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Importance Analysis of Nodes for the Resilience of an Oil & Gas Supply Chain Network

Master's thesis in Mechanical Engineering
Supervisor: Yiliu Liu

January 2022

Master's thesis

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Preface

This thesis marks the end of a master's degree in Mechanical Engineering, with specialization in Reliability, Availability, Maintainability and Safety (RAMS) at the Norwegian University of Science and Technology (NTNU). The purpose of the thesis is to study resilience-based importance analysis in an oil and gas supply chain network during node disruptions.

I wish to thank my supervisor, Yiliu Liu, for his guidance and availability throughout the whole thesis period. His great knowledge and useful inputs have been invaluable.

Trondheim, January 2022

Lelan Khalaf

Summary

Resilience is a growing term that has gained increased attention during the last years, especially in the context of supply chain management. It can be characterized as an adaptive capacity, where the resilience of a system, also referred to as a network, can be considered as an ability to withstand, adapt to and recover from unforeseen disruptions.

Industries, such as the oil and gas, have supply chains that have become large and complex, containing several interdependent activities. Small disruption can cause large damages and ripple effects. This creates a need for more resilience-based strategies, which focus on creating robust systems that can withstand and operate sufficiently during disruptions.

In order to strengthen the resilience of a system, knowledge about topological properties, as well as system behavior during disruptions, can be beneficial. By choosing important indicators, such as node indicators, different disruption scenarios can be performed to analyze the importance of the nodes in a network and their contribution to the loss of performance during node disruption.

The results from this study showed that node indicators can be seen as a beneficial way of measuring resilience, increasing the knowledge about system behavior during node disruptions. It also appeared that there is a high correlation between node importance, based on topological properties and node flow, and impact on network performance, calculated as a loss of performance.

Sammendrag

Resiliens er et voksende begrep som har fått økt oppmerksomhet de siste årene, spesielt i sammenheng med forsynings- og verdikjeder. Det kan karakteriseres som en adaptiv kapasitet, hvor resiliensen til et system, også referert til som et nettverk, kan betraktes som en evne til å motstå, tilpasse seg og komme seg etter uforutsette forstyrrelser.

Industrier, som olje-og gassvirksomheten, har forsyningskjeder som har vokst seg store og komplekse, og som inneholder flere gjensidig avhengige aktiviteter. Små forstyrrelser kan føre til store skader og ringvirkninger. Dette skaper et behov for mer resiliensbaserte strategier, hvor fokuset ligger i å skape robuste systemer som kan motstå og fungere tilstrekkelig under forstyrrelser.

For å kunne styrke resiliensen til et system, kan kunnskap om topologiske egenskaper, samt systematferd under forstyrrelser, være gunstig. Ved å velge viktige indikatorer, som for eksempel nodeindikatorer, kan det dannes ulike forstyrrelsesscenarioer for å analysere viktigheten av nodene i et nettverk og deres innvirkning på systemets prestasjon under nodeforstyrrelse.

Resultatene fra denne studien viste at analyse basert på nodeindikatorer kan sees på som en god metode å måle resiliens på, og for å øke kunnskapen om systematferd under nodeforstyrrelser. Det viste seg også at det er høy korrelasjon mellom nodeviktighet, basert på topologiske egenskaper og nodeflyt, og innvirkning på systemprestasjon, beregnet som et tap av prestasjon.

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1 Introduction

This introducing section presents the study, with its background, motivation, research objectives, scopes and delimitations, and outline.

1.1 Background

Resilience is a growing term that has become an important part of supply chain management. It can be characterized as an adaptive capacity, where the resilience of a system, also referred to as a network, can be considered as an ability to withstand, adapt to and recover from unforeseen disruptions (Ramirez-Marquez et al., 2018). In order to implement resilience-based strategies to a certain system, such as a supply chain network, there is a need for some kind of system evaluation, and an understanding of how the system works and is compounded. Knowledge about how the system reacts to certain disruptions can be useful.

Industries, such as the oil and gas, have supply chain networks that have become large and global. They contain several activities and have interdependent connections and complex infrastructure. Large amount of oil and gas is distributed every day, all around the world through pipelines, tankers, trucks and railroad. This type of large scaled supply chain network requires constant monitoring and high reliability.

The increased interest around resilience has resulted in several ways of measuring and evaluating it (Hosseini et al., 2016; Li et al., 2017), where usually fast recovery and adaptation to the current situation are properties that are highlighted. By measuring important components, a resilience-based importance analysis can be performed to help increase knowledge about the network behavior before, during and after disruptions. An understanding of how the supply chain network is constructed and designed can be used as a tool to evaluate important indicators, such as node indicators, which further can be used to increase the network reliability and strengthen the resilience (Barker et al., 2013).

1.2 Motivation and Research Objectives

Traditional risk management has been applied for many years, but there has been calls for a shift from risk to resilience (Aven and Thekdi, 2018; Kochan and Nowicki, 2018). This shift might have been motivated by the effects of climate change or terrorist attacks, and sudden disruptions that have not been thoroughly evaluated in the risk picture before. The need for a more resilience-based strategy have been highlighted with the focus of creating robust systems that can withstand and operate sufficiently during disruptions.

