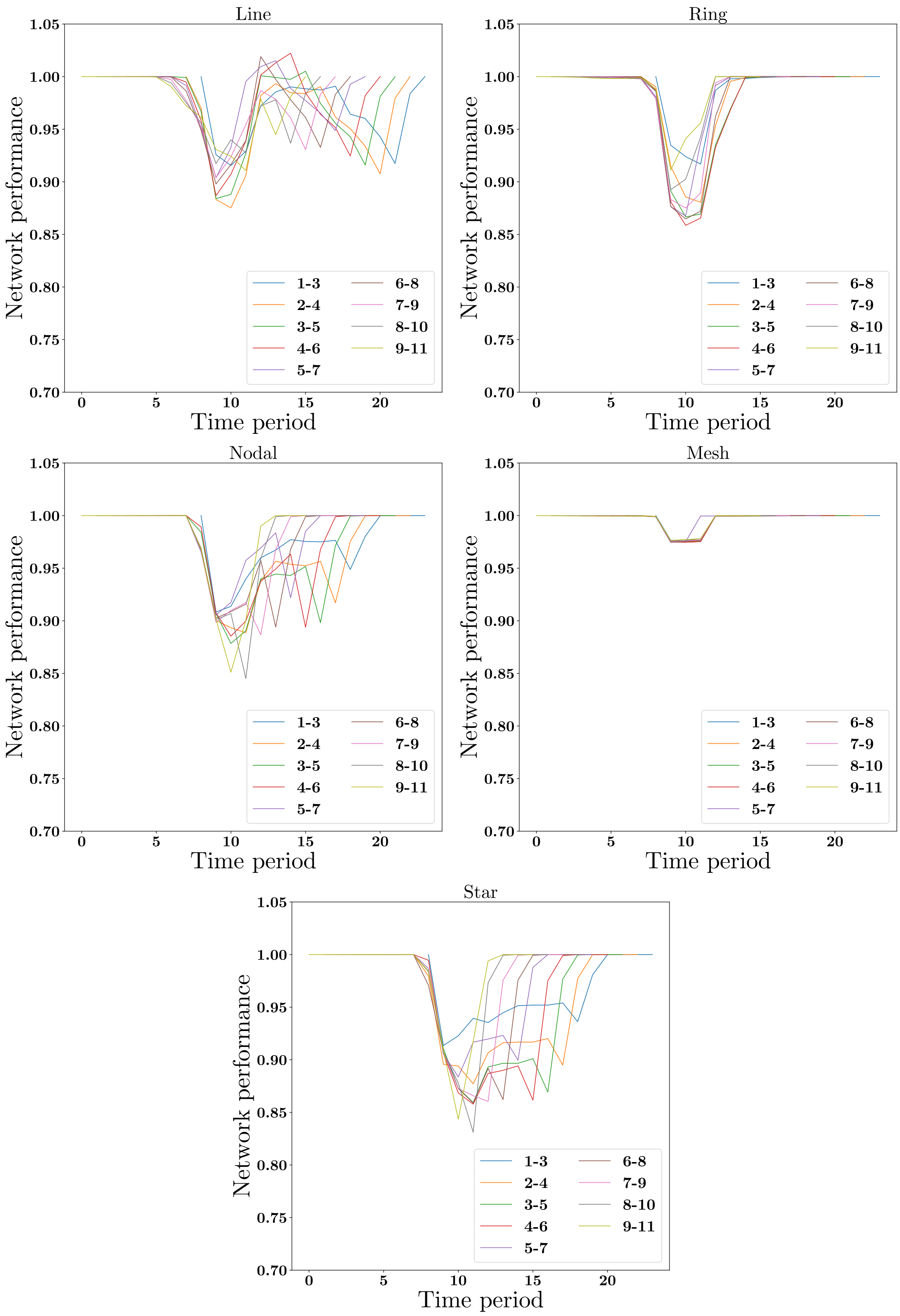


Figure 10.5 – Travel time network performance with the incident in different time periods, the average network performance is represented by the black line.

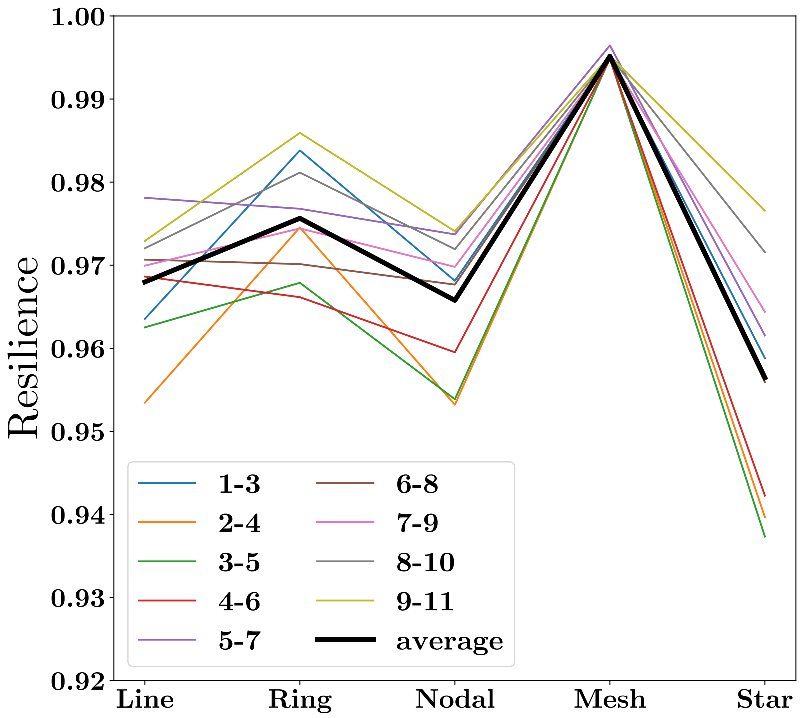


Figure 10.6 – Travel time resilience with the incident in different time periods, the average resilience is represented by the black line.

11 Five node networks - Discussion

11.1 Network performance

The Sohouenou and Neves (2021) network performance is based on travel time. Due to the incident, the network performance declines, the travel time becomes longer. The network performance is already below one before the incident starts, as observed in figure 10.1a, this is because some vehicles that leave before the incident, arrive during or after it and experience the congestion caused by the incident. This increased travel time is reflected in this network performance, because it is based on route travel times. From the tenth to the thirteenth time period the network performance of the line network becomes higher than one; the travel time is shorter in the situation with the incident. These shorter travel times are observed because less vehicles are present in the links downstream of the incident. Thus, there is less congestion there, and the average travel time is shorter. The mesh and the ring network lose network performance during the incident, but it goes back to one right after. The nodal and the star network have a shape similar to each other, the network performance is around 0.93 during the incident, and goes up to around 0.96 afterwards. The network performance only goes back to one after the twelfth time period, when there is no more demand, and the system has started to empty. In the nodal network the network performance is increasing until the tenth time period, but it is lower again in the eleventh time period. The ratio between the travel time in the normal situation and the travel time in the incident situation is lower in this time period than the one before and after it. This decrease is not caused by the incident travel time increasing, but because the incident travel time and normal travel time are decreasing at different rates.

The network performance based on network outflow is higher than one at some point in time for all networks, see figures 10.1b and 10.1c. The performance of the mesh network stays around one during the entire simulation period, the impact of the incident is low because the network has many links and all nodes are directly connected to each other. The performance of the other networks declines during the incident and increases when it is over. In the ninth time period the network performance is one for all network except the ring network. At this time the outflow is the maximum outflow, both in the incident and normal situation. The network performance of the nodal and line network then descend again in the eleventh time period, and their performance ascends to above one again in the twelfth time period. The performance of the star and ring network is above one in the eleventh time period. When the network performance based on network outflow is above one, the outflow of the network in the incident situation is higher than the outflow in the normal situation, which can be observed in figure 10.1d. The reason that the outflow is higher for the incident situation is that because of the incident the vehicles arrive at their destination later than they do in the normal situation. So, the outflow in the last few time periods are from vehicles who would have already reached their destination in the normal situation. The network performance becomes higher than one, because there is more outflow in the incident situation than in the normal situation, but this is not a sign of a well-performing network.

There is a clear difference in performance between the networks, indicated clearly by the difference in queue length, see figure 10.1e. The line network performs badly, even without the incident, while the mesh network has no queues even with an incident. The congestion in the line, nodal and star network is such that some vehicles are unable to leave the origin, as can be observed in figure 10.1f. This could impact the result, because the travel time is only calculated from the time vehicles leave the origin. Thus the TT resilience and network performance might be lower for these networks than is represented in the data.

The mesh and the ring network perform the best when looking at queue length and vehicles in origin, and the line network performs the worst. The mesh network also performs the best when looking at the travel time network performance and the outflow network performance, but the line network does not perform the worst. The ring network performs second best for both network performance types.

11.2 Resilience metrics

The mesh network has the highest TT resilience, which can be seen in figure 10.2. The ring network has the second highest value, closely followed by the line network. The nodal network has the lowest followed, the star network has a resilience that is a little higher. The ring and the mesh network have a standard deviation that is a lot smaller than the standard deviation of the other networks, the line network has the highest standard deviation. The standard deviation indicates how much the resilience is impacted by the link in which the incident happens. If the network has a high standard deviation, the resilience is much higher or lower when the incident is in a different link. Sohouenou and Neves (2021) did an experiment in a larger network, with incidents in multiple links. For two link failure their results were between 0.75 and 1. The results for networks with five nodes and an incident in one link are between 0.96 and 1, which means the five node networks are more resilient than the Sioux Falls network or the five node networks impacted less by the incident. Most likely the impact of the incident is less, because in this thesis there is only a failure in one link and in the original paper there is a failure in two links.

The values of the flow resilience are all very close to zero, at the scale of 10^{-10}, both above and below zero, see figure 10.2b. The networks can be ranked according to their proximity to zero. The star network is then the best, followed by the line network, then the ring network, then the nodal network and lastly the mesh network. The results by Amini *et al.* (2018) are not as small as the results in this thesis. For the scenario where a central link is closed for 25 minutes, and 15% receive information about the road closure, their result is -4. In their experiment, the performance of the system is very similar in the incident scenario with re-routing and the normal scenario. In the experiment where there is no re-routing, the result is -1666. These numbers are interpreted as that in the first case 4 vehicles do not arrive at their destination, and in the second case 1666 vehicles do not arrive at their destination. If the numbers represent vehicles they should be rounded, which makes the resilience of all networks zero. The results makes sense, because in this experiment the simulation time is chosen such that all vehicles arrive at their destination. Although that makes this metric not useful to compare the resilience in these experiments.

The resilience based on outflow, in figure 10.2c, has the same outcome as the Patil and Bhavathrathan (2016) experiment (see figure 5.1c). The mesh network has the value closest to zero, it is the most resilient, followed by the ring network, then the star network and then the line network. The nodal network has the highest value, it is almost twice as high as the resilience value of the line network. The resilience of the nodal has this high value due to the high network performance, explained in the previous section. Although the ranking of the networks is the same as Patil and Bhavathrathan (2016), the difference between the values is not the same. In the Patil and Bhavathrathan experiment the resilience values steadily increases between the networks, with the exception of the line network. The outflow resilience steadily decreases from the nodal, to the line, to the star network but then it levels off for the ring and mesh network. Patil and Bhavathrathan consider networks with a higher value more resilient, instead of closer to zero as was done here. The resilience is also measured in a very different way, based on the expected system travel time.

The resilience results on the same scale are in figure 10.3. From these results it can be concluded that it matters which resilience metric is used, they will not all give the same result. The TT and the outflow resilience give similar results, the mesh network performs the best, the ring network second best and the nodal network performs the worst. Although the ranking is similar, the values are not. The resilience values are higher for the outflow resilience, even when the values are normalized. The ranking of the flow resilience differs a lot from the other resilience metrics, for example the mesh network performs the worst. The results of the flow resilience all have very low values, because the way that resilience is defined is incompatible with the way the experiments are designed. The outflow resilience has results with values not as close to zero, but it is difficult to distinguish between the reasons for a higher resilience value. The network performance could be higher because the network performs well, or because there is a lot of delayed outflow.

11.3 Network parameters

When considering network parameters the mesh network stands out, it has the highest values for all network parameters. Thus it is not surprising that the mesh network also has the highest TT resilience. From the plots of network parameters and resilience in figure 10.4, it seems that there is a relationship between all network parameters and resilience. Higher average degree, number of links, link length, connectivity and link density result in a higher resilience. The mesh network has the highest value for all these parameters, so it is difficult to say if all of them influence the resilience. The line network and the nodal network have very similar characteristics, the most important difference is that the nodal network has a higher average link length. Although the network characteristics are very similar their resilience values are not that close together. With more data points from more different networks a relationship between network parameters and resilience could be found.

Patil and Bhavathrathan (2016) did the same experiment with the five node networks, and concluded that resilience increases with the number of links. The results of the experiment in this section indicate that other network parameters might explain the higher resilience. An experiment with more networks could show which network parameters cause a higehr resilience.

11.4 Incident time

For most networks the incident start time impacts the shape of the TT network performance curve, see figure 10.5. The mesh network is an exception, all curves overlap. The network performance of the ring network is only impacted in the well caused by the incident, the depth of the well changes somewhat. The ring network and the mesh network are the networks without queue formation. In the nodal and star networks some queues form, and in those networks there is a larger difference between the average curve and the curves per incident start time. Some of this is because the time period when it the network performance goes back to one is later for curves where the incidents happens in an earlier time period. This makes sense, because the last six time periods have no demand, so the network performance can quickly go back up to one. The last six time periods are further away from curves where the incident happens at an earlier time. The line network is the network with the most congestion, and it is also the network where the network performance per incident start time differs most from the average network performance curve.

The resilience values of the five networks were also compared for different incident start times, the results of which are in figure 10.6. Similar to the network performance, the resilience does not vary a lot for the mesh and the ring network. It varies more for the ring and star network, and most for the line network. The ranking of networks is mostly maintained, except for the line network. The mesh network has the highest resilience, ring the second highest, and nodal and star have a similar, low value. The resilience of the line network is higher than the ring network in some cases, and lower in others. It is lower for the incidents that start in the first, second, third and fourth time period.

In the line network, the network performance is above one after the incident for some incident start times. For the incidents starting in the first, second and third time period the network performance stays below one. For the incident starting in the fourth time period it is above one shorter and less high than the later incident start times. This explains why the resilience is lower in these time periods. This might be due to the shape of the demand curve, the demand of the network is uniform between nodes, but not over time (see figure 9.2). The demand is highest during the fourth, fifth, and sixth time period. The impact of the shape of the demand curve on the network performance and resilience is left for further research.

Thus the incident time has an impact on the shape of the network performance curve and on the resilience values. There is not one incident start time which has a network performance closest to the average, it changes for each network type. The average network performance curve has a different shape than the other curves, it is much smoother. Because of that the average curve does not have some of the features of the other curves, such as the network performance quickly going up to one in the star network.

12 Five node networks - Conclusion

The experiment with the five node network was done to draw conclusions about several different aspects. First there was a comparison made between different network performance measures. The network performance measures can all be used to look at different aspects of the network. The total network outflow, total queue length and vehicles in origin can be used to show how different the networks perform, even without the incident. The network performance based on the travel time ratio, and the network performance based on the outflow ratio show how the network is impacted by the incident. The line, nodal and star networks have a lot of queuing, and a some vehicles left in the origin. These networks already perform badly without the incident. Due to the vehicles left in the origin the network performance based on travel time is somewhat distorted. In further research it would be better to choose the demand and the networks such that there is a more realistic congestion pattern. If the networks are more similar the demand can be chosen such that there are no vehicles left in the origin, and there is some congestion an all networks.

A comparison between three different resilience metrics was also made. It matters which resilience metric is used, since they all result in a different rating of the best networks. The mesh network is the best, followed by the ring network for both the travel time resilience and the outflow resilience. For the TT resilience this is followed by the line network, then the nodal network, and then the star network. For the outflow resilience the last three networks are the star network, then the line network and then the nodal network. The flow resilience results in resilience values very close to zero, due to the way the simulation is designed. This method is better suited for a different simulation design where vehicles do not necessarily arrive at their destination. The outflow resilience can result in high peaks, which can distort the resilience value. The TT resilience was concluded to be the best in this type of experiment. If the demand and networks are designed such that there is a realistic congestion pattern this resilience metric will give the most reliable results.

The relation between network parameters and the resilience was also researched, there seems to be some relations. With more data points a relation could be determined, from the results of these experiments higher average degree, number of links, link length, connectivity and link density could all cause a higher resilience. In a new experiment networks could be designed such that only one network characteristic differs, for example comparing some networks that have the same number of links, same average degree, connectivity and link density but a different average link length.

Last, a comparison between different incident start times was made. In most of the networks the incident timing does impact the shape of the network performance curve, the impact is less pronounced for networks with lower congestion.

Part III

Random Networks

13 Random Networks - Introduction

In this part the fourth research question will be answered: *Is there a relationship between road network parameters and resilience to accidents in networks with comparable network capacity?* The experiment that is used is similar to the experiment with the five node networks in part II, but in this part larger, random networks are used.

In the previous part the networks had a high difference in capacity, which caused some problems with choosing the demand. Thus, the random networks should have a more similar capacity. Also, there were different resilience and network performance metrics used. Based on the conclusions in part II, only the TT resilience will be used to compare the networks.

In part II there were indications for a positive relation between resilience and link density, connectivity and some other network parameters. In this part, the relation between resilience and these network parameters and more will be tested. There were only five data points in the experiment with the five node networks, the random networks will provide more data points to know more about the relation between resilience and network parameters.

14 Random Networks - Methods

14.1 Network design

In this experiment, a number of random networks is generated, and their resilience is calculated. The networks are loosely based on the motorway network in the Randstad, which has nine cities, two large (over 600,000 inhabitants), two medium (between 200,000 and 600,000 inhabitants) and five small cities (less than 200,000 inhabitants) (CBS (2022)).