Oil and gas supply chain networks are crossing national borders and have become important for the world economy. Many countries rely heavily on oil and gas import and export. Even with high technology and advanced tools, the oil and gas industry and its supply chain networks still faces many risks and challenges. The scale and global interconnection makes them vulnerable, where small disruptions can cause large damages and ripple effects. Risk mitigation is hence extremely important, and also highly prioritized, but it can be difficult in the light of unforeseen disruptions and hazards. This points out the need of strategies beyond traditional risk assessment, such as resilience-based strategies where the aim is not only to mitigate disruption consequences, but to create systems that can absorb shocks.

Since importance analysis, such as one based on network topology, can be utilized as a tool to evaluate network resilience, the study effect of node disruptions can be implemented. By measuring how loss of capacity at different nodes affects the overall network performance, the nodes can be compared to each other. A method based on topological properties and node flow can be used to identify important nodes. The connection of node disruption and performance function can be used to gain knowledge about the network behavior, and where additional reliability strategies and attention should be made to ensure a satisfactory performance. This type of analysis and evaluation can contribute to increase the system resilience.

The purpose of this thesis is to study resilience-based importance analysis in an oil and gas supply chain network during disruptions, with focus on node indicators. The loss of performance will be evaluated regarding to reduced flow capacity at selected nodes, to determine how this influences the overall network performance.

The chosen system is the Norwegian oil and gas supply chain network, where the main research objective and sub-objectives are:

1. To analyze how disruptions at certain selected nodes affect the network resilience, as a function of performance.
    1.1 To evaluate the connection between nodes that are considered as critical, and their importance for the overall network in terms of loss of performance during disruptions.
    1.2 To compare a resilience-based evaluation of network behavior based on a selected recovery plan and an alternative recovery plan.

1.3 Scopes and Delimitations

The scope of this thesis is limited to a small section of the Norwegian oil and gas supply chain network, with main focus on network topology and node indicators. The Norwegian oil and gas supply chain network is extremely large and complex and in constant development, where new and modern strategies are still evolving and being implemented. In order to conduct an analysis, the following system delimitations are made:

- The network construction of the case study is delimited, where some nodes and edges have been excluded.
- Connecting edges will not be affected by disruptions, and hence not evaluated. This means that properties, such as distances, will not be considered in terms of topological network properties.

- The performance function and resilience-based evaluation of network behavior will be studied around the recovery phase of the system. Analysis of the degradation phase will be left out.
- All of the selected disrupted nodes will recover with the same plan and within the same time frame.
- The performance function will only be considered and measured on the basis of average flow.

1.4 Outline

First, a section about oil and gas supply chain networks are presented. This includes supply chain activities within the sector, description of network construction and risks and challenges. Section 3 provides information about supply chain resilience, especially in the oil and gas industry. Resilience as a concept and a quantitative evaluation of it is included. Section 4 explains a methodology of resilience-based importance analysis, where a framework, containing three main steps, is presented. To create context, a numerical example is provided in section 5, where the Norwegian oil and gas supply chain network is utilized as a case study. The results are discussed in section 6, and lastly, conclusions and recommendations for further work are provided in section 7.

2 Oil and Gas Supply Chain Network

This chapter gives a description of how oil and gas supply chain networks are constructed and operated, as well as risks and challenges within the sector.

2.1 System Description

The concepts of supply chain and supply chain management have gained increased attention, becoming more and more important fields (Cooper and Ellram, 1993). A supply chain includes all aspects of the production process, the activities involved at each stage, natural resources that are transformed, information and communication, human resources, and other components that results in the finished product or service (MacCarthy et al., 2016). Supply chains are in constant evolvement, always aiming to deliver products in the right quantity, place and time. Energy supply chains are no exception, and industries, such as the oil and gas, have built supply chain networks that have become large and global (Urciuoli et al., 2014).

Since the discovery of the oil and gas, belonging industries and supply chains have kept on growing and improving. Multiple products are made, both direct and indirect, by oil and gas, which makes this industry an important area. Several countries rely on the export and import of oil and gas, and the demand and supply play a major role in the world economy (Torraca and Fanzeres, 2021; Kumar and Barua, 2021).

2.1.1 Supply Chain Activities

The oil and gas industry is among the industries which have the most complex and advanced supply chains in the world. The different activities can be seen as similar to many other supply chain activities, but they involve complicated and well-developed elements. Every stage, from exploration and production, to transportation and distribution requires careful planning and logistics (Briggs et al., 2012; Kazemi and Szmerekovsky, 2015). The large-scaled supply chain creates a need for highly structured and safe systems that can maintain efficient production and transportation.