The random networks are created by first creating nine nodes with random locations on a square of eighty by eighty kilometers, with at least twenty kilometers between them. The nodes represent cities with a motorway network, like the Randstad there are two large cities, two medium cities and five small cities.

Next, random links are generated between the nodes. The probability of a link generating depends on the size of the nodes, two nodes are selected in between which a link will be generated. Large nodes have a probability of $\frac{3}{15}$ of being selected, medium nodes $\frac{2}{15}$ and small nodes $\frac{1}{15}$. To prevent parallel and overlapping links, there is a minimum angle between two links going out of a node (0.2 radians or 11.5°). The new link then gets assigned a random number of lanes, the number of lanes generated depends on the size of the nodes, the exact probabilities are in table 14.1. If the network is connected (there is a path from each node to every other node), it depends on the network type whether new links are created.

	Large node			Medium node			Small node		
	2 lanes	3 lanes	4 lanes	2 lanes	3 lanes	4 lanes	2 lanes	3 lanes	4 lanes
Large node	0.1	0.25	0.65	0.1	0.3	0.6	0.28	0.44	0.28
Medium node	0.1	0.3	0.6	0.27	0.46	0.27	0.69	0.3	0.01
Small node	0.28	0.44	0.28	0.69	0.3	0.01	0.79	0.2	0.01

Table 14.1 – Table with probabilities for lane generation. The number of lanes generated on a link between two nodes depends on the size of the nodes.

For each set of nodes, three networks are created, a high, medium and low link density network. Link density refers to the amount of links in the network, compared to the maximum possible links in the network. If the network is a high density type, only new links will be created. In some cases no more links can be added due to the angle constraint, then an extra lane will be added. If the network has low density, extra lanes on existing links will be created after the network is connected. This is done until all links have four lanes, afterwards a new link will be generated. For networks with medium density, there is a 50% chance whether a new link or an extra lane will be created.

The process stops generating new links and lanes once a threshold has been reached, which is based on the total number of lane kilometers and the distance between nodes. The program calculates the sum of the distance between every node, so if the network were fully connected and there were two links (with one lane) from every node to every other node (one from i to j and one from j to i). Once the total number of lane kilometers is at least 80% of this distance, the program stops creating links and lanes. After the threshold is reached the program checks whether the network is connected, and if it is not a new link is added to make sure it is. In places where links overlap, a new connection node is added, which is accounted for in the check whether the network is connected.

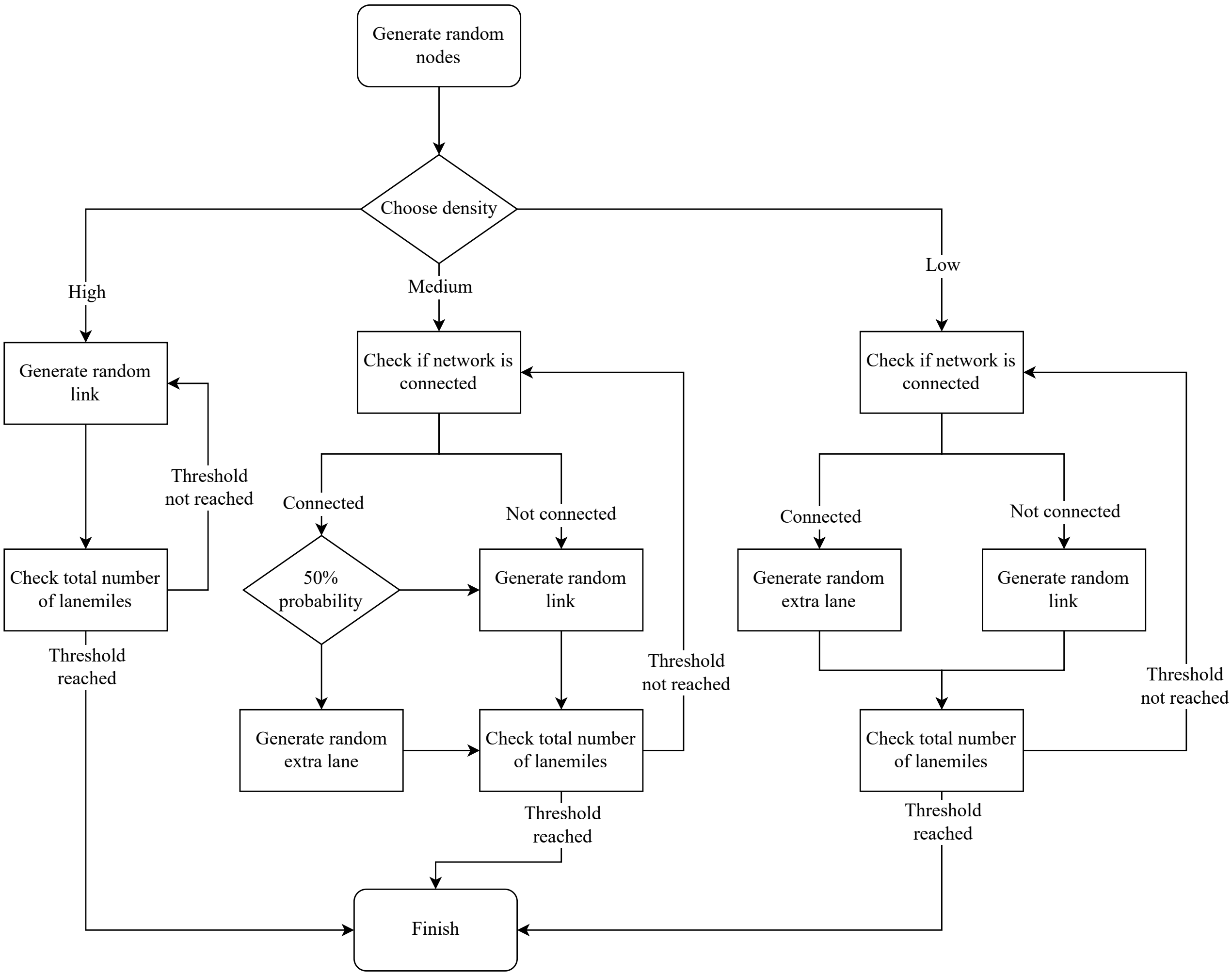
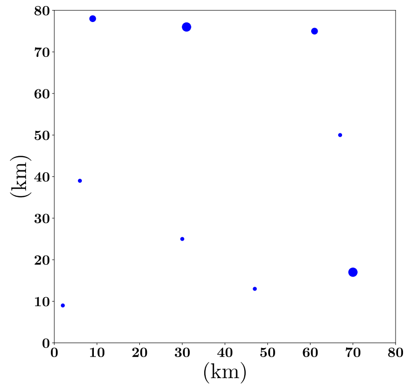
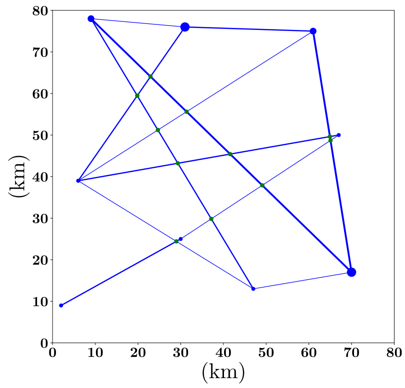


Figure 14.1 – Flowchart to explain the generation of random networks. For each set of nodes in random locations, three different types of networks are created, with low, medium or high link density. Edge cases are excluded from this figure for simplicity.

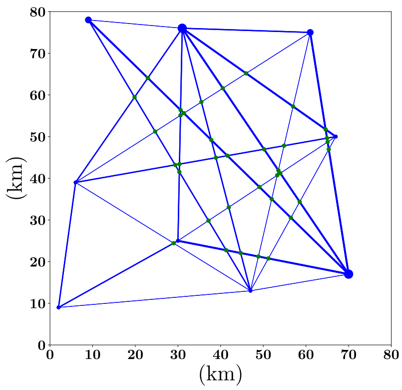
Figure 14.1 explains how the networks are created with a flowchart. Figure 14.2 shows the stages of the random networks. First, nine nodes are created in random locations, see figure 14.2a. Then, links are generated until the network is connected, see figure 14.2b. Up to when the network is connected, the high, medium and low density networks are the same. After that links are generated in different ways, and the set of nodes has three different networks, 14.2c, d and e.



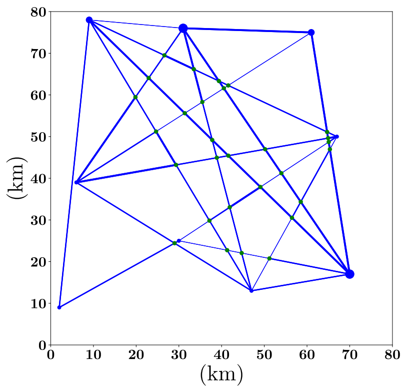
(a) Random nodes



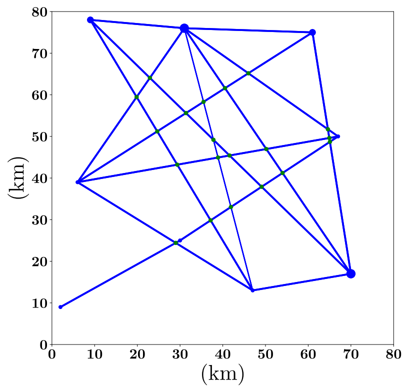
(b) Connected network



(c) High link density



(d) Medium link density



(e) Low link density

Figure 14.2 – The random networks are created by first creating nine nodes with random locations, figure a. Then links are generated until the network is connected, figure b. Then, links and extra lanes are generated in different ways such that there are three different networks, with high, medium, and low link density (figure c, d and e).

14.2 Simulation

A script was written to run simulations of the random networks to quantify their resilience. The same simulation model is used for the random networks as for the five node networks (part II), MARPLE. The script to run the simulations is also similar. MARPLE input files are created, MARPLE simulations are ran, and the resilience is calculated. Some of the simulation properties are also the same, links have a maximum speed of 100 km/h and a saturation flow of 2100 veh/h/lane. The number of lanes varies from two to four, depending on the link. The OD nodes have the same construction as the five node networks, with an origin node and a destination node one kilometer away (see figure 9.1). In contrast with the five node networks, the random networks also have connection nodes which are only used to change links and have no demand. A SDUE assignment is chosen again, the simulation runs for 16 time periods of 9 minutes for a total of 144 minutes.

Contrary to the five node networks, the demand is not uniform between nodes. Instead a gravity model is used. In this model, the larger the distance between nodes, the less demand between those nodes:

$$t_{ij} = p_i \frac{p_j \cdot \frac{1}{d_{ij}}}{\sum_j p_j \cdot \frac{1}{d_{ij}}} \tag{14.1}$$

In this equation p_i is the production/attraction factor of a node, the weight of which is based on the size of the node. Production/attraction of large node is six times that of a small node, and production/attraction of a medium node is three times larger than that of a small node. d_{ij} is the Euclidean distance between node i and node j. t_{ij} is a measure for the number of trips between node i and node j, which is multiplied by the maximum demand of a time period to get the OD matrix. The total demand varies per time step, see figure 14.3. The exact demand at the peak depends on the t_{ij}, but it is no higher than 10000 vehicles per time period.

The accident is also similar as in part II. Saturation flow is reduced by 66%, and maximum speed is reduced to 52.4 km/h, this lasts for 63 minutes (seven time periods). In links with two and three lanes, one link is closed, and in links with four lanes, two lanes are closed.

Instead of simulating an incident in one link, and repeating it for each link in the network, 10% of links are chosen randomly to have the incident. This is done for two reasons. The simulation time is shorter this way because most networks have over fifty links, and since these random networks are larger than the five node networks, the impact of an incident in one lane is much smaller. At random 10% of links are chosen to have an incident (all at the same time), this is repeated eight times to ensure the results can be compared. If it is done only once, it could be that unimportant links are chosen and it will seem like the network has a high resilience when this is not the case. To make sure there is a high and a low resilience included, two more simulations are done. One with the 10% of links with the highest edge betweenness centrality, and one simulation with the 10% of links with the lowest edge betweenness centrality. Edge betweenness centrality is a measure for the number of shortest paths through an edge, and thus a measure for the importance of links.

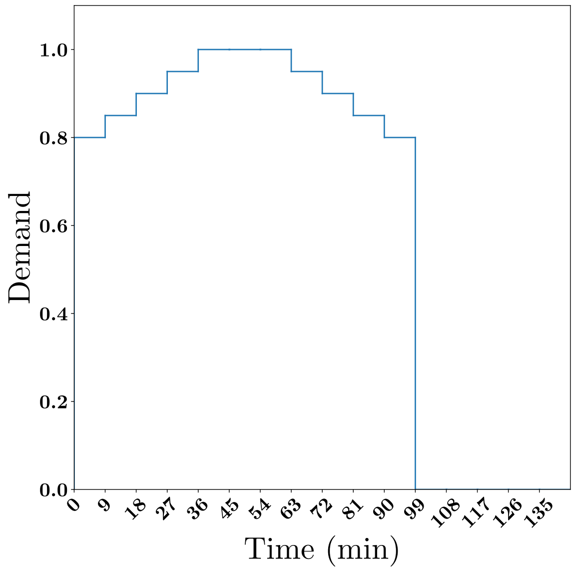


Figure 14.3 – Demand curve of the demand between nodes in the random networks. The exact demand varies per network and node, but the shape of the demand curve is as in the figure for all networks.

It is defined as follows:

$$c_B(e) = \sum_{s,t \in S} \frac{\sigma(s,t|e)}{\sigma(s,t)} \tag{14.2}$$

In this equation S is the set of OD nodes, $\sigma(s,t)$ is the number of shortest paths from s to t, and $\sigma(s,t|e)$ is the number of those shortest paths crossing through edge e.

Lastly, the Python script calculates the resilience of the network, with the TT resilience. It is explained in the literature review, section 3.1. This resilience metric is chosen based on the conclusions of part II.

14.3 Network parameters

The resilience of the networks will be compared with some of their network parameters. In part II, some parameters were already introduced. In the results chapter the following network parameters will be used:

- Average edge betweenness centrality: measure of the number of shortest paths going through an edge, see equation 14.2. The (unweighted) average of all links is used as the network parameter.
- Average number of lanes: the weighted average of the number of lanes of each link, weighted by link length.
- Connectivity: the minimum number of links that need to be removed before the graph becomes disconnected (two separate graphs), also used in part II.

- Link density: the number of links divided by the total possible number of links, if all nodes were directly connected. This metric was also used in part II.
- Number of nodes: the number of nodes in the network, each network as nine OD nodes, but when links cross extra crossing nodes are added.
- Total lane length: the sum of all link lengths, multiplied by the number of lanes that link has.

There are also two network parameters which are affected by traffic, and not exclusively based on network structure. These parameters are added to look at the performance of the networks. These parameters are:

- Average link saturation (in the normal situation): the inflow of a link divided by the saturation flow of the link is defined as the link saturation. The weighted average by link length is used as the network parameter.
- Total distance travelled (in the normal situation): the distance all vehicles have travelled, in the situation without the incident.

There are also some other network parameters used which are only presented in the appendix, the explanation of those is also in appendix D.

14.4 Regression

A linear regression analysis is done to analyse the resilience results. The regression is done with SciPy stats (Scipy (2023b)). The *linregress* module calculates a least-squares regression with the regression values and their corresponding network parameter values.

A multiple regression analysis is done with SciPy optimize (Scipy (2023a)). The *curve_fit* module was used to fit the line in equation 14.3 with the regression (R) and three different network parameters (x_i), connectivity, number of nodes and total distance travelled.

$$R = \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 + \beta_4 \tag{14.3}$$

Before doing the multiple regression, the parameters are min-max normalized using this formula:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{14.4}$$

Where x is the the network parameter and x' is the the normalized parameter, between 0 and 1.

Some statistics were used to calculate the statistical significance, and the correlations between parameters. The explanation of this is in appendix E.

15 Random Networks - Results

15.1 Network generation

266 networks were generated, but some were removed from the data set because there were still vehicles in the origin. In total 95 of the 266 networks had vehicles in the origin, in some networks this was only a few hundred vehicles for a few time periods, and for some a lot of vehicles in all time periods. Vehicles in the origin will impact the resilience, which is based on travel time, as discussed in part II. For this reason networks where there are more than 4500 vehicles in the origin in total over all time periods were removed from the data set. This number is chosen because it is roughly five percent of the total number of vehicles (around 900,000). In the end, 45 networks were excluded from the data.

A few of the networks that were created are presented in figure 15.1.

The average network parameters for the three different network types are presented in table 15.1. For most of the parameters, the average of all medium density networks and low density networks are very similar.