The structure of an oil and gas supply chain can be divided into three main activities; (1) upstream, (2) midstream and (3) downstream (Briggs et al., 2012; Kazemi and Szmerekovsky, 2015; Torraca and Fanzeres, 2021). The upstream activities are related to operations such as exploration and production of oil and gas at offshore fields. The midstream includes the storing and the infrastructure used to transport the oil and gas, which is usually by pipelines, tankers or trucks. The downstream activities consist of the processing, marketing and distribution to the customers. A representation of the different activities, divided by their streams, can be seen in figure 1.

The three mentioned activities are interconnected and each stage has an important role in the overall supply chain. After the oil and gas have been explored, the production has to be separated and treated in order to get marketable products (Norwegian Petroleum, 2021c). Then the oil and gas is transported through pipelines or tankers to terminals and refineries onshore, where it is further distributed. The pipelines are important carriers for transportation, making it possible to transport large amounts of oil and gas over long distances (Tarei et al., 2021). Since the storage capacity at the offshore fields usually is limited, the oil and gas is stored on large storage tanks at the facilities onshore. These normally have large storage space, making it possible to transport large amounts of custom-made deliveries of oil and gas to other destinations (Norwegian Petroleum, 2021a).

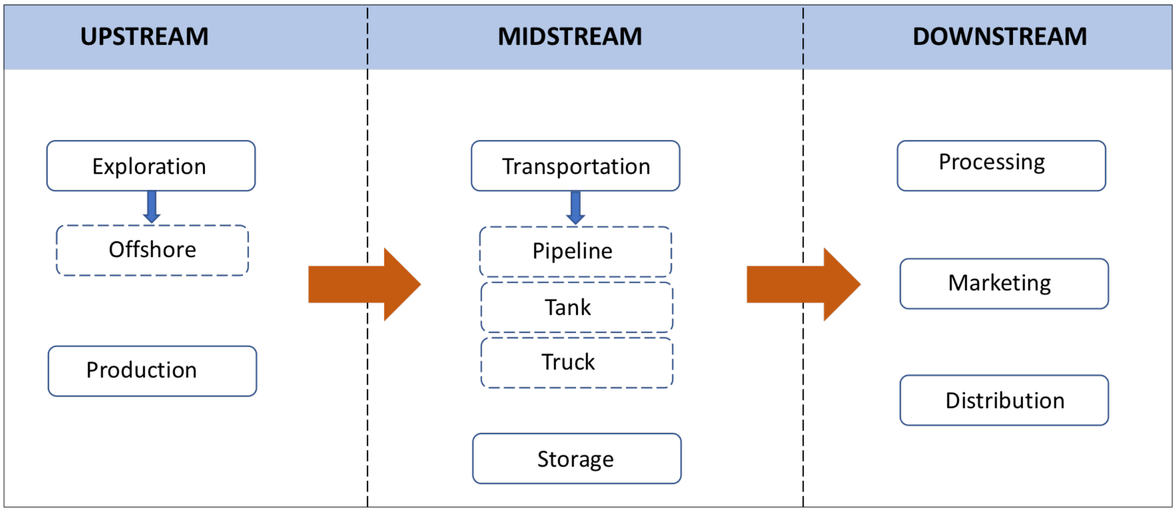

Figure 1: Oil and gas supply chain activities divided by upstream, midstream and downstream.

2.1.2 Supply Chain Network Construction

Supply chain processes and their activities are not linear, and can be modeled as networks with a set of nodes and a set of edges. The nodes represent independent business units, and the edges represent connections that link these firms together in order to create a product or service (Hearnshaw and Wilson, 2013). For an oil and gas supply chain network, the nodes can illustrate fields, terminals, refineries and countries, and the edges can illustrate transport methods, such as pipelines, tankers and trucks. The nodes can have several connections, usually including international borders (Kumar and Barua, 2021). Oil and gas from one field and country can be distributed to long-distant countries, which naturally creates large-scaled networks and cross-border cooperation.

The representation of a system as a network makes it possible to get an overview, giving a better understanding of the flow of materials, information and finances. The network describes a structure where the involved organizations can be cross-linked in a two-way communication over long distances. The interconnections and dependencies of the different nodes and their edges can make supply chain networks vulnerable, depending on how they are structured. Small disruptions at a node or an edge can have little overall effect if they occur, but they can also cause major damages and consequences for the whole network.

When designing a supply chain network, the goal should be to create an efficient, but also strong network. There should be a certain distribution of nodes and connections, but the connections should not cross more than necessary. Since oil and gas reserves are limited and not distributed evenly geographically, the countries with large consumption rely heavily on imports, hence the network construction is influenced by this factor, making it natural to export oil and gas to countries that lack production (Biresselioglu et al., 2015).

Oil and gas networks constructions are determined by several other factors as well, such as supply and demand, production and transportation costs, and transportation alternatives (Samet et al., 2017). Considering that exploration and production are activities located at the sea, the transportation to the terminals and refineries are done by pipelines and tankers, which makes these facilities usually located along the coast. The area is determined by the transportation options, both when transporting the oil and gas to land, but also regarding further export. Since the pipeline system makes it possible to export large amount of oil and gas in short time, this transportation method is considered very efficient and is utilized when possible (Tørhaug, 2006; Yuan et al., 2019). But with this method there are also negative outcomes, such as limitations in terms of distance. Oil and gas that can not be transported by pipeline are transported with tankers and trucks, which is also sufficient methods, but can lead to longer path lengths, due to factors such as fixed sea and road routes.

Topological Properties

The network of a supply chain can be an important tool when describing and analyzing the structure and dynamical behavior of the system (Cerqueti et al., 2019). The construction design and the topological properties can influence how vulnerable the network is. Dependencies are important, where the vulnerabilities at one stage of the supply chain network can influence the other activities and create ripple effects (Wagner and Neshat, 2010).

The network vulnerability is related to the study of the adverse effect on a system performance after a disruptive event, which can correspond to reduced capacity in the network components, such as flow reduction (Barker et al., 2013). Hence, the vulnerability can be studied in the context of the topological properties and chosen indicators that are considered as important, such as node indicators. Some nodes can be reviewed as more important than others, depending on various metrics like the number of connections, amount of flow and number of shortest paths passing through it (Ding et al., 2020).

The robustness of a network can be evaluated in terms of its ability to perform in a sufficient way, even with missing elements such as nodes or edges (Cerqueti et al., 2019). This robustness can in many ways be connected to the topological properties, like node and edge distribution. Knowledge about topological properties in a network can be used in the decision-making of the sector, determining how the network should be constructed. The relationship between different drivers can be measured and utilized to create a strong and robust supply chain network (Wagner and Neshat, 2010).

2.2 Supply Chain Network Risks and Challenges

When systems continue to grow in size and complexity, they also get more exposed to safety and risk management challenges (Wagner and Bode, 2006; Zhao et al., 2019; Tarei et al., 2021). Oil and gas supply chain networks are examples that address how interconnections and a large number of international markets can cause vulnerability and thus challenges (Wagner and Neshat, 2010). Simultaneously with the increasing network size, there are usually higher requirements of risk management and risk mitigation in order to minimize damages and ripple effects in the network (Urciuoli et al., 2014).

A disruptive event can have major impacts on oil and gas producing companies, because it can affect other companies and distributors that are involved in the supply chain network (Tørhaug, 2006). Consumers require a certain amount and quality of the product they are buying, and a reduction in capacity can cause a decrease in reliability and lead to loss of customers.

When carrying out risk management, the approach is to identify and address different types of risks, including equipment failure, demand risks, natural catastrophes and terror attacks (Saad et al., 2014; Urciuoli et al., 2014). The purpose is to prevent and minimize potential damages and hazards that can occur. The oil and gas supply chain face many risks and challenges, both predictable and unpredictable.

2.2.1 External and Internal Disruption Risks

Among a variety of risks within the oil and gas industry, fires, explosions and blowouts are dominating the risk picture considering serious accidents (Tørhaug, 2006). Nevertheless, unforeseen disruption risks are also highlighted as important to evaluate, even though they can be difficult, or even impossible, to predict. Their consequences, and the potential damages they can cause, can affect the whole network in a negative way (Hosseini et al., 2019).

The unforeseen events can be seen in the context of risks with a low probability of happening, but a high potential for damage. This includes both natural and man-made disasters, which can be categorized as external and internal disruptions, based on the sources they arise from. The external sources include natural disasters, such as earthquakes, hurricanes and tsunamis. Whereas man-made disasters can be accidents, wars, terrorist attacks, strikes and financial crises. The internal sources can include elements such as uncertain demand, supply yields, lead times, low capacity and high costs (Kochan and Nowicki, 2018).

Disruptions caused by external sources can often be more difficult to prevent and foresee, compared to those arising from internal sources. There are many external sourced risk factors and vulnerabilities within the oil and gas industry that can affect parts of, or the whole, supply chain network. These factors can be human performance, operational failures, tanker collisions during transportation, blowouts, explosions, natural disasters and pandemics. The on and offshore facilities can for example be struck by natural disasters, accidents or get attacked.

Difficult geographic areas, climate zones and regions that are sensitive of the environment are large risk factors within the oil and gas sector. Climate change has become a huge challenge, as many of the operations and activities are taking place either at the sea or along the coast. The main transportation is also taking place in the sea, and hard conditions can make it difficult to export. If a natural disaster strikes, it can cause large damages and even shutdowns. These types of events are difficult to predict, and even more difficult to prevent.

Disasters can occur both at facilities and during transportation, but the facilities are considered especially vulnerable since the construction of boundary barriers to limit access is not seen as feasible. The open location creates a natural vulnerability, making the facilities prone to sudden attacks (Urciuoli et al., 2014).

With increasing digitization and reliability on information technology systems, cybersecurity threats and attacks are becoming potential risks that can have a large negative impact on the oil and gas industry. The complexity of the supply chains includes several systems with high technological equipment that are exposed to security threats that can cause loss and damage (Wagner and Neshat, 2010; Equinor, 2020).