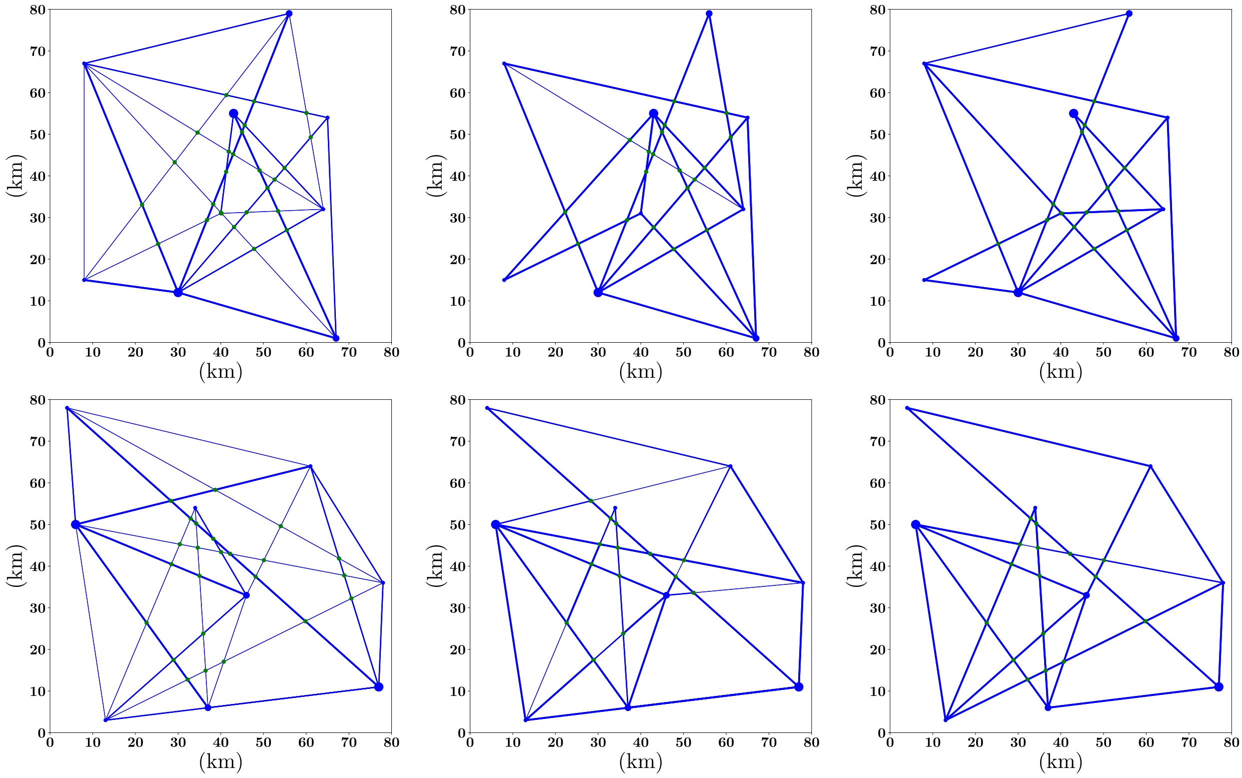


Figure 15.1 – Two sets of random networks. For each set of nodes (all the same in each row) three different networks are created, with high, medium and low link density (left to right).

	High link density	Medium link density	Low link density	Average
Average edge betweenness centrality	1.198	2.058	2.368	1.883
Average number of lanes	2.778	3.608	3.934	3.449
Average link saturation (normal situation)	0.219	0.244	0.242	0.235
Connectivity	3.329	1.957	1.692	2.317
Density	0.621	0.475	0.431	0.508
Number of nodes	38.356	25.771	23.5	29.127
Total distance travelled (normal situation) (km)	6248937.456	6510562.769	6600004.784	6455711.318
Total lane length (km)	2797.368	2779.938	2786.362	2787.963

Table 15.1 – Average network parameters for the three types of networks, High, Medium and Low density.

15.2 Resilience

The resilience results of the random networks are presented in figure 15.2. There are some other parameters analysed, the results of which are included in appendix D.

From these figures, average edge betweenness centrality, average number of lanes, density and number of nodes seem to have a positive relation with resilience. Connectivity seems to have a negative relation with resilience. For the other three parameters it is not clear whether there is a relation.

To see whether the spread of the resilience depends on the resilience of the network, figure 15.3 was added. From this figure it seems that when the resilience is higher, the spread is lower.

The resilience values were also split between networks density types, see table 15.2. Networks with medium and low density are added together, because their densities are not clearly separate as discussed in the previous section. High density networks have a lower average resilience, and medium and low density networks have a very similar average resilience, but the average of the medium density networks is the highest.

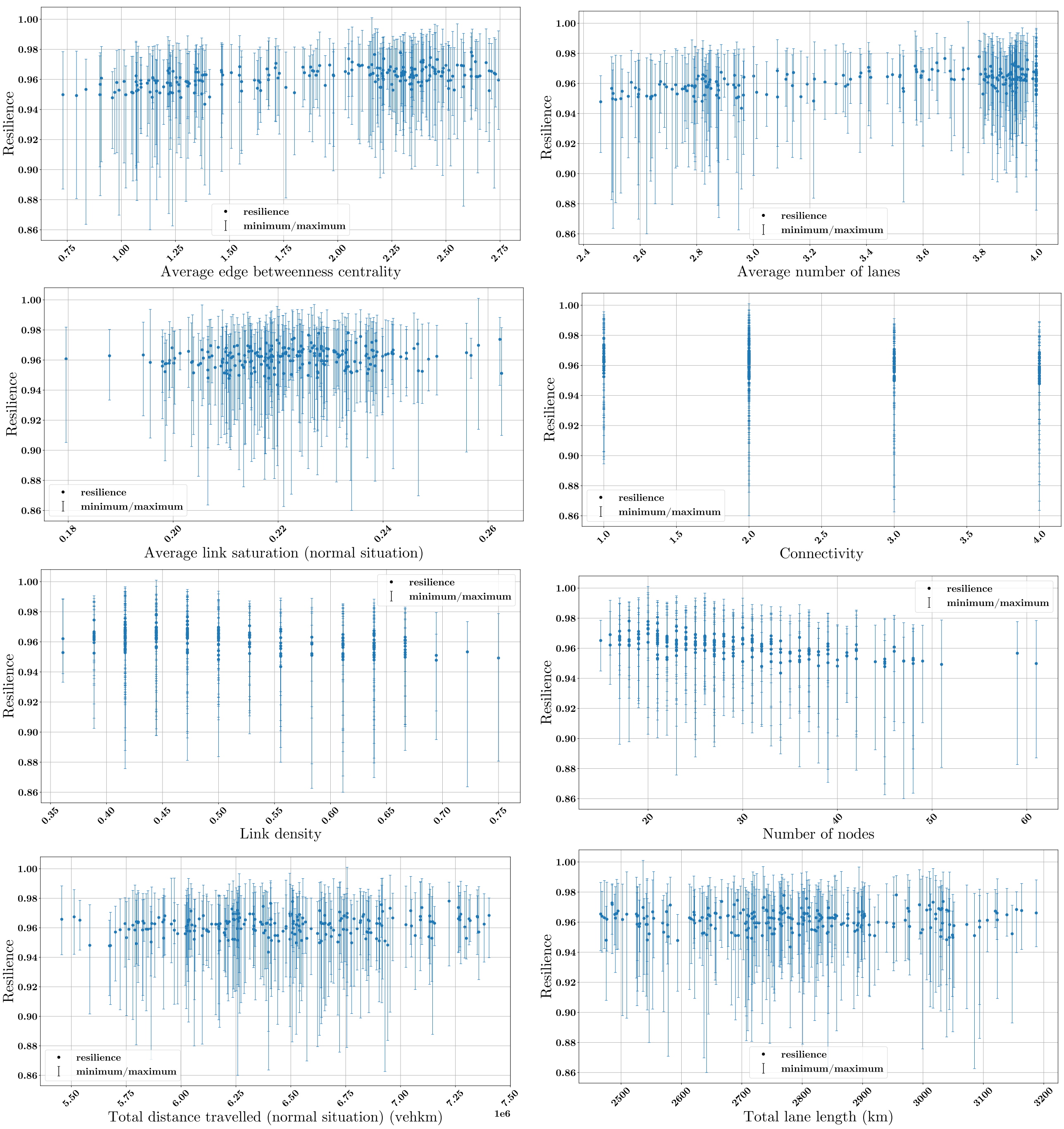


Figure 15.2 – Average, minimum and maximum resilience plotted with network parameters. The average resilience of the network is represented by the dot, and the minimum and maximum is represented by the error bars.

Density	Average	Minimum	Maximum
High	0.957	0.943	0.968
Medium/Low	0.964	0.948	0.978
All	0.962	0.943	0.978

Table 15.2 – Resilience values for different networks densities.

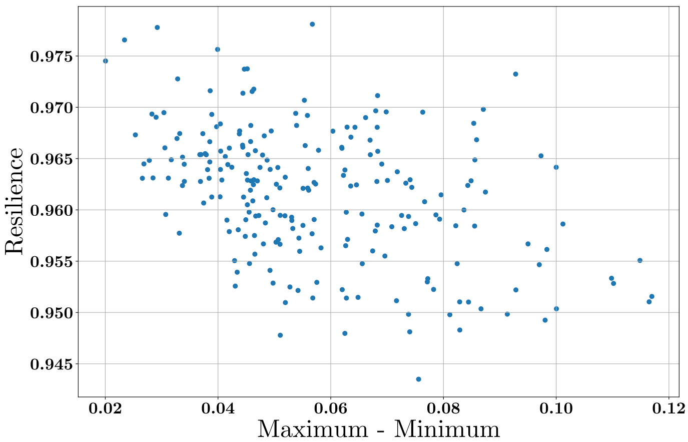


Figure 15.3 – Difference between maximum and minimum resilience plotted with average resilience.

15.3 Regression

This section present the results of the regression analysis on the average resilience and different network parameters. As in the previous section, some parameters are only included in appendix D. This results in the regression lines in figure 15.4. The slopes and intercepts of the lines are written in table 15.3, as well as the R^2-error and whether the lines are statically significant compared to a horizontal line.

The regression line of resilience and total lane length has a slope which is almost zero, and it is also not significantly different from a line with a slope of zero. Thus, there seems to be no relation between total lane length and resilience. The other parameters do have a significant difference from a horizontal line. Higher average betweenness centrality, higher average number of lanes, higher average link saturation and higher total distance travelled result in a higher resilience, the slope is positive. Higher connectivity, density and number of nodes will result in a lower resilience, the slope is negative.

To compare the impact of different network parameters the regression was also done with normalized parameters, which are in the last two columns of table 15.3. The normalized parameters will be used for the multiple regression analysis. The results show that resilience is influenced most by the number of nodes, and least by total lane length.

Network parameter	Slope	Intercept	R^2	1% significant?	Normalized slope	Normalized intercept
Average edge betweenness centrality	$6.266 \cdot 10^{-3}$	0.950	0.296	yes	$1.261 \cdot 10^{-2}$	0.954
Average number of lanes	$6.820 \cdot 10^{-3}$	0.938	0.309	yes	$1.050 \cdot 10^{-2}$	0.955
Average link saturation	$8.016 \cdot 10^{-2}$	0.944	0.029	no	$6.654 \cdot 10^{-3}$	0.958
Connectivity	$-2.652 \cdot 10^{-3}$	0.968	0.151	yes	$-7.955 \cdot 10^{-3}$	0.965
Density	$-3.320 \cdot 10^{-2}$	0.978	0.221	yes	$-1.291 \cdot 10^{-2}$	0.966
Number of nodes	$-4.743 \cdot 10^{-4}$	0.975	0.412	yes	$-2.182 \cdot 10^{-2}$	0.968
Total distance travelled	$2.624 \cdot 10^{-9}$	0.945	0.033	yes	$5.109 \cdot 10^{-3}$	0.959
Total lane length	$-5.146 \cdot 10^{-7}$	0.963	-0.0002	no	$-3.712 \cdot 10^{-4}$	0.962

Table 15.3 – Regression parameters for the relation between resilience and different network parameters.

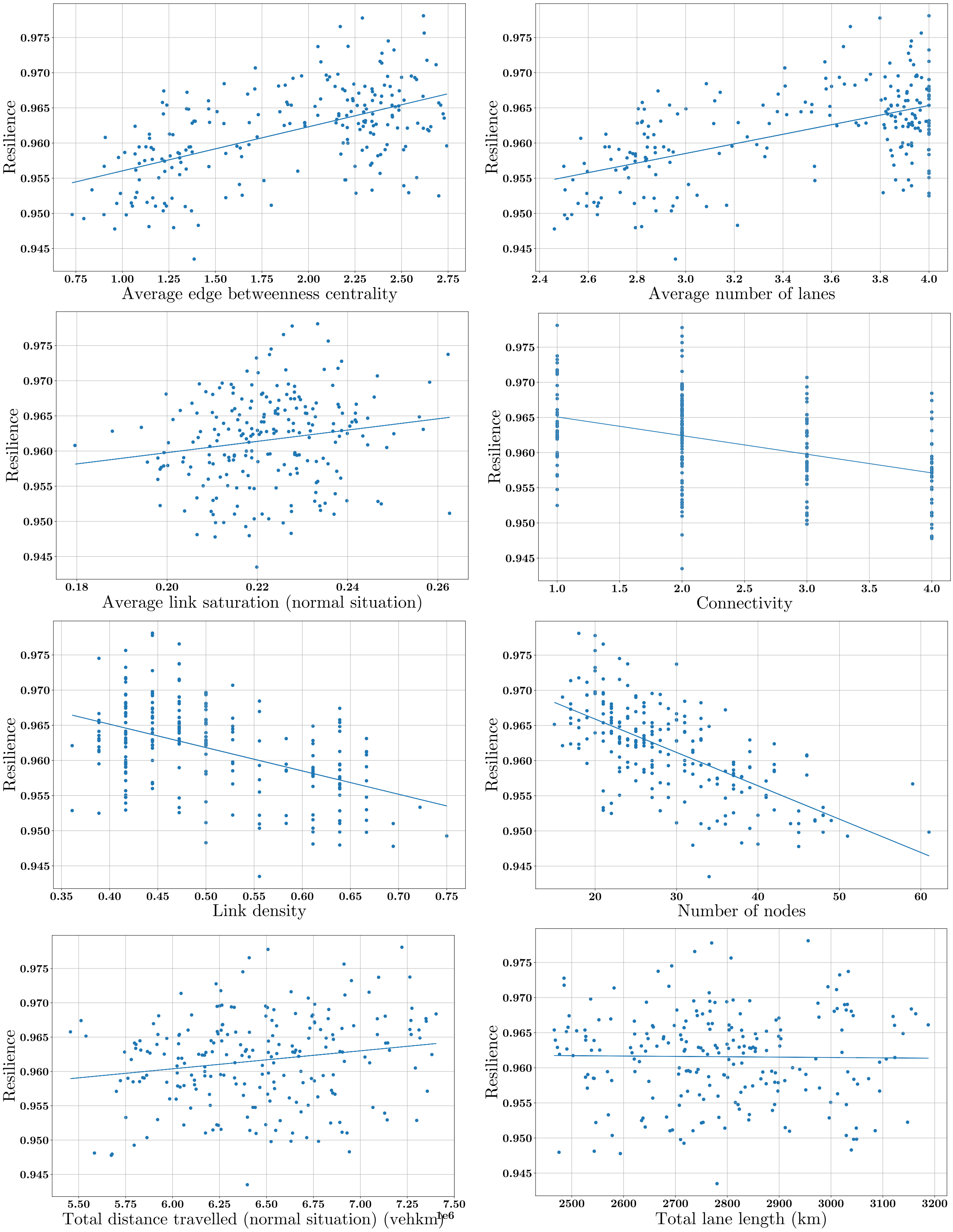


Figure 15.4 – Average resilience with different network parameters, plotted with the resilience lines.

15.4 Multiple regression

A multiple regression was done to compare the impact of different network parameters on resilience. This type of analysis should be done with independent variables, the correlation between parameters is presented in table 15.4. Most parameters have high correlations with each other, average link saturation, total distance travelled and connectivity have the lowest correlation with each other. Thus, the multiple regression analysis is done with these parameters.

	Average edge betweenness centrality	Average number of lanes	Average link saturation (normal situation)	Connectivity	Density	Number of nodes	Total distance travelled	Total lane length
Average edge betweenness centrality	1	0.958	0.388	-0.767	-0.923	-0.856	0.367	-0.046
Average number of lanes	0.958	1	0.337	-0.787	-0.928	-0.836	0.343	-0.020
Average link saturation (normal situation)	0.388	0.337	1	-0.347	-0.454	-0.321	0.525	-0.280
Connectivity	-0.767	-0.787	-0.347	1	0.810	0.586	-0.324	-0.001
Density	-0.923	-0.928	-0.454	0.810	1	0.712	-0.448	-0.007
Number of nodes	-0.856	-0.836	-0.321	0.586	0.712	1	-0.233	0.136
Total distance travelled	0.367	0.343	0.525	-0.324	-0.448	-0.233	1	0.627
Total lane length	-0.046	-0.020	-0.280	-0.001	-0.007	0.136	0.627	1

Table 15.4 – Correlation between network parameters.

The result of the triple regression is in table 15.5. The resilience is influenced most by the total distance travelled, and least by the connectivity, the result of which is not statically significant.

Network parameter	Slope	1% significant
Connectivity	$-3.015 \cdot 10^{-4}$	no
Number of nodes	$3.982 \cdot 10^{-3}$	yes
Total distance travelled	$-8.846 \cdot 10^{-3}$	yes
Intercept	0.963	
R^2	0.224	

Table 15.5 – Multiple regression parameters.

15.5 Incident duration

To calculate the impact of the incident duration on the resilience the experiment was also done with an incident that lasts a shorter time. The other incident parameters were the same, and the criteria for excluding networks with more than 4500 vehicles in the origin over all time steps total was also the same. There are six more networks included, for a total of 227.

The results of the regression for these shorter incidents is plotted together with the regression of the longer incidents in figure 15.5. The regression data is in table 15.6, including the difference between the slope and intercept for a longer and shorter incident (long incident minus short incident).

From the figures and the table a clear difference can be seen: the resilience is higher when the incident is shorter. This is most clear from the difference in intercept, but for most network parameters there is also a difference in the slope.

Network parameter	Slope	Intercept	R^2	1% significant?	Difference slope	Difference intercept
Average edge betweenness centrality	$4.503 \cdot 10^{-3}$	0.963	0.252	yes	28.134%	-1.352%
Average number of lanes	$4.930 \cdot 10^{-3}$	0.954	0.269	yes	27.715%	-1.709%
Average link saturation	$5.172 \cdot 10^{-2}$	0.960	0.020	no	35.478%	-1.679%
Connectivity	$-1.906 \cdot 10^{-3}$	0.976	0.127	yes	28.118%	-0.806%
Density	$-2.353 \cdot 10^{-2}$	0.983	0.182	yes	29.116%	-0.472%
Number of nodes	$-3.490 \cdot 10^{-4}$	0.981	0.371	yes	26.419%	-0.602%
Total distance travelled	$1.777 \cdot 10^{-9}$	0.960	0.025	no	32.276%	-1.587%
Total lane length	$-2.652 \cdot 10^{-7}$	0.972	-0.0001	no	48.458%	-0.917%

Table 15.6 – Regression parameters for the relation between resilience and different network parameters, for the shorter incident. The relative difference in regression parameters between the longer and the shorter incident is also included.