Other examples of supply chain disruptions are epidemics and pandemics. The oil and gas industry has, among many other industries, been affected by the global Covid-19 pandemic. As an example, in the Norwegian oil and gas industry, certain operations have been set back or delayed due to quarantine rules, limited mobility for personnel, social distancing and reduced workers. The actions connected to the pandemic have also led to reduced energy demand on the basis of travel restrictions from the governments (Equinor, 2020).

2.2.2 Risk Prevention and Mitigation

To prevent and minimize the impact and damages caused by disruptive events, prevention and mitigation strategies are important to prioritize (Barker et al., 2013). This is a critical phase of supply chain risk management, and involves a selection of different strategies and implementations that will help to reduce risks and consequences (Tarei et al., 2021). These strategies can be proactive or reactive strategies, where the proactive focus on preventive implementation prior to a disruption to reduce the probability of risk events, and the reactive focus on the recovery after a disruption has occurred (Sheffi and Rice, 2005; Meng, 2020). The risk mitigation can be seen in the light of the vulnerabilities, challenges and risks that faces the oil and gas industry and its supply chain network.

Since topological properties of a supply chain network can determine the vulnerability of the system, high-risk nodes can be considered as more exposed to attacks and disruptions. It is natural to think that attacks would occur at a node with high importance rather than a node with low importance. Hence implementation of extra safety barriers or recovery strategies for these nodes can be useful, since a disaster at one of these nodes can create larger damage and ripple effects in the supply chain network (Ding et al., 2020).

Geographical distribution of production facilities, protection of manufacturing sites, and flexibility in capacity and inventory can also be helpful when wanting to mitigate the negative effects of a disaster. In case of a disruptive event and loss of suppliers, a greater geographical distribution can contribute to less harm and delay, and minimize the negative consequences, rather than having all of the suppliers located in the same area (Hosseini et al., 2019).

The safety at oil and gas industries is usually high and prioritized, due to dangerous accidents that can be harmful both for the workers and the equipment. Accidents, such as fires, explosions and blowouts can cause extremely large damage, and the emphasis is usually on prevention. In many cases these accidents occur during oil or gas release, or as a failure consequence. Even though the possibility of such an accident is low, it is still existing. Therefore control and mitigation measures are required in addition to the prevention (Equinor, 2020).

Natural disasters are difficult to prevent, but risk mitigation can be done by building robust facilities that can withstand the climate they are facing. Depending on country and location, the specific area they are located at can be more prone to certain natural disasters than others. The offshore installations are usually constructed to handle rough climate and specific accident scenarios (Tørhaug, 2006). In addition, the focus on a common long-term goal of reducing greenhouse gas emissions can be seen as a prevention of natural disasters and climate change (Equinor, 2020).

3 Supply Chain Network Resilience

This chapter provides information about resilience in context of supply chains. This includes definitions of resilience, why resilience is important and how it can be evaluated in terms of supply chains, especially in oil and gas networks.

3.1 Definitions of Resilience

Resilience is a widely used and growing term, especially in terms of supply chains. The word "resilience" originates from the Latin word "resiliere" and translates to "bounce back" (Aldunce et al., 2014). Depending on the system under consideration, the term takes on different meanings. From an engineering point of view, resilience can be characterized as an adaptive capacity, with different specific definitions (Engle, 2011; Hohenstein et al., 2015).

Hosseini et al. (2016) connected resilience to the ability of an entity or system to return to normal condition after the occurrence of an event that disrupts its state. Allenby and Fink (2000) defined resilience as the capability of a system to maintain its functions and structure in the face of an internal and external change and to degrade gracefully when it must, while Pregenzer (2011) defined it as the measure of a system's ability to absorb continuous in unpredictable changes, while still maintaining its vital functions. Patriarca et al. (2018) described resilience as a feature of some systems that allow them to respond to an unanticipated disturbance that can lead to failure and then resume normal operations quickly.

The resilience of a system can be expected to have the ability to survive and recover from unexpected disruptions. It must be able to return to the original state, or transfer to a new and more ideal state after being disturbed (Chen et al., 2020). This means that resilience cannot simply be engineered just by adding procedures, safeguards and barriers, as it requires continuous monitoring of system performance and behavior in order to manage unforeseen occurrences. For the purpose of this study, the resilience of a system will be considered as an ability to withstand, adapt to, and recover to a stable state after the occurrence of an unexpected disruptive event. The stable state can either be equal to the original state or it can be better (Ramirez-Marquez et al., 2018).

3.2 Resilience as an Extension of Risk

Supply chain networks are usually interdependent and connected, where small disruptions can, in the worst case, influence the whole network in a negative way. An unforeseen disruption can typically occur if it has not been included in the risk picture, and hence has not been evaluated before. The potential impact of such disruption on a firm and its supply chain makes a reason for the importance of establishing resilience, with a focus on preparing for the unexpected and acknowledgment of unknown hazards (Tukamuhabwa et al., 2015).

Some supply chain risks and hazards can be foreseen and prevented, or the damage can somehow be minimized by having an efficient risk assessment. In other cases, this hazard can not be identified forehand and when the event occurs, it can lead to huge damages, and even permanent shutdown. In reality, supply chain risk management is only possible if the probabilities and consequences of the disruptions are determined, which means that it can not manage unexpected events (Wagner and Bode, 2008). This is where the concept of resilience becomes important, being related to events that have a low probability of happening, but high impact. It creates a new way of thinking, beyond normal risk analysis, or perhaps as an extension of it.

Resilience analysis, and the concept of it, have emerged from the traditional concept of risk. It can be seen as a reaction to limited risk analysis (Aven, 2019). While traditional risk analysis has been applied for several years, resilience is still developing and growing. It has gained increased attention, and during the last years there have been calls for a shift from risk to resilience (Aven and Thekdi, 2018; Kochan and Nowicki, 2018). This shift might have been motivated by effects of climate change, or terrorist attacks and sudden disruptions that have not been evaluated in the risk picture before. Risk assessment usually highlights the effort to prevent threats and hazards before they occur, while resilience focuses more on the parts that include recovery and adaptation to the current changed situation (Linkov et al., 2018a,b). This means that the system under consideration should be able to recover to a stable state, which can be equal to, or even better than, the original state.

Risk management strategies usually focus on the prevention of hazards, wanting to reduce the likelihood of disruptive events, while resilience management might focus more on the post-event and the behavior of the network during the disruption. Nevertheless, risk and resilience can be used to complement each other by, for instance, adopting risk-based approaches to resilience assessments, focusing on the ability to withstand and respond quickly to threats. Risk and resilience both aim to reduce likelihoods and consequences, wanting to design systems that can avoid or absorb unwanted events (Hosseini et al., 2016). This way risk considerations can be utilized in order to provide useful input to the resilience analysis (Aven and Thekdi, 2018). Despite that some disruptions and hazards can not be avoided, preparation in advance can still contribute to minimizing the damages and ripple effects. A positive outcome of improving the resilience of a system is that the system can get safer and stronger, and be able to withstand disruptions without the need to perform risk calculations (Aven, 2019).

3.2.1 Properties of System Resilience

Since the resilience of a system is characterized as an adaptive capacity, certain properties can lead to higher resilience. When a system is prone to an unwanted disruption, the combination of uncertain conditions and resilience properties can determine how the system behaves and performs.

The resilience properties of a system can be understood in context of the system performance and uncertain conditions. A set of uncertain conditions can influence the system performance negatively, but an implementation of resilience properties can increase the robustness of the system. The relationship between the three variables can be seen in figure 2, where the performance of a system is determined by a set of uncertain conditions, and a set of resilience properties (Wied et al., 2020).

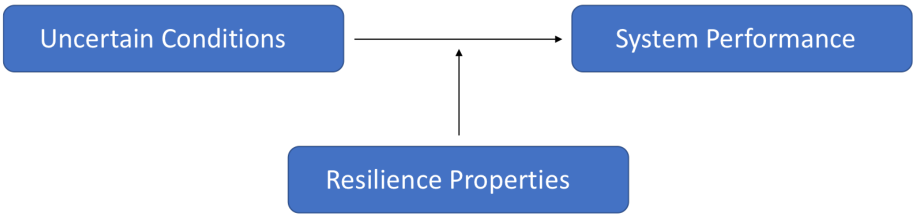

Figure 2: Resilience properties of a system seen as a set of variables. Figure adapted from Wied et al. (2020).

Certain properties of system resilience can be highlighted, for example how the system reacts to disruptive events, such as loss of a supplier, labor strikes, transportation disasters, etc. Depending on the system under consideration, certain key characteristics and factors can be identified as drivers of resilience. Both prevention and mitigation are highlighted, such as prediction, anticipation and adjustment. The different properties can be seen as a way to strengthen resilience, which can also lead to higher system performance.

Since systems with high resilience should be able to react quickly to disruptive events, there is a necessity of properties of flexibility in the system. Flexibility can be seen as the ability to adapt to changing environments, preferably with minimum effort and time. Through adaptation, the system can adjust to undesired changes, and be forced to be flexible, and hence less vulnerable. The flexibility can be related to investments in infrastructure and resources before they are needed, alternative transport, sourcing, postponement, etc. Resilience increases by having rapid adaptability during unpredictable conditions.

Having certain properties of deliverability can also contribute to increasing the system performance, in terms of being available and able to deliver, even during uncertain conditions. Greater geographical distribution of production facilities, protection of manufacturing sites and flexibility in capacity and inventory, are highlighted factors that can contribute to increasing the deliverability of the system. In case of a disruptive event and loss of suppliers, a greater geographical distribution can lead to less harm and delay, and ripple effects in the supply chain network (Hosseini et al., 2019).