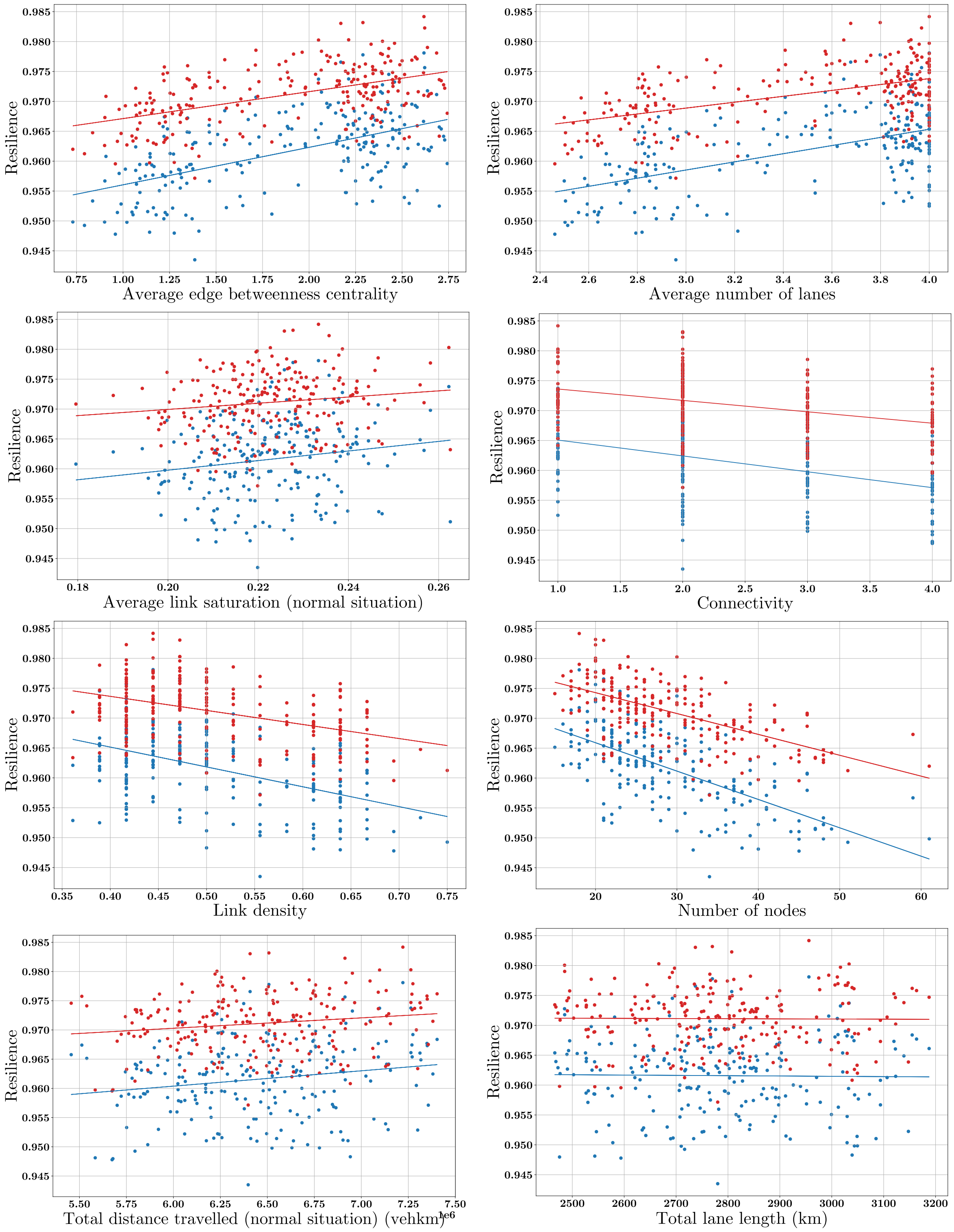


Figure 15.5 – Average resilience, and regression lines for the long and short incident duration. The short incident is plotted in red, the longer incident in blue.

16 Random Networks - Discussion

16.1 Resilience

In this experiment, 266 networks were simulated to measure their resilience. 45 of these networks were excluded from the analysis due to excessive vehicles in the origin, which is a little over 15% of the networks. Vehicles are unable to leave the origin when the link going out of the origin is too congested. This is most likely caused by the way the demand is divided over the origins. In future research it might be better to determine the distance in the gravity model in another way than the Euclidean distance between nodes, for example based on travel time or distance based on shortest path. Even though there is only a constraint on the maximum demand per time period (as explained in section 14.2), the total demand of the networks is very similar. It ranges from 899575 to 899639, which is a range of less than 100 vehicles, which makes the experiments more comparable.

In the five node networks the average resilience ranged from 0.94 to 0.99, the range of the random networks is similar, from 0.94 to 0.98, see figure 15.2. These random networks are bigger than the five node networks, but there are also more incidents. Instead of one link with an incident, 10% of links have an incident. Although, the percentage of links is similar to the five node networks where one link is between 5% and 12.5% of the network. Not all links are tested, but random links are chosen 8 times. To make sure there is a good minimum and maximum included, there are two more simulations. One with the 10% links with the highest edge betweenness centrality, and one with the 10% of links with the lowest edge betweenness centrality. It is not always the case that these are actually the simulations with the lowest/highest resilience. Out of the 221 included networks, 73 times (or 33%) the links with the highest betweenness centrality did not result in the lowest resilience, and 144 times (65%) the links with the lowest betweenness centrality did not result in the highest resilience. A reason for this is that the edge betweenness centrality is based on shortest paths, while in the simulation vehicles may choose a different route if there is congestion. Another reason is that the links crossing each other can result in very short links, an incident in those might have a smaller impact on the rest of the network, because a detour is likely nearby. Also, depending on the link the detour will be longer or shorter, or not even possible, which will also change the impact.

The average resilience values split by link density in table 15.2 shows a difference between high and medium/low density networks. The high density networks have a lower resilience than the medium and low density networks. The low and medium density type networks are added together because their range of link density is very similar.

From figure 15.3 it is clear that there is a relation between the average resilience and the difference between the maximum and the minimum resilience. A higher resilience corresponds to a lower difference between the maximum and the minimum. A lower difference means that it matters less which links are chosen for the incident. This can be explained by the medium and low density networks performing better than the high density networks. The lower density networks have a lower number of links, which results in more equal links. There are less link crossings, so fewer very short links, and more links have the maximum number of lanes (four).

16.2 Regression

The regression results of the relation between resilience and density, number of nodes, total link length, average number of lanes and connectivity can all be used to draw the same conclusion: networks with less links that have more lanes have a higher resilience than networks with more links with fewer lanes. Networks with a lower density will have a lower number of nodes, lower total link length, higher average number of lanes and a lower connectivity, which all result in a higher resilience, according to the regression results (table 15.3 and figure 15.4). This result was also clear from the average resilience of the high and medium/low network types. A reason that networks with lower density have higher resilience is that the links in these networks have more lanes on average, the queues on them will not spill back as fast as in links with fewer lanes. The incident will thus have a more localised impact. In future research this theory could be proved by not only looking at what happens at a network level, but also what happens at a link level.

It should be noted that networks with a higher resilience do not necessarily perform better. This is shown by the relation between resilience and total distance travelled, which is positive. If the total distance travelled is higher, vehicles have to travel more kilometers to get to their destination, since demand is almost the same across networks. In networks with a higher density, there are more links so there are more direct routes between origins and destinations. In networks with lower densities vehicles will take more of a detour to their destination. Total distance travelled does not only depend on the number of links, but it also depends on the distance between nodes. There are many vehicles, so even a small difference in network size could result in a higher total distance travelled.

The performance of the network can also be measured with average link saturation, which seems to be somewhat higher for higher resilience, although the relation is not 1% statically significant. If the link saturation is higher there is a higher chance of congestion when demand is higher. The relation between resilience and average links saturation is probably not statistically significant in this experiment, because of the small range of average link saturation in the networks. These relations are also illustrated by the correlations (table 15.4). Density and total distance travelled have a correlation of -0.448, and density and average link saturation have a correlation of -0.454. This means that lower density results in a higher total distance travelled and a higher average link saturation.

There is no regression relation found between resilience and total lane length in this experiment, which indicates that network size does not impact resilience. Total lane length is a measure for network size, because there will be no more links/lanes generated after a certain threshold is reached, based on the total length of all links that could be generated. It is interesting that there is no relation, because demand is almost the same for all networks (the difference is less than 100 vehicles). The total capacity of a network with more lane length is higher, so it would be expected that these networks perform better, but as discussed before, better network performance does not mean better resilience. Right now all networks are created on a plane of 80 by 80 kilometres, so all networks still have a similar size. To test if there is really no relationship between network size and resilience, networks on smaller and larger planes could be compared with these results. It is also possible that if the total demand is higher, differences in total lane length would become more evident.

The R^2 error of the regression is between 0.033 and 0.412 for the statically significant parameters, which is not very high. The closer the error is to 1, the better the model fits the data. The R^2 error is highest for number of nodes, which also has the highest normalized slope. The regression values are statistically significant, with the exception of the total lane length. This means that there is 99% probability that the data will reject the null hypothesis, that there is no relation between the network parameter and resilience. It can be concluded that there is a positive/negative relation between the network parameters and resilience (except the total lane length). The data is not significant enough to state the exact rate with which the parameters and resilience depend on each other. If this were possible, the rate would only be for the exact incident used in this experiment, which is not entirely realistic. The chances of the exact same incident happening in 10% of the links in a network are very low. A different incident will result in a different slope and intercept, as is illustrated by the results of a different incident duration.

16.3 Multiple regression

A multiple regression analysis was done to find the influence of connectivity, number of nodes and total distance travelled on resilience, see table 15.5. These three parameters were chosen because they have little correlation in comparison to other parameters, and their regression results are statically significant. The correlations between network parameters are in figure 15.4. Total distance travelled has the most influence on resilience according to these results, and connectivity the least. The latter does not have a statically significant influence on the resilience, which means that the regression result would be the same if this parameter was excluded. This is different from the normalized slope, where connectivity has a steeper slope than total distance travelled. The results are impacted by the high correlations between the parameters. Number of nodes has a positive relation with the resilience according to the regression, but a negative relation according to the multiple regression. The sign of the slope of total distance travelled also changes. This change is most likely caused by the high correlation between parameters.

16.4 Incident duration

From the figure 15.5 it can be concluded that incident duration does influence the resilience. A longer incident will result in a lower resilience, the intercept is lower. The slope is also different due to the different incident, for some network parameters more than others, based on the height of the slope. The slopes would only be the same if the difference in resilience was the exact same amount for each network. It is more logical that the difference in resilience is based on the height of the resilience, which will result in a different slope. The conclusion that can be drawn from this is that it matters how long it takes to clean up after an incident, the impact of the incident will be greater if it takes longer.

17 Random Networks - Conclusion

The experiment with random networks was done to answer the last research question *Is there a relationship between road network parameters and resilience to accidents in networks with comparable network capacity?* From the results it is clear that there is a relation, most network parameters that were tested have a relation with resilience. It seems that networks with a lower density have a lower resilience. This might be because there is less spillback in these networks, there are more links with four lanes so there is more space for queues in the links. Also there are fewer short links in lower density networks, so there is again more room for queues.

The networks with a higher resilience do not necessarily have a better performance. Networks with a higher resilience have a higher total distance travelled, so vehicles have to travel further to get to their destination.

Incident duration also influences the resilience; the longer the incident takes, the lower the resilience. This means that if there is an incident on the motorway response time is crucial.

In future research it would be interesting to look at the impact of the incident on a link level, to see how the congestion spreads between links. All data gathered about the networks is at the network level, so what exactly happens with the congestion and how it spreads across links is unclear. With more information about the impact of the incidents in the links, the mechanisms that impact the resilience can be studied more closely.

In this experiment there seems to be no relation between network size and resilience. However, all nodes were created on a square of eighty by eighty kilometers. In future research the network generation described in section 15.1 could be changed, to generate nodes on different sized squares. The resilience in these networks can then be compared, to study whether there is a relation between network size and resilience.

Part IV

Conclusions

18 Conclusions and recommendations

18.1 Findings

The aim of this thesis was to answer the question *What are the properties of a resilient road network?* This was done in three steps, first with a literature review to find the aspects of resilience that should be considered, and to find existing resilience indicators. The second step was a small scale simulation with five-node networks, and the last step was a large scale simulation with random networks.

The first sub-research question, *Which aspects of resilience should be considered in this research?*, was answered with the literature search. There are different resilience definitions in the literature, and also different types of disruptions. This thesis considers resilience as the ability of a transport system to resist external disturbances, and quickly return to a normal state after a disruption. This definition includes both the disruption and recovery phase. Only short term disruptions such as accidents and road works are considered.

With a systematic literature search the second sub-research question, *Which resilience indicators are used in the literature?*, was answered. The literature was searched for papers about resilience in road networks with short-term disruptions. Eleven papers were found that presented a resilience metric. These metrics can be placed into three categories, road focused metrics, user focused metrics and metrics that focus on both. Road focused metrics look at the performance of the system on a road level, while user focused metrics look at the performance from the perspective of the user. The papers were evaluated based on whether they look at resilience on a network level, and the number of variables used. Based on this evaluation, two metrics were chosen. A road focused metric, the flow resilience, based on space-mean flow (Amini *et al.* (2018)), and a user focused metric, the travel time resilience, based on travel time between origin-destination pairs (Sohouenou and Neves (2021)). A third metric based on the outflow of the system was also added (see equation 9.2).

These three metrics were used in the five node networks, five networks with the same origin-destination nodes and different link configurations, first presented by Patil and Bhavathrathan (2016). This experiment was done to answer the third and fifth sub-research questions, and to study the difference between the three resilience metrics. The resilience metrics resulted in different rankings of the best networks, so it does matter which resilience metric is used. The travel time resilience was chosen to use in the rest of the research, because it is the best of the three. The flow resilience is not well-suited for the way the experiments are designed. It looks at vehicles that have not reached their destination, and the simulations are done such that the system starts and ends empty, so all vehicles will always reach their destination. The outflow resilience has high peaks, which can give distorted results. These peaks happen because the outflow of vehicles is delayed in the incident situation.

The third sub-research question, *Is there a relationship between road network parameters and resilience to accidents in networks with different network capacity?*, is answered with the results of the experiments with the five-node networks. There seems to be a positive relationship between the tested network parameters and resilience. There were only five data points, so not enough to draw conclusions, especially about which network parameter influences the resilience. This experiment also partially answers the fifth sub-research question, *What is the impact of incident start time and duration on the resilience?*, by looking at incident start time. The shape of the travel time network performance curve changed with different incident start times, except for the network with the highest capacity, which has very little congestion. The impact on the resilience is not as big, except for the most congested network, the networks had the same rankings of which is the most resilient.

The fourth sub-research question, *Is there a relationship between road network parameters and resilience to accidents in networks with comparable network capacity?*, was answered by doing an experiment with random networks. These networks were designed with nine origin-destination nodes representing cities. The nodes are placed on random locations of an 80 by 80 kilometer grid, and there are random links in between the nodes with 2, 3 or 4 lanes. The random links and lanes are generated until a threshold based on the distance between nodes and the number of lane kilometers is reached. The result of 221 networks is that there is a relation between network parameters and resilience. Networks with a higher density have a lower resilience, these networks have a higher number of links and due to that a higher number of crossing nodes, a higher connectivity and a higher average number of lanes. Although the networks with a lower density have a higher resilience, they do not necessarily have a better performance. It was observed that networks with a higher resilience also have a higher total distance travelled and a higher link saturation. By looking at incident duration the fifth sub-research question, *What is the impact of incident start time and duration on the resilience?*, was answered. A longer incident will result in a lower resilience.

18.2 Conclusions

The aim of this thesis was to answer the research question *What are the properties of a resilient road network?* There are several conclusions from the literature. There are different resilience metrics, they were tested with the five node networks, and it was concluded that the same metrics do not result in the same conclusions about which networks are the most resilient.

From the eleven papers used in the literature search there was not much information about the relation between network parameters and resilience. This relation was first tested with the result of the five node networks. Since there were only five networks and thus only five data points, the results were not very clear about which network parameter influence the resilience. It seemed that networks with more links had a higher resilience, which makes sense because all five networks had the same demand and the links had the same characteristics, so networks with more links have more capacity.

The relation between network parameters and resilience was tested further in the experiment with the random networks. These networks gave more clarity, because there are much more data points. The relation of resilience with most network parameters, such as density, number of nodes and average number of lanes, point to networks with a lower density having a higher resilience. The reason for this might be that there is less spillback in these type of networks, congestion will not spread to other links as fast. The lower density networks have less links, which are longer and have more lanes on average than links in higher density networks. Therefore there is more room for congestion in these links. This conclusion differs somewhat from the conclusion of the experiment with the five node networks, where it was concluded that more links results in a higher resilience. The difference between the experiments is in the capacity of the networks, the random networks all have similar capacity while the five node networks have very different capacities. From the results of the random networks, no conclusion can be drawn about the relation between capacity and resilience.

18.3 Recommendations for practice

The random networks represent highway networks, which are loosely based on the Randstad. The conclusion from the experiment with the random networks can thus be used for the highway network in the Randstad. As described in the previous sections, there is a trade off between network performance and resilience. The networks that have a higher resilience, do not necessarily have a better network performance. This is because in the random networks, network capacity is similar. In the five node networks, higher network capacity (networks with more links) did have a higher resilience. The experiment with the random networks concluded that networks with lower density have a higher resilience. Therefore, if the capacity of the network will be improved, the network will be more resilient if it is improved by adding a lane to an existing link, than if it is improved by adding an extra link.