3.3 Quantitative Evaluation of System Resilience

The increased interest around the evaluation of system resilience has resulted in several ways of measuring it (Hosseini et al., 2016; Li et al., 2017). Both deterministic and probabilistic methods have been applied, where most of the measures have underlying logic similarities. Usually, the focus of the evaluation lies in comparing the performance and behavior of a given system before, during and after disruptions (Hosseini et al., 2016). The system behavior can be analyzed with weight on different chosen performance measures and indicators, such as a system delivery function. Network topology analysis can be utilized to identify important nodes and edges, in order to use them as indicators when determining system vulnerabilities. Scenarios can also be created and the resilience can be evaluated based on the system behavior and the outcome of the consequences.

3.3.1 System Transition

When a system is experiencing a disruption, it will go through a set of states or transitions. The behavior can be analyzed, and the states can be divided into three important stages (Hosseini et al., 2016), seen in figure 3. The first stage is the stable original state, which refers to the initial system state before any disruption. The second stage is the disrupted state, which is triggered after a disruptive event has occurred. The third, and last stage, is the stable recovered state. This state can be the same, similar or different from the original state, but indicates that the system again is stable after facing a disruptive event. Between these three stages, the system is going through degradation and recovery.

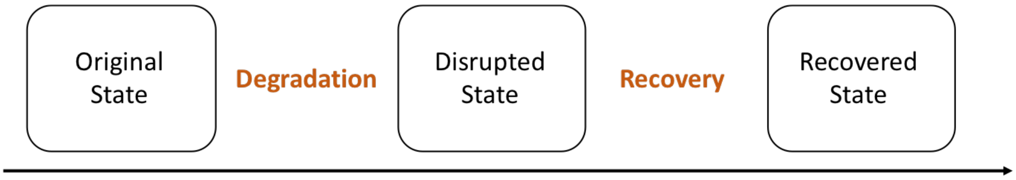

Figure 3: System state transition (Hosseini et al., 2016).

The important dimensions of resilience within the different states are reliability, vulnerability and recoverability (Aldunce et al., 2014; Hosseini et al., 2016). Before any disruption, during the original state, the ability of the system to maintain normal operations determines the reliability and how reliable the system is. During the disrupted state, the vulnerabilities of the system are brought out, showing how or where the system is weak and needs strengthening. The ability to minimize damages depends on how the system recovers, which is visible after the system has fully recovered and entered the last stage. After the recovered state, the effects of the prevention and mitigation strategies can be seen, and whether they have been helpful or not.

3.3.2 Resilience as a Metric of Performance

When the system behavior changes as a consequence of a disruption, the system performance can also be affected in a negative way. Henry and Emmanuel Ramirez-Marquez (2012) quantified system resilience as a time-dependent metric, by using a system performance function. This system performance function can be utilized to measure several things, such as reliability, flow, delay and recovery. Multiple performance functions can be studied for a single system under consideration. Based on one, or several, chosen performance function(s), the system resilience can be assessed by measuring the system performance at different moments before, during and after a disruptive event. Through studying how the network behaves, including how it withstands, adapts to and recovers from disruptions, the resilience can be evaluated by the system performance. A strong and robust supply chain network, with high resilience, should have the ability to perform in a sufficient manner, with minimal damages and negative consequences, during an interrupted state.

Figure 4 shows the system performance as a function of time before, during and after a disruptive event e_j. $F(t)$ describes the value of the performance function at a given time t. The function starts with a value $F(t_0)$ at an initial time t_0, which corresponds to the original state. The state and function remain constant until a disruptive event e_j strikes at time t_e. The system then starts to degrade, and at time t_d it enters the disrupted state. This state lasts until a resilience action is initiated at time t_s. The performance function $F(t_d) = F(t_s)$ is at this point lower than the initial value $F(t_0)$. After the initiation of the resilience action, the system starts to recover, where a resilience action is considered successful when it can start to restore the system to a recovered state (Barker et al., 2013). At the time t_f the system has recovered fully and is entering the recovered state, with a performance function equal to $F(t_f)$.