18.4 Recommendations for science

In future work some improvements to the random networks could be made. The network parameters are very correlated, so it is difficult to say which network parameters influence the resilience most. In future research the networks should be designed differently such that the network parameters can be separated. In these experiments no relation between network size and resilience was found, it would be interesting to look at this relation some more. The same random network design could be used, but instead of the random nodes being on a square of eighty by eighty kilometers, different sized squares could be used.

In future research it could be tried to understand the relation between link density and resilience further. This could be done by looking at what happens in the networks at a link level. The results presented in this thesis are at a network level, so it is not clear what exactly happens at a link level, and why networks with lower density are more resilient. By looking at what happens in the links, and how congestion spreads, the theory that lower density networks are more resilient because there is less spillback can be tested.

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Part V

Appendices

Appendix A

Research Paper

Resilience in road networks: relation between network density and resilience

Abstract

The resilience of a road network indicates the magnitude and consequences of a disruption, which can be something like a traffic accident or a flood. The literature is not in agreement about the exact definition of resilience, and the way to quantify it. A literature search is done to look for definitions and resilience metrics. Eleven metrics are found that quantify resilience in road networks to accidents.

To see how density influences the resilience, a simulation with random networks is done. 266 networks with nine nodes in random locations, and random links between them are simulated. It is concluded that networks with a lower density have a higher resilience. This is not only illustrated by the relation between resilience and density, but also by several other network parameters such as average number of lanes and connectivity. A reason that these networks are more resilient is that there is less spillback, the links in the high density networks are longer and have more lanes, so congestion will not spread to other links as fast.

1 Introduction

The national road network is an essential part of most people's daily lives, disruptions on the road happen everyday. They cause injuries and deaths, but they also impact the traffic flow. The resilience of a road network is an indicator for the magnitude and consequences of a disruption.

A disruption can be split into two parts, the disruption phase and the recovery phase, as explained by Zhou and Wang (2019). During the disruption phase the disruption is still active and the network performance goes down, when the disruption ends recovery starts and the network performance goes back up. This results in the resilience triangle, see figure 1. Sometimes only one part of the resilience triangle is used in the resilience definition, but in this paper both parts will be considered, because for short-term disruptions both parts have a large impact on the resilience. The resilience definition of Pan *et al.* (2021) uses both the disruption and recovery phase:

"The abilities of the transportation system to resist and adapt to external disturbance and then quickly return to a normal service level to meet the original travel demand after being disturbed by internal or external factors."

1.1 Research objective

This research aims to answer the question *What are the properties of a road network that is resilient to accidents?* In section 2 some aspects of resilience are discussed, followed by a literature review of resilience to accidents in road networks. Then a study on random networks is done, the methods of which are in section 3, followed by the results in section 4. The discussion and conclusion of the paper are in section 5.

2 Literature review

2.1 Factors influencing resilience

Many types of disruptions exist, ranging from an accident to an earthquake. There are several ways to classify them, Ge *et al.* (2022) list some examples, such as whether disturbances are man-made or natural, whether they are planned or unplanned and whether they have high or low probability. In this paper a distinction is made between short-term and long-term disruptions, based on the two types described by Sullivan *et al.* (2009). The difference between the two types is the ability to restore the functionality of the system before the disruption. For short-term disruptions, such as accidents or a lane closure, the system can easily get back to the state before the disruption. For long-term disruptions, such as earthquakes or floods, there may be a permanent change in the system. A graphic representation of the disruption types is in figure 2. This paper considers only short-term disruptions, because they happen more often and are more relevant for practical applications in the Netherlands.

2.2 Resilience metrics

A literature search was done for literature that presents a resilience metric for resilience in road networks to short-term disruptions. Eleven papers that meet the criteria were selected. The resilience metrics are all very different, but they can be placed into three categories: user focused metrics, road focused metrics and metrics that are both road and user focused. User focused metrics focus on the performance from the perspective of the user, road focused metrics have a focus on road level performance.

Four of the eleven papers in the literature search presented a user focused metric. Three of these are by the same authors (Bhavathrathan and Patil (2015b), Bhavathrathan and Patil (2015a), Patil and Bhavathrathan (2016)), and use a metric based on the expected system travel time. In the Patil and Bhavathrathan (2016) paper the metric is tested in five small networks with five nodes and different topologies. The writers concluded that the resilience increased with the number of links in the network.

The other user focused metric, presented by Sohouenou and Neves (2021), is based on the travel time between OD pairs. The resilience of the network is the integral of the travel time over the time of the disruption:

$$\mathrm{RE} = \frac{\int_0^{\tau_H} \mathrm{NP}(\tau)d\tau}{\tau_H} \tag{1}$$

$$\mathrm{NP} = \sum_w k_w \left(\frac{TT_0^w}{TT_d^w}\right) \tag{2}$$

In these equations w indicates an OD pair, k_w is a weighting factor (the ratio between the demand for w and the total network demand), TT_0^w are the travel times along w in

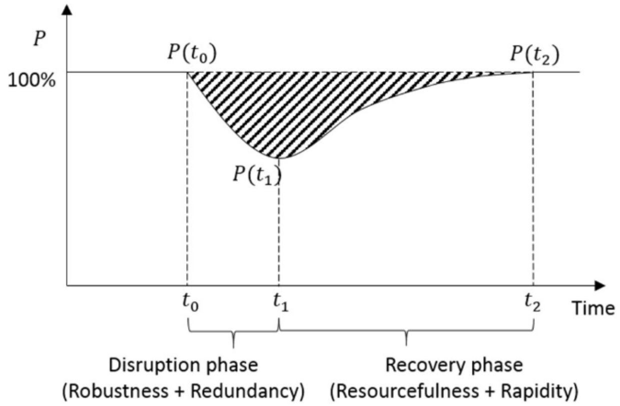


Figure 1 – The resilience triangle with two phases of resilience measurement. P indicates the performance of the system. (From Zhou and Wang (2019))

an undisrupted situation and TT_d^w are the travel times along w during a disruption. The network performance indicator (NP) is integrated over the time elapsed since the start of the recovery, τ, for the duration of the time horizon, from 0 to τ_H.

Of the eleven papers found in the literature search, four present a road focused metric. Two of these metrics are split into two parts, the first is by Calvert and Snelder (2018). The writers use one equation for the resistance and one equation for the recovery of a road section during a disturbance, both based on the flow and the speed. Nogal and Honfi (2019) also split their resilience metric into two parts, one part for the perturbation, based on the flow, and one part for the recovery, based on the recovery time. Yu *et al.* (2022) integrate the ratio of the free flow speed and the speed during the disruption over the time of the disruption.

Amini *et al.* (2018) look at the difference of the performance in the normal situation and the situation during the incident to find the resilience index RI:

$$\mathrm{RI} = \mathrm{PI}_n - \mathrm{PI}_a \tag{3}$$

$$\mathrm{PI} = \frac{q^w \times L}{\mathcal{L}} \tag{4}$$

The performance indicator (PI) is based on the weighted space-mean flow q^w, the total network length L, and the average trip length in the road network $\mathcal{L}$.

There were also three metrics in the literature search that present metrics that have both user focused and road focused characteristics. The metric by Flores-González *et al.* (2022) is based on the product of the flow and the travel time in links. Serdar and Al-Ghamdi (2021) present a resilience metric based on the travel time and the betweenness centrality of links (the number of shortest paths through a link divided by the total number of shortest paths). Mehrabani *et al.* (2022) present two metrics, the travel time resilience R_T and the speed resilience R_S:

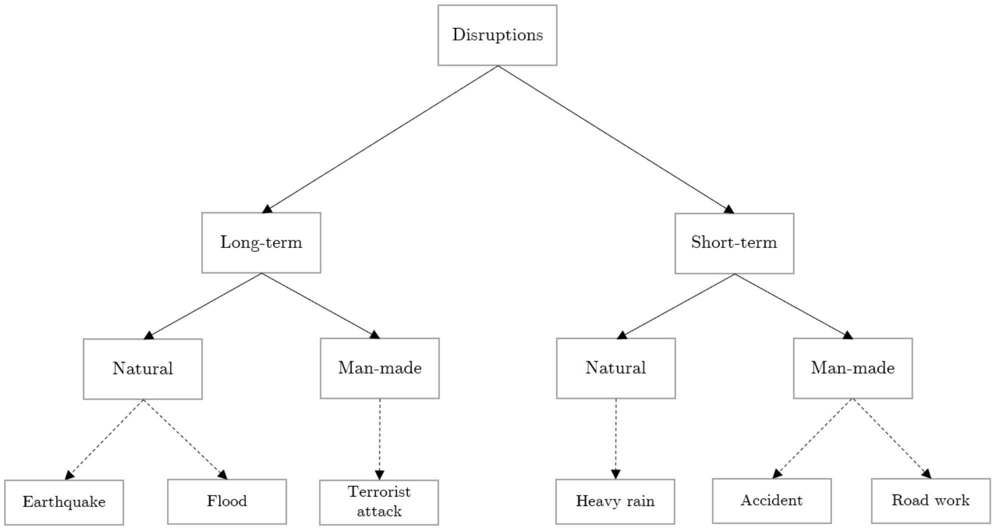


Figure 2 – A graphic representation of the disruption types in a road network. The first distinction is made between long and short-term disruptions (as done by Sullivan et al. (2009)), then the distinction is made between natural and man-made disruptions (as done by Ge et al. (2022)). Some examples are listed at the bottom.

Network parameter	Slope	Intercept	R^2
Density	-3.320 $\cdot 10^{-2}$	0.978	0.221

Table 1 – Regression parameters

$$\mathrm{R_T} = \frac{\text{Travel time (abnormal conditions)}}{\text{Travel time (normal conditions)}} \tag{5}$$

$$\mathrm{R_S} = \frac{\text{Mean speed (normal conditions)}}{\text{Mean speed (abnormal conditions)}} \tag{6}$$

3 Methods

To test the relation between network parameters and resilience MARPLE (TrafficQuest (2023)) simulations were done with random networks. The random networks are based on motorway networks. First, nine random nodes are created, with a random location on an 80 by 80 kilometer grid, at least 20 kilometers apart. The nodes have a size (small, medium or large) representing the size of the city, the size influences the demand to and from the city, as well as the probability of links being created. Between random links are created, with a higher probability of links being created between larger cities. The links can have 2, 3 or 4 lanes, and the larger the two cities are, the larger the probability for four lanes. For each set of nodes, three different networks are created, one with higher density, one with lower density and one in between. For the higher density networks, new links will be created until the threshold based on the total number of lane kilometers is reached. The lower density networks will stop creating new links once the network is connected, after that it will create extra lanes (up to four) until the threshold is reached. The networks with medium density have a 50% probability of creating a new link or adding an extra lane after the threshold is reached.

The demand in the origin-destination matrix is based on a gravity model.

$$t_{ij} = p_i \frac{p_j \cdot \frac{1}{d_{ij}}}{\sum_j p_j \cdot \frac{1}{d_{ij}}} \tag{7}$$

Where p_i is the production/attraction factor of a node, the weight of which is based on the size of the node. Production/attraction of large node is six times that of a small node, and production/attraction of a medium node is three times larger than that of a small node. d_{ij} is the Euclidean distance between node i and node j. t_{ij} is the factor for the number of trips between node i and node j, which is multiplied by the maximum demand of a time period to get the OD matrix. The total demand varies per time step, it has a trapezoid shape. The exact demand at the peak depends on the trip factor, but it is no higher than 10000.

Incidents are then simulated in the random networks. In each network an incident occurs in 10% of links, which lasts 63 minutes, the speed is reduced to 52.4 km/h, half of the lanes are closed and the saturation flow in the remaining lanes is reduced by 12%. These random incident links are chosen eight times, to have a good selection of links. To make sure there is a good minimum and maximum resilience outcome, a simulation is done where the 10% of links with the highest edge betweenness centrality have an incident, and a simulation is done where the 10% of links with the lowest edge betweenness centrality have an incident.

Lastly, with the results from the simulations with and without incident, the resilience is calculated.

4 Results

266 networks were simulated, and their resilience was calculated. In some of the simulation there are vehicles left in the origin due to too much congestion. This may impact the results, because travel time is counted starting when vehicles leave the origin, and the resilience metric is based on travel time. Vehicles in the origin are measured per time period by MARPLE, and if there are more than 4500 vehicles (around 5% of the total demand) in total the network is excluded from the data. 45 networks are removed, and the average resilience of each network is plotted with a regression line in figure 3. The regression parameters are in table 1.

From the figure and the table it seems that networks with a higher density have a lower resilience. The R^2 of the prediction is not very high, but the line is statistically significant compared to a horizontal line. There is not a clear difference in density between networks that were created with lower and medium density. The high density networks have an average resilience of 0.957, which is lower than the average of the medium/low density networks, which is 0.964 on average.

5 Discussion and conclusion

There is a relation between network density and resilience, networks with a higher density have a lower resilience. This conclusion is also supported by the relation with other parameters such as total link length and connectivity, see Baert (2023). Networks with a lower density will have less links, because of the way the networks are designed. Due to this, links are longer (there are fewer places where they cross and separate) and have more lanes on average. Because of that there is less spillback, and the incident does

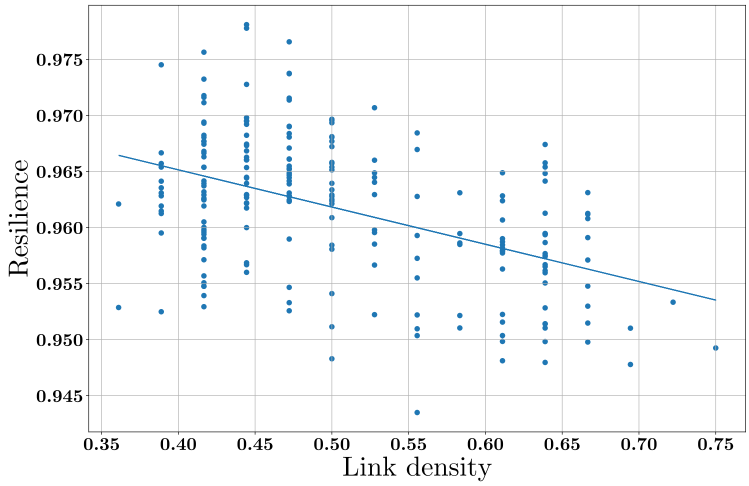


Figure 3 – Regression fit

not affect the other lanes as fast if there were more links with fewer lanes. The impact of the incidents stays more localized, and thus fewer vehicles are affected, and the resilience is higher.

The R^2 error is high enough to state there is a negative relation between network density and resilience. It is difficult to state what the exact relation is, the regression slopes calculated here are only valid for this type of incident. The probability of the exact same incident happening at the exact same time in 10% of links is not very high. A different incident will result in a different slope and intercept for the regression (Baert (2023)).

It should be noted that networks with a higher resilience do not necessarily perform better. The resilience is calculated based on the ratio between travel time in the normal situation and travel time of the incident situation. If the travel time is already long, this is not taken into account in the resilience. Furthermore, if the same absolute amount of travel time is added in all networks, the relative impact is lower in networks where travel time is longer, and resilience would then be higher.

To learn more about the reasons why resilience is higher when network density, in further research the network could also be studied on a link level, instead of only on the network level. The theory that the resilience is higher because there is less spillback could then be tested.

Appendix B

Incident timing

This chapter includes the figures for the performances and resilience values for incidents starting in different time periods. The network performance based on travel time, as described by Sohouenou and Neves (2021) is in figure B.1.

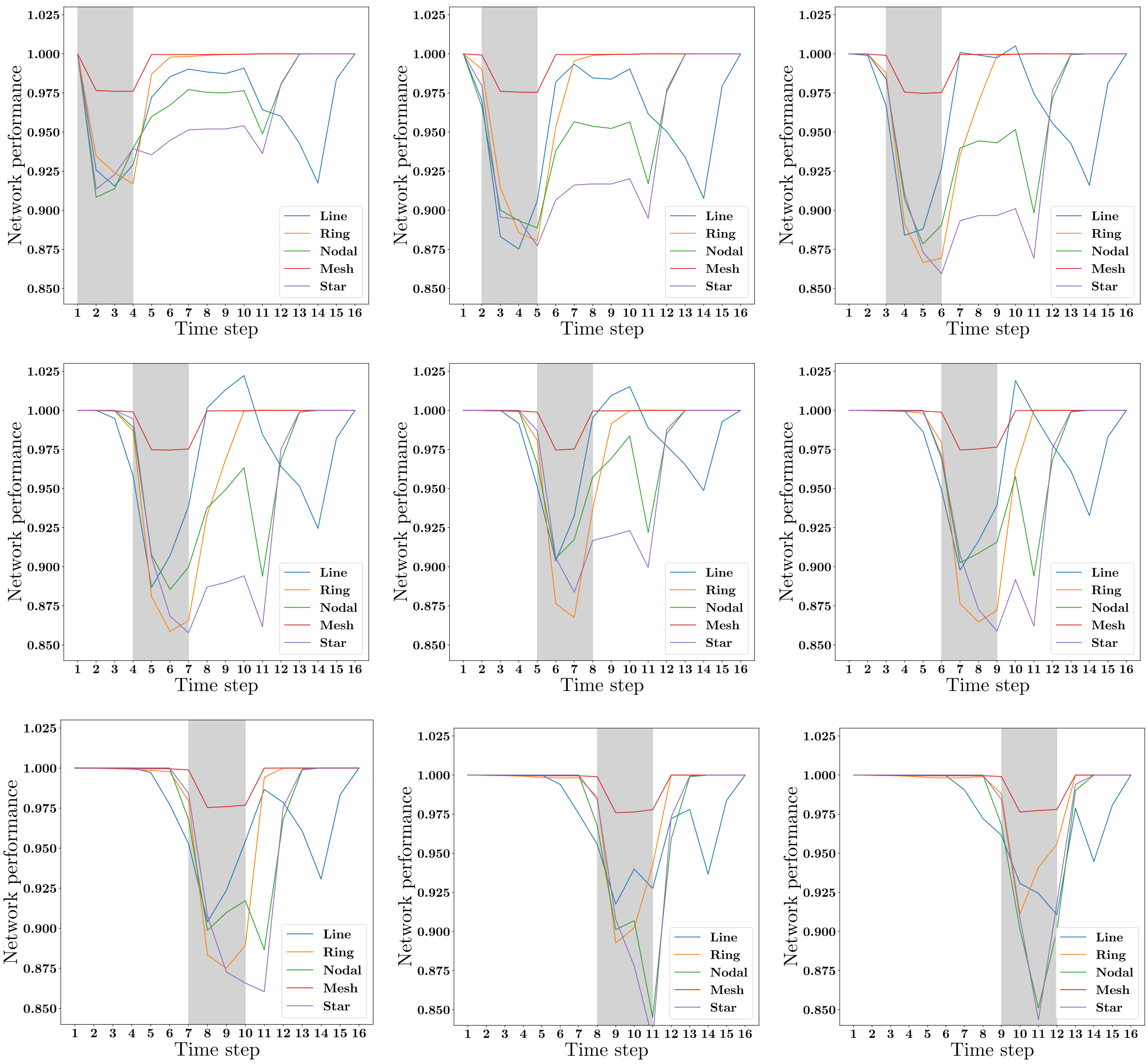


Figure B.1 – TT network performance for different incident timings.

The network performance based in the outflow is in figure B.2. It is calculated according to equation 9.1.

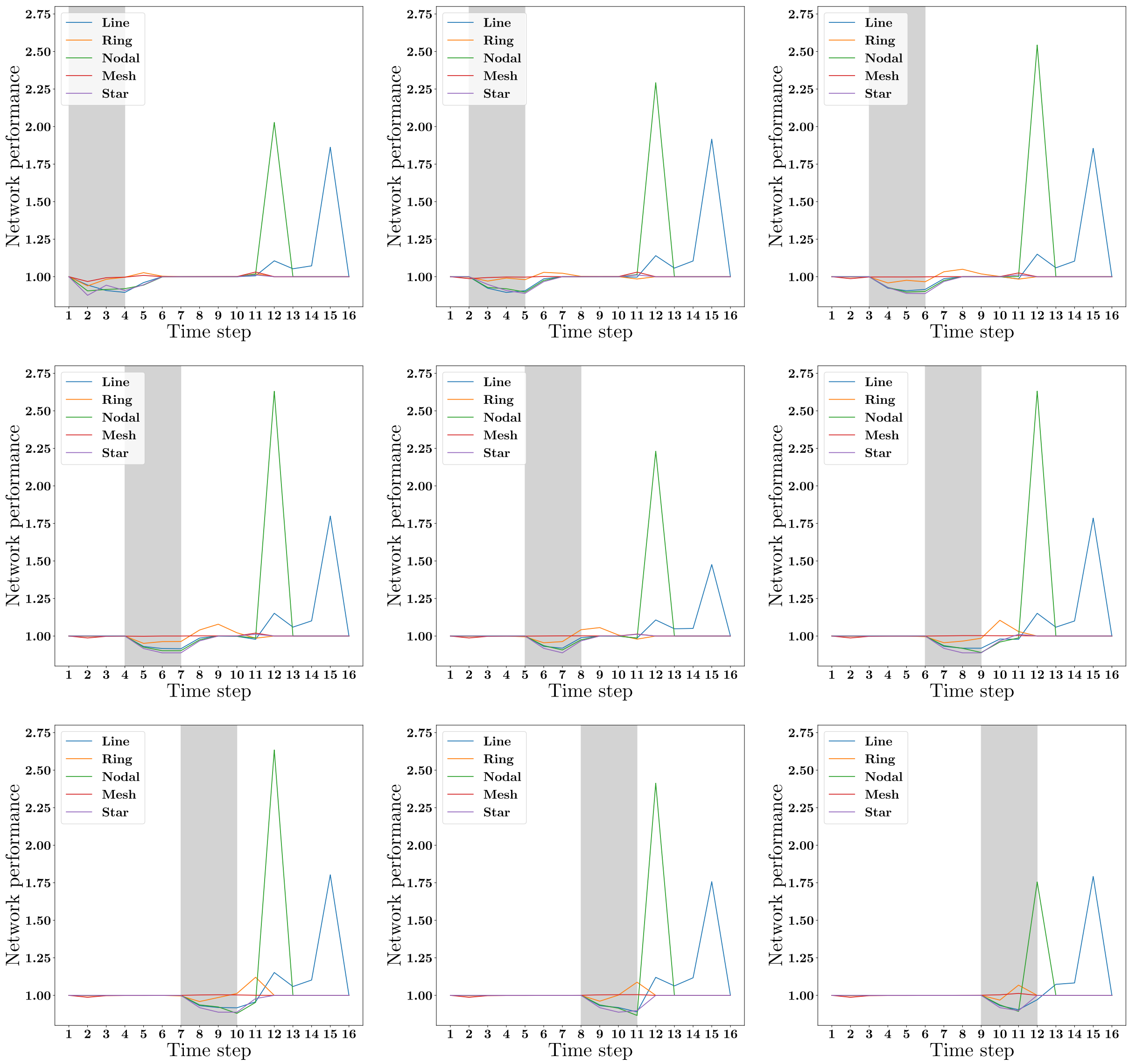


Figure B.2 – Network performance based on outflow for different incident timings.

The total network outflow in each time period is in figure B.3

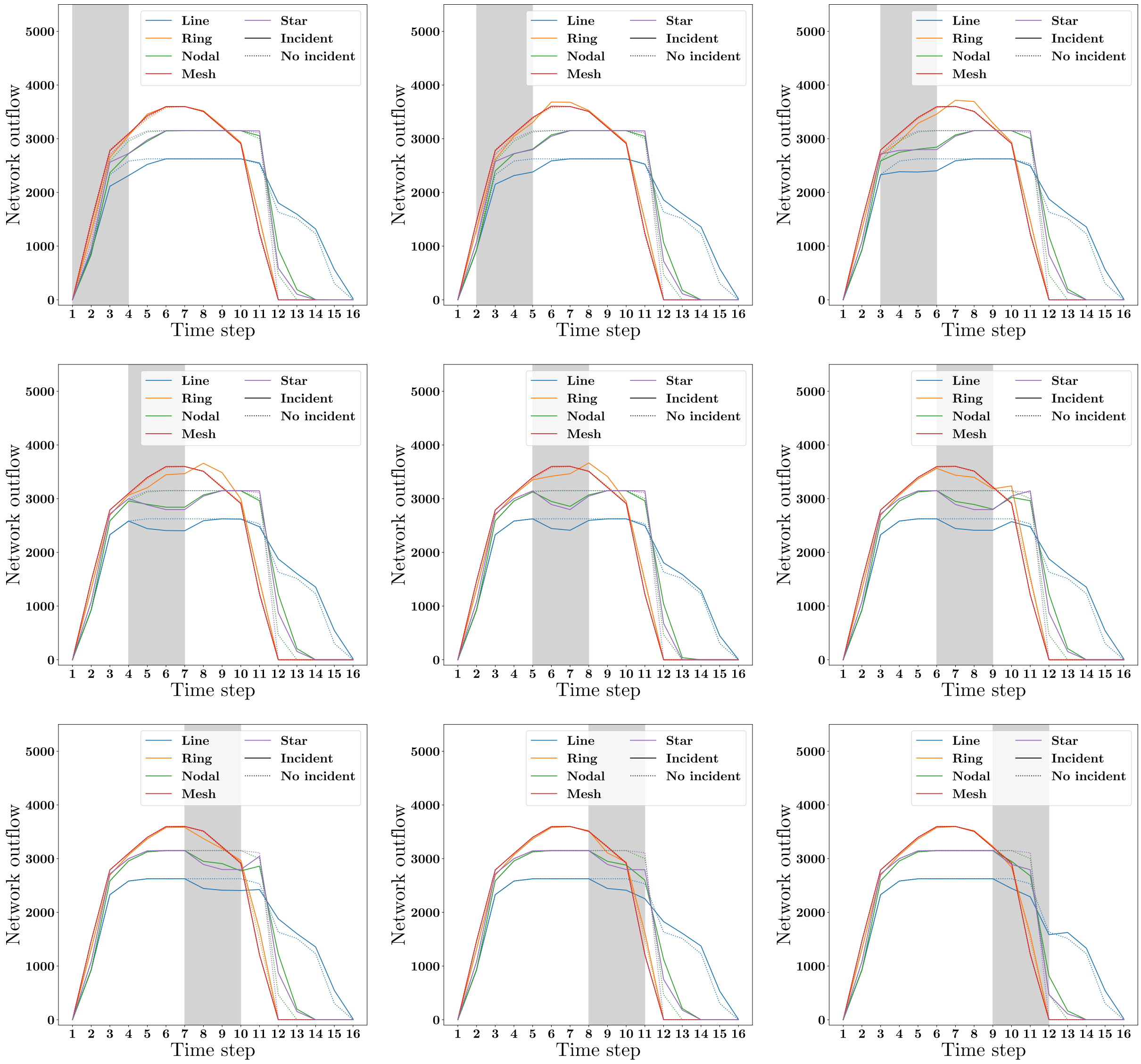


Figure B.3 – Outflow of the network for different incident timings.

Figure B.4 shows the total queue length in the network with and without the accident.

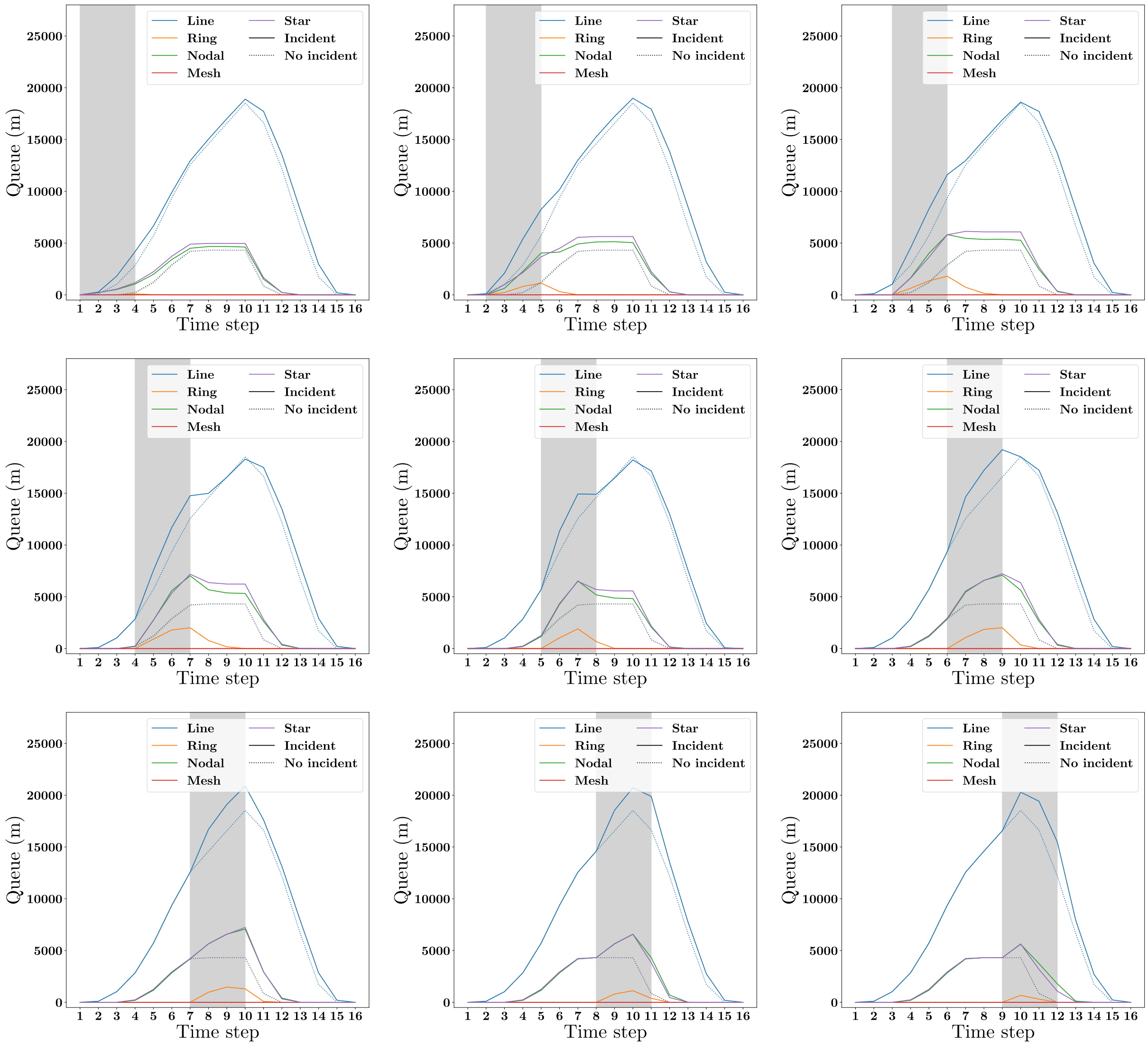


Figure B.4 – Total queue length in the network for different incident timings.

Figure B.5 shows the total number of vehicles still in the origins in the network with and without the incident.

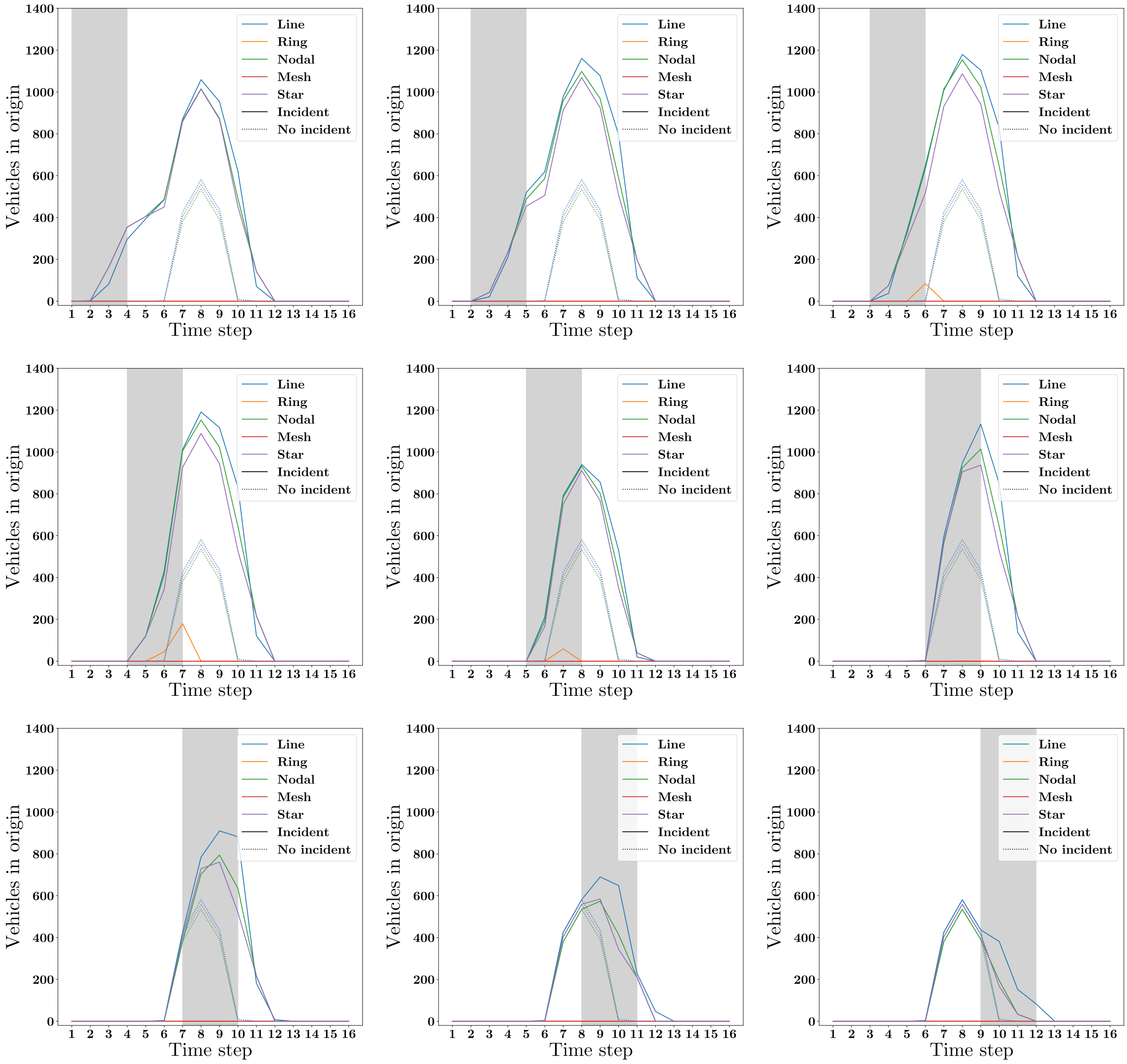
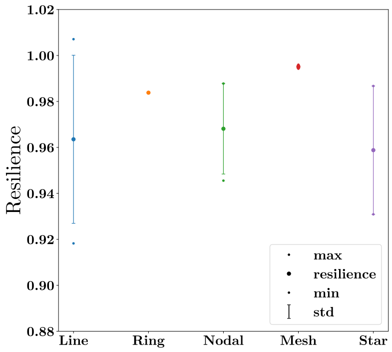
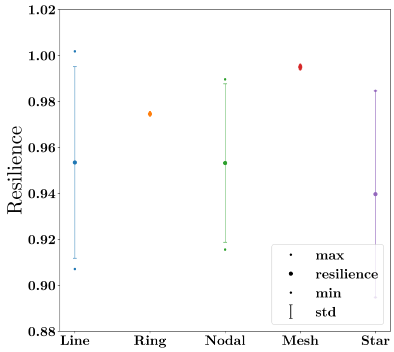


Figure B.5 – Total number of vehicles in the origin for different incident timings.

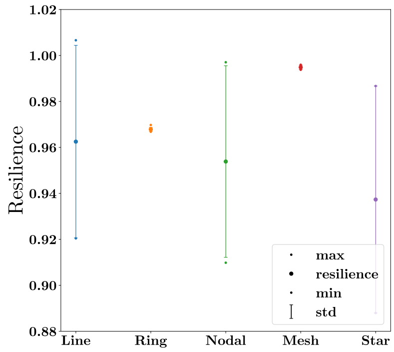
The TT resilience is shown in figure B.6 for each of the nine incident start times.



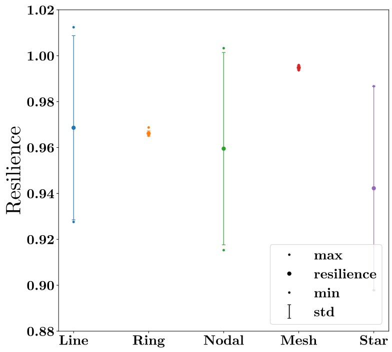
(a) Incident in time period 1, 2, 3



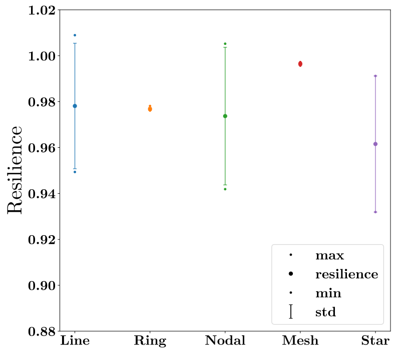
(b) Incident in time period 2, 3, 4



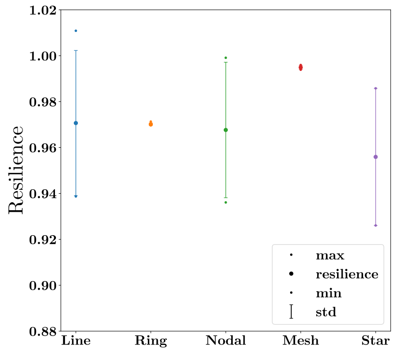
(c) Incident in time period 3, 4, 5



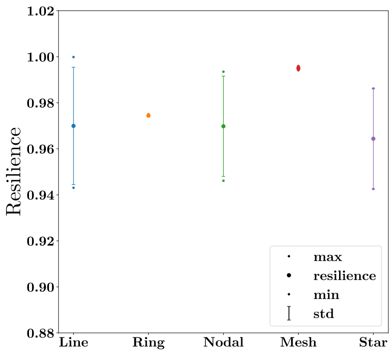
(d) Incident in time period 4, 5, 6



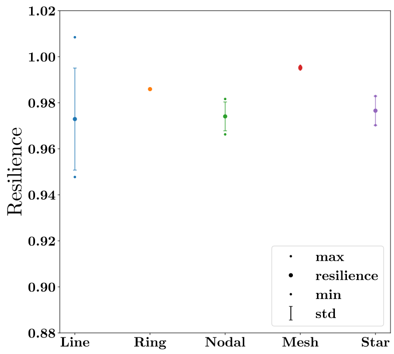
(e) Incident in time period 5, 6, 7



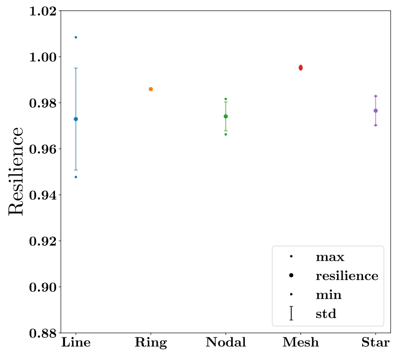
(f) Incident in time period 6, 7, 8



(g) Incident in time period 7, 8, 9



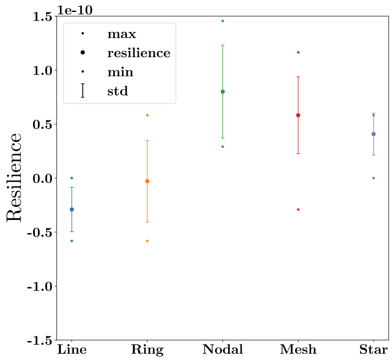
(h) Incident in time period 8, 9, 10



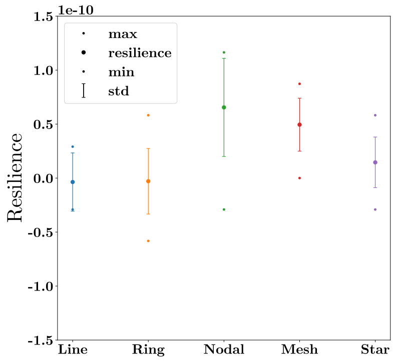
(i) Incident in time period 9, 10, 11

Figure B.6 – Travel time resilience for different incident timings.

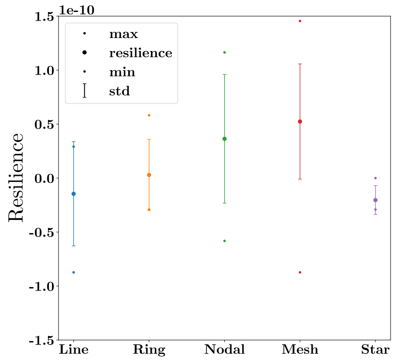
The flow resilience is shown in figure B.7.



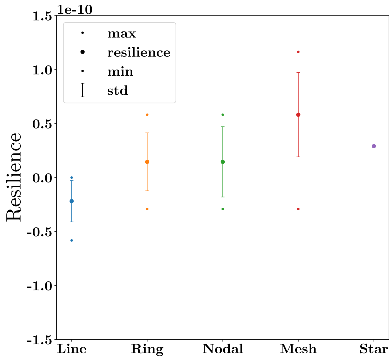
(a) Incident in time period 1, 2, 3



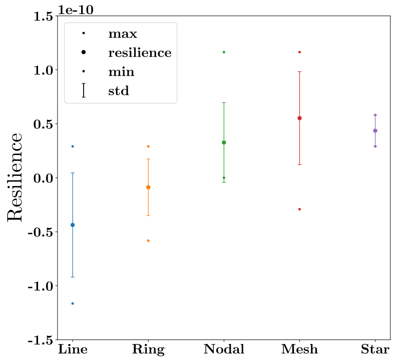
(b) Incident in time period 2, 3, 4



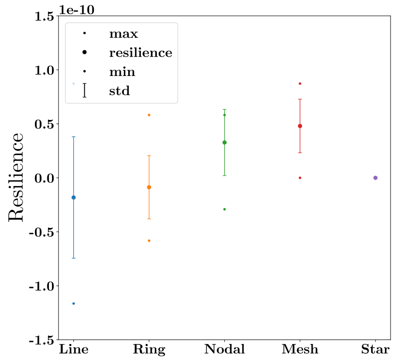
(c) Incident in time period 3, 4, 5



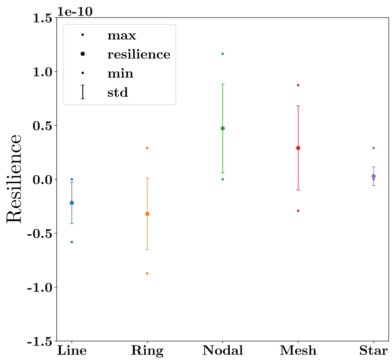
(d) Incident in time period 4, 5, 6



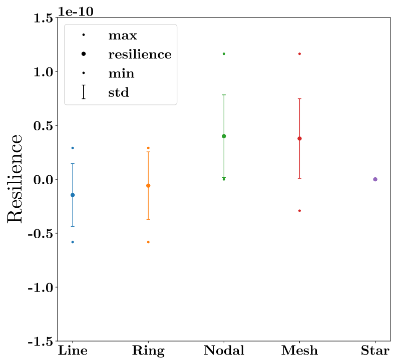
(e) Incident in time period 5, 6, 7



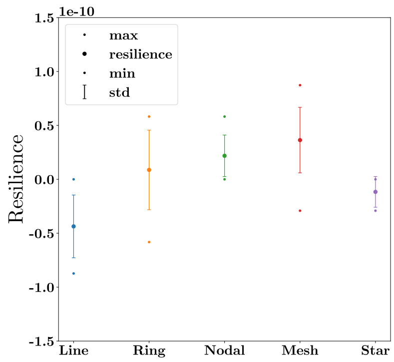
(f) Incident in time period 6, 7, 8



(g) Incident in time period 7, 8, 9



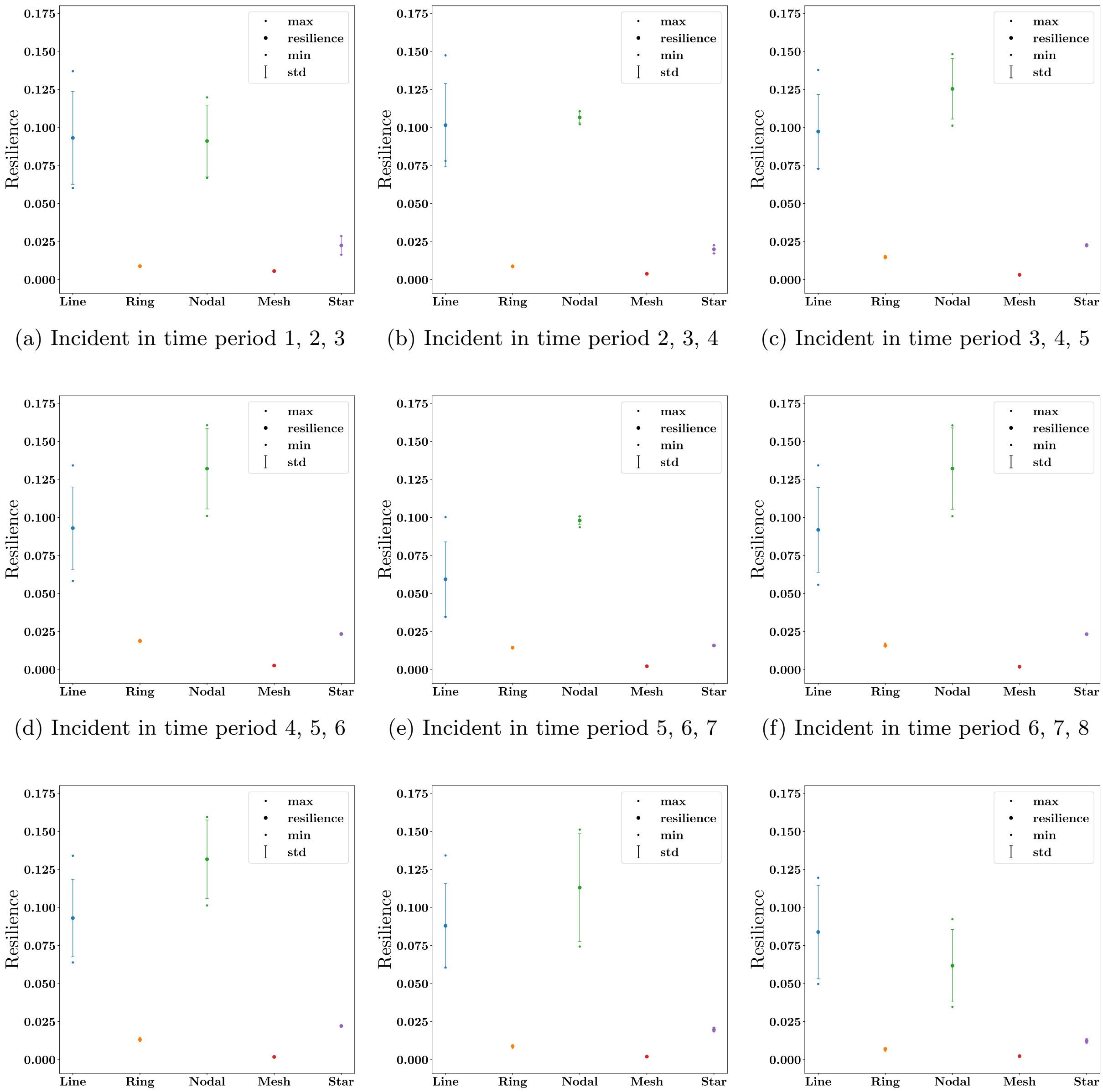
(h) Incident in time period 8, 9, 10



(i) Incident in time period 9, 10, 11

Figure B.7 – Flow resilience for different incident timings.

The resilience calculated from the outflow (equation 9.2) can be seen in figure B.8.



(a) Incident in time period 1, 2, 3

(b) Incident in time period 2, 3, 4

(c) Incident in time period 3, 4, 5

(d) Incident in time period 4, 5, 6

(e) Incident in time period 5, 6, 7

(f) Incident in time period 6, 7, 8

(g) Incident in time period 7, 8, 9

(h) Incident in time period 8, 9, 10

(i) Incident in time period 9, 10, 11

Figure B.8 – Resilience based on the network outflow for different incident timings.

Appendix C

Resilience values

This chapter includes tables with the exact resilience values for the five node networks. The resilience values for the resilience metrics are in table C.1, for the incident starting in time period 4, 5 and 6.

Network	Travel time resilience	Flow resilience	Outflow	Travel time resilience (transformed)	Flow resilience (transformed)
Line	0.9686	$-2.1828 \cdot 10^{-11}$	0.0930	0.0400	$2.1828 \cdot 10^{-11}$
Ring	0.9661	$1.4552 \cdot 10^{-11}$	0.0188	0.0339	$2.0373 \cdot 10^{-11}$
Nodal	0.9595	$1.4552 \cdot 10^{-11}$	0.1321	0.0421	$2.9104 \cdot 10^{-11}$
Mesh	0.9948	$5.8208 \cdot 10^{-11}$	0.0027	0.0052	$6.1118 \cdot 10^{-11}$
Star	0.9423	$2.9104 \cdot 10^{-11}$	0.0234	0.0577	$2.9104 \cdot 10^{-11}$

Table C.1 – Resilience values

The values of the difference between the average TT network performance, and the TT network performance for different incident start times is in table C.2.

Incident time periods	Line	Ring	Nodal	Mesh	Star	Total
1-3	0.217	0.125	0.165	0.0067	0.259	0.155
2-4	0.263	0.072	0.183	0.0058	0.274	0.160
3-5	0.268	0.124	0.222	0.0059	0.317	0.187
4-6	0.253	0.148	0.186	0.0067	0.321	0.183
5-7	0.252	0.107	0.247	0.0231	0.214	0.169
6-8	0.178	0.101	0.192	0.0051	0.285	0.152
7-9	0.172	0.078	0.206	0.0042	0.275	0.147
8-10	0.177	0.096	0.212	0.0039	0.302	0.158
9-11	0.166	0.162	0.196	0.0053	0.312	0.168
Average	0.216	0.113	0.201	0.0074	0.284	

Table C.2 – Difference between average network performance and network performance per incident start time.

The values of the difference between the average TT resilience, and the resilience for different incident start times is in table C.3.

Incident time periods	Difference
1-3	0.017
2-4	0.045
3-5	0.045
4-6	0.031
5-7	0.026
6-8	0.011
7-9	0.015
8-10	0.031
9-11	0.044

Table C.3 – Difference between average resilience and resilience per incident start time.

Appendix D

Resilience of other network parameters

D.1 Network parameters

This appendix presents the results of the resilience experiments with some other network parameters.

- Average betweenness centrality: a measure for the number of shortest paths going through each node. The betweenness centrality of a node v is defined as $c_B(v) = \sum_{s,t \in S} \frac{\sigma(s,t|v)}{\sigma(s,t)}$, where S is the set of OD nodes, $\sigma(s,t)$ is the number of shortest paths from s to t, and $\sigma(s,t|v)$ is the number of those shortest paths crossing through node v. The average of all nodes is used in the results.
- Average degree: the degree of a node is the number of links it connects to. The average of this is used in the results, and was also used in part II.
- Density by length: the total link length divided by the length of all possible links, if all nodes were directly connected.
- Network size: the total length of all possible links, if all nodes were directly connected. This is a measure of network size, because it depends on the distance between nodes.
- Total demand: the total demand of all nodes over all time periods.
- Total link length: the length of all links added together, this parameter was also used in part II.

	Density H	Density M	Density L	Average
Average betweenness centrality	1.561	2.543	2.914	2.350
Average degree	4.234	3.916	3.790	3.977
Density by length	0.588	0.451	0.414	0.483
Network size	1717.556	1718.135	1713.164	1716.190
Total demand	899606.192	899605.129	899604.308	899605.190
Total link length	1010.002	775.298	708.556	829.269

Table D.1 – Average network parameters for the three types of networks, High, Medium and Low density.

D.2 Resilience

The average, minimum and maximum resilience for the six network parameters is in figure D.1.

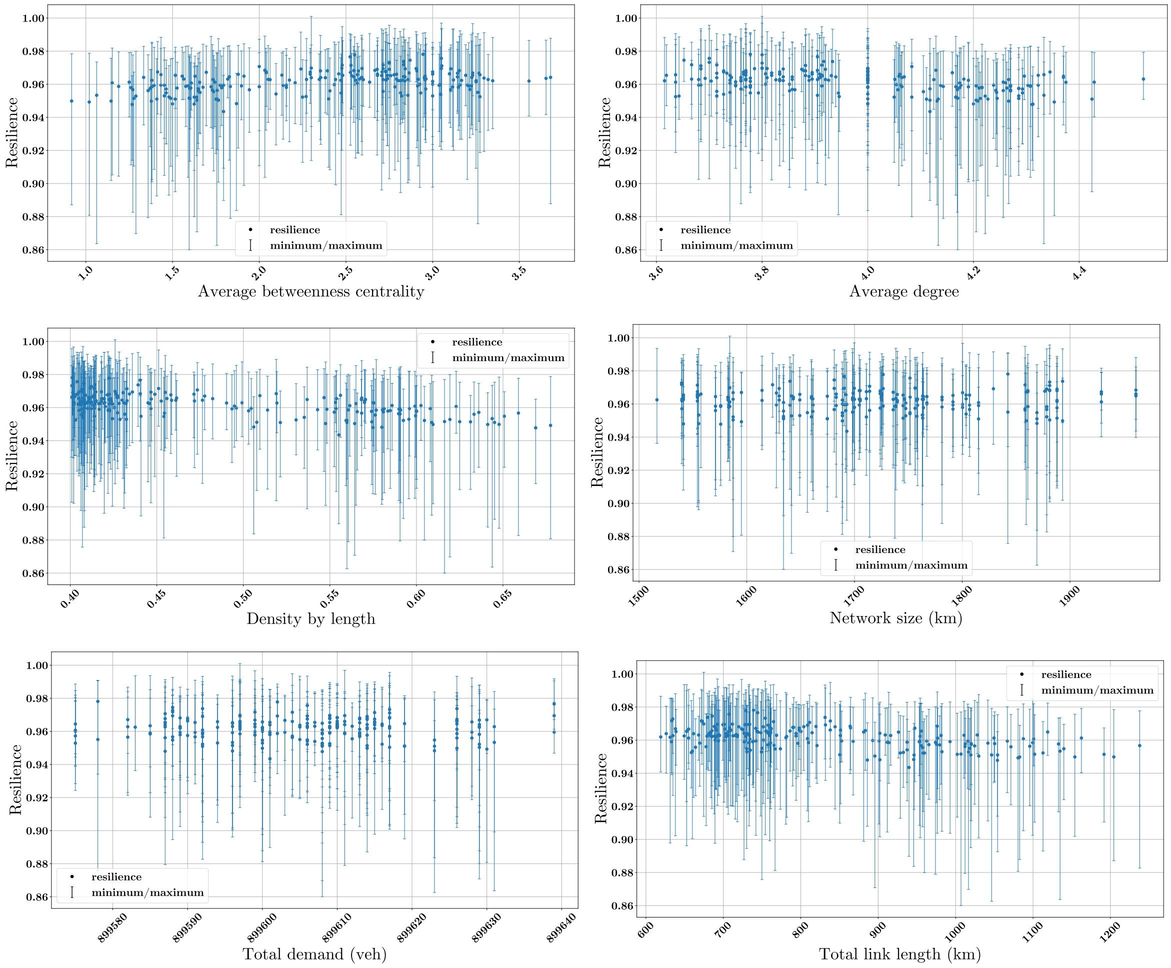


Figure D.1 – Average, minimum and maximum resilience plotted with network parameters. The average resilience of the network is represented by the dot, and the minimum and maximum is represented by the error bars.

D.3 Regression

The regression lines with the average resilience are in figure D.2. The regression information for all network parameters is in table D.2, this includes the correlations and t-values, which were not included in the results in chapter 15.

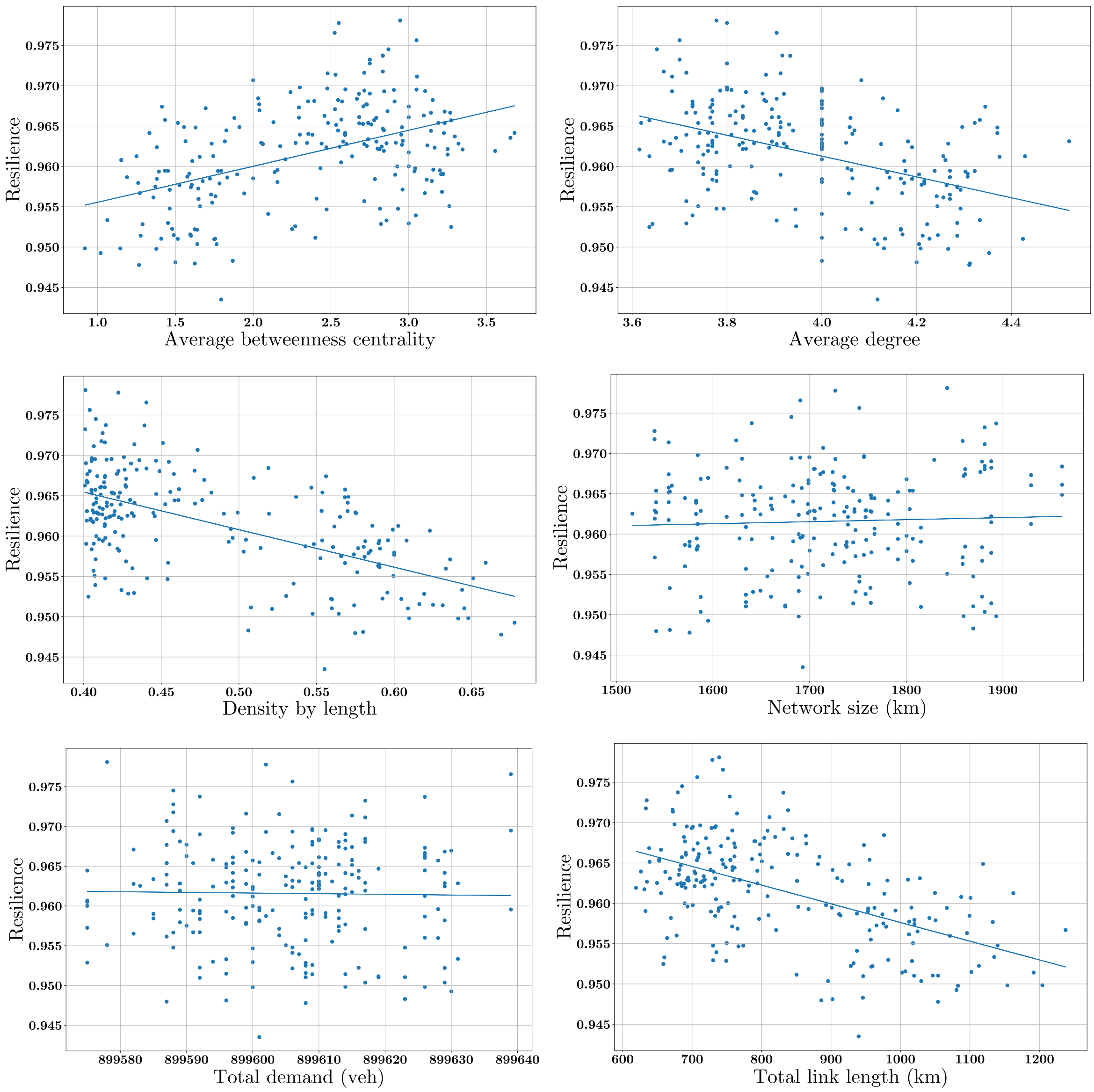


Figure D.2 – Average resilience with different network parameters, plotted with the resilience lines.

Network parameter	Slope	Intercept	Correlation	R^2	t-value	1% significant?	Normalized slope	Normalized intercept
Average betweenness centrality	$4.463 \cdot 10^{-3}$	0.951	0.456	0.208	7.581	yes	$1.233 \cdot 10^{-2}$	0.955
Average degree	$-1.291 \cdot 10^{-2}$	1.013	-0.432	0.186	-7.079	yes	$-1.170 \cdot 10^{-2}$	0.966
Average edge betweenness centrality	$6.266 \cdot 10^{-3}$	0.950	0.544	0.296	9.589	yes	$1.261 \cdot 10^{-2}$	0.954
Average number of lanes	$6.820 \cdot 10^{-3}$	0.938	0.556	0.309	9.901	yes	$1.050 \cdot 10^{-2}$	0.955
Average link saturation	$8.016 \cdot 10^{-2}$	0.944	0.171	0.029	2.575	no	$6.654 \cdot 10^{-3}$	0.958
Connectivity	$-2.652 \cdot 10^{-3}$	0.968	-0.389	0.151	-6.243	yes	$-7.955 \cdot 10^{-3}$	0.965
Density	$-3.320 \cdot 10^{-2}$	0.978	-0.470	0.221	-7.787	yes	$-1.291 \cdot 10^{-2}$	0.966
Density by length	$-4.657 \cdot 10^{-2}$	0.984	-0.585	0.342	-10.676	yes	$-1.289 \cdot 10^{-2}$	0.965
Network size	$2.532 \cdot 10^{-6}$	0.957	0.042	0.002	0.617	no	$1.126 \cdot 10^{-3}$	0.961
Number of nodes	$-4.743 \cdot 10^{-4}$	0.975	-0.642	0.412	-12.391	yes	$-2.182 \cdot 10^{-2}$	0.968
Total demand	$-8.206 \cdot 10^{-6}$	8.343	-0.0178	0.0003	-0.263	no	$-5.252 \cdot 10^{-4}$	0.962
Total distance travelled	$2.624 \cdot 10^{-9}$	0.945	0.182	0.033	2.732	yes	$5.109 \cdot 10^{-3}$	0.959
Total lane length	$-5.146 \cdot 10^{-7}$	0.963	-0.014	-0.0002	-0.205	no	$-3.712 \cdot 10^{-4}$	0.962
Total link length	$-2.319 \cdot 10^{-5}$	0.981	-0.534	0.285	-9.354	yes	$-1.434 \cdot 10^{-2}$	0.966

Table D.2 – Regression parameters for the relation between resilience and different network parameters.

D.4 Correlation

Table D.3 shows the correlation between all network parameters.

	Average betweenness centrality	Average degree	Average edge betweenness centrality	Average number of lanes	Average link saturation (normal situation)	Connectivity	Density	Density by length	Network size	Number of nodes	Total demand	Total distance travelled	Total lane length	Total link length
Average betweenness centrality	1	-0,897	0,962	0,917	0,369	-0,77	-0,924	-0,914	0,003	-0,733	-0,051	0,36	-0,021	-0,856
Average degree	-0,897	1	-0,91	-0,906	-0,449	0,793	0,978	0,889	-0,03	0,653	0,048	-0,465	-0,023	0,821
Average edge betweenness centrality	0,962	-0,91	1	0,958	0,388	-0,767	-0,923	-0,953	-0,015	-0,856	-0,039	0,367	-0,046	-0,898
Average number of lanes	0,917	-0,906	0,958	1	0,337	-0,787	-0,928	-0,989	-0,007	-0,836	-0,071	0,343	-0,02	-0,929
Average link saturation (normal situation)	0,369	-0,449	0,388	0,337	1	-0,347	-0,454	-0,361	-0,225	-0,321	0,103	0,525	-0,28	-0,417
Connectivity	-0,77	0,793	-0,767	-0,787	-0,347	1	0,81	0,781	0,008	0,586	0,072	-0,324	-0,001	0,732
Density	-0,924	0,978	-0,923	-0,928	-0,454	0,81	1	0,928	-0,022	0,712	0,06	-0,448	-0,007	0,861
Density by length	-0,914	0,889	-0,953	-0,989	-0,361	0,781	0,928	1	0	0,86	0,06	-0,34	0,041	0,936
Network size	0,003	-0,03	-0,015	-0,007	-0,225	0,008	-0,022	0	1	0,084	0,058	0,647	0,966	0,345
Number of nodes	-0,733	0,653	-0,856	-0,836	-0,321	0,586	0,712	0,86	0,084	1	0,042	-0,233	0,136	0,837
Total demand	-0,051	0,048	-0,039	-0,071	0,103	0,072	0,06	0,06	0,058	0,042	1	0,064	0,017	0,072
Total distance travelled	0,36	-0,465	0,367	0,343	0,525	-0,324	-0,448	-0,34	0,647	-0,233	0,064	1	0,627	-0,095
Total lane length	-0,021	-0,023	-0,046	-0,02	-0,28	-0,001	-0,007	0,041	0,966	0,136	0,017	0,627	1	0,372
Total link length	-0,856	0,821	-0,898	-0,929	-0,417	0,732	0,861	0,936	0,345	0,837	0,072	-0,095	0,372	1

Table D.3 – Correlation between network parameters.

D.5 Incident duration

The regression lines for normal and shorter incident duration are in figure D.3, the regression parameters are in table D.4

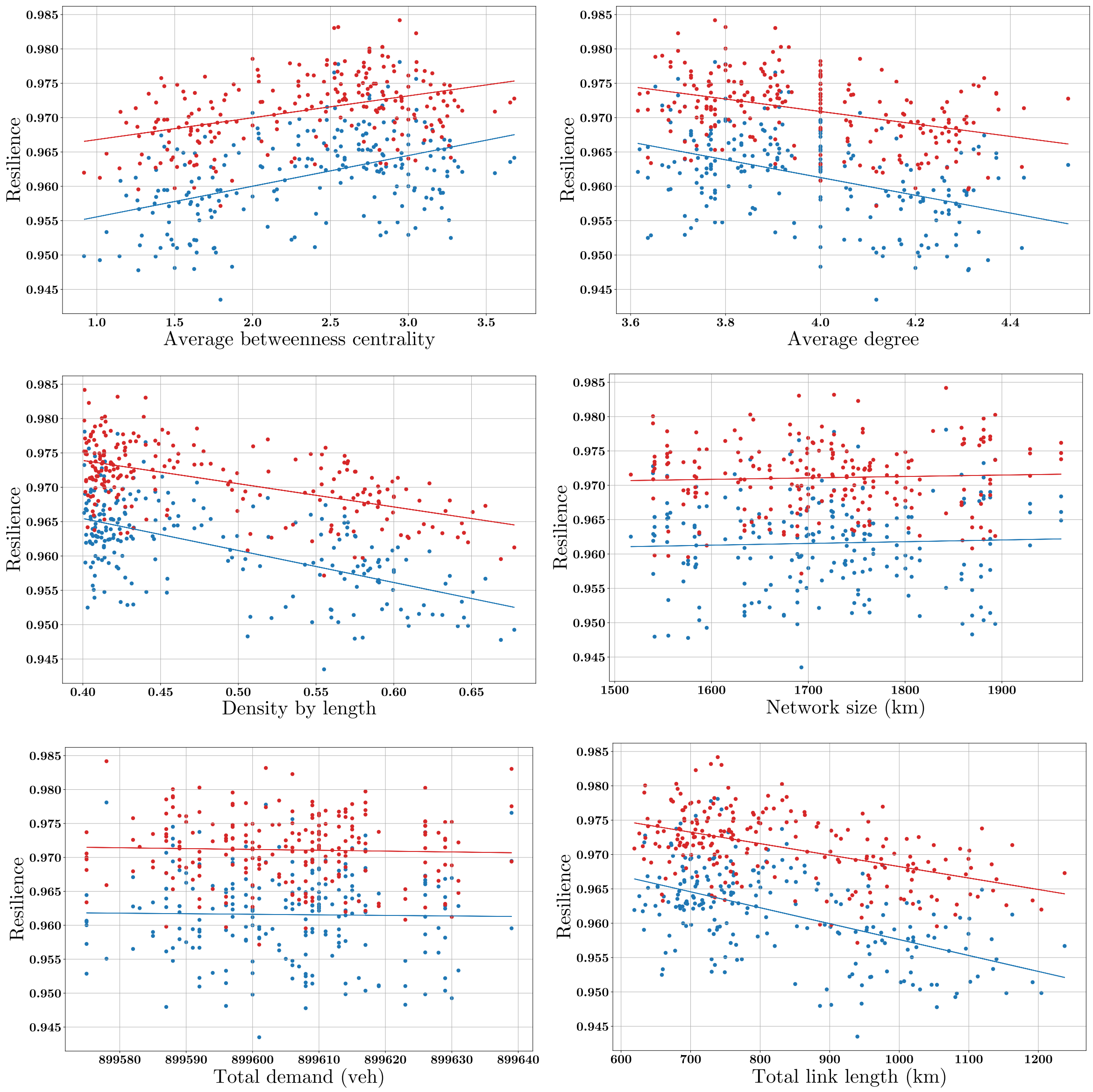


Figure D.3 – Average resilience, and regression lines for the long and short incident duration. The short incident is plotted in red, the longer incident in blue.

Network parameter	Slope	Intercept	R^2	1% significant?	Difference slope	Difference intercept
Average betweenness centrality	$3.182 \cdot 10^{-3}$	0.964	0.174	yes	28.699%	-1.317%
Average degree	$-9.068 \cdot 10^{-3}$	1.007	0.151	yes	29.766%	0.568%
Density by length	$3.379 \cdot 10^{-2}$	0.987	0.300	yes	27.445%	-0.339%
Network size	$2.077 \cdot 10^{-6}$	0.968	0.002	no	17.977%	-1.077%
Total demand	$-2.240 \cdot 10^{-5}$	12.126	0.001	no	-51.115%	-45.338%
Total link length	$-1.669 \cdot 10^{-5}$	0.985	0.247	yes	28.032%	-0.421%

Table D.4 – Regression parameters for the relation between resilience and different network parameters, for the shorter incident. The difference in regression parameters between the longer and the shorter incident is also included.

Appendix E

Statistics

This chapter explains the statistics used when analysing the results of the random networks.

The R^2 error is calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{E.1}$$

In this equation, there are n data points i. y_i is the value of the data point, $\hat{y}_i$ is the predicted value of the data point, and $\bar{y}$ is the average of the data points.

To calculate the statistical significance of the β in a regression line, the standard error first needs to be calculated:

$$SE(\beta) = \sqrt{\frac{\frac{1}{n-2}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}} \tag{E.2}$$

Where x_i is the x-value (the value of a network parameter) of the data point, and $\bar{x}$ is the average of the x-values. The t-value is then:

$$t = \frac{\beta}{SE(\beta)} \tag{E.3}$$

For 200 degrees of freedom, the β is statistically 1% significant when the t-value is higher than 2.6.

The correlation between parameters is calcated with the correlation coefficient:

$$r_x y = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i) \cdot (x_i - \hat{x}_i)}{\sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \cdot \sum_{i=1}^{n}(x_i - \hat{x}_i)^2}} \tag{E.4}$$