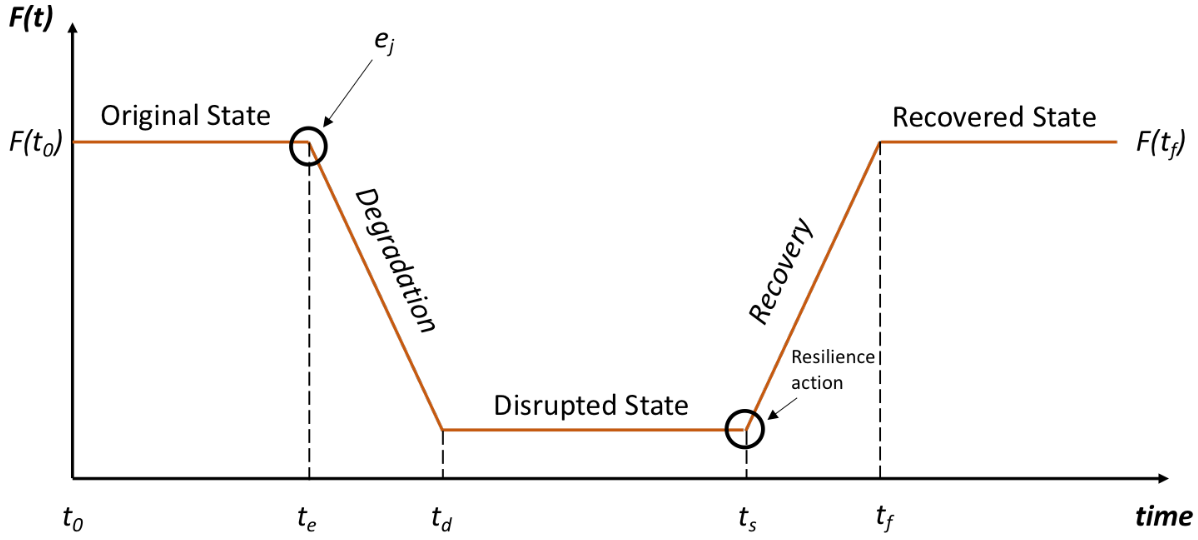

Figure 4: Representation of system performance before, during and after disruption. Figure adapted from Henry and Emmanuel Ramirez-Marquez (2012).

3.3.3 Topology-Based Resilience Measures

Considering that the construction design of a network and the topological properties can affect the vulnerability and behavior of the system, topology-based measures can be useful when analyzing the system resilience. This usually includes determining which components are important in terms of their influence on the network performance and behavior, and using this information to decide where to implement strategies and changes that can contribute to higher system reliability (Barker et al., 2013).

The important component measures can be nodes or edges in a network, where they can be utilized as indicators when evaluating the network resilience, and when deciding where in the network the reliability should be strengthened (Kim et al., 2017; Zhang et al., 2020; Ding et al., 2020). Zhang et al. (2020) analyzed characteristics of node and edge failures, and obtained results which showed that nodes have a greater influence on network resilience than edges. For the purpose of this study, only node indicators will be assessed and explained in dept.

Node Indicators

The investigation of node removal has been studied by several researchers, for the purpose of resilience analysis or robustness strengthening (Barabási et al., 2000; Holme et al., 2002; Zheng et al., 2007; Gilsing et al., 2008; Annibale et al., 2010; Bellingeri et al., 2014; Cerqueti et al., 2019; Ding et al., 2020). Some common strategies include removing nodes sequentially, either caused by random failures or as a consequence of targeted attacks. For the latter, the nodes can be ranked from most important to least important on the basis of certain node properties, since high-risk nodes usually are more exposed and prone to attacks. The node removal strategy can be helpful when evaluating how the different removals affect the network and its performance. In some cases, the negative effect may be minimal, while in other cases the removal of certain nodes may cause large disconnections (Bellingeri et al., 2014).

The importance criterion for ranking the nodes in a network can vary. Different node properties, how they are interconnected and structured, and their role in the network can be analyzed. Zheng et al. (2007), Annibale et al. (2010) and Bellingeri et al. (2014) investigated failures in complex networks by node removal, focusing on nodes with a large amount of connected edges, also referred to as high node degree. Gilsing et al. (2008) considered the nodes in the network from a global perspective, by evaluating the betweenness centrality, which is done by calculating the fraction of shortest paths passing through the specific node. Holme et al. (2002) utilized both node degree and betweenness centrality when studying the response of complex networks subject to attacks, where the removal of the nodes was done by descending order of degree and betweenness centrality. Ding et al. (2020) assessed the resilience of China's natural gas import during node removal, determining important nodes by combining node degree, betweenness centrality and node import flow.

When the performance of a network is reduced due to a node removal, the node can be seen as defective with a flow equal to zero, and all of the connected nodes and edges will not receive any flow from the removed node. While this strategy has been used as a way to measure network robustness, the real case may be that an attack or disruption at a node does not necessarily lead to complete shutdown, but rather a reduction in capacity. This means that the disrupted node might still be functioning and be able to perform, but most likely with a lower performance. Depending on which node is disrupted, and the recovery rate and mitigation strategies, the outcome and consequences for the network can range.

3.4 Resilience in Oil and Gas Supply Chain Networks

Section 2.2 addresses the many risks and challenges that the oil and gas industry is facing. Nevertheless, unexpected and sudden disruptions reveal the importance of resilience in supply chains, where it is considered extra important in energy supply chains, since lack of access to energy affects multiple sectors (Urciuoli et al., 2014).

Resilience in oil and gas supply chain networks can be seen in the context of the vulnerabilities of the network, and scenario analysis (Shafieezadeh and Ivey Burden, 2014). By identifying the vulnerabilities and potential disruption scenarios of the supply chain network, as well as topological properties, knowledge can be gained about dependencies and connections. This information can be utilized to build resilience, even if there is poor, or uncertain, knowledge about the specific hazards and disruptions within the sector.

Although oil and gas facilities are built to handle rough climates, it is, according to Equinor (2020), important to strengthen the resilience in light of the multiple risks caused by climate change. The possible hazards and damages after a potential hazardous event are difficult to prevent, but strategies based on adaptation according to climate changes can be useful. This includes factors such as stricter climate policies and capacity to predict the market effect after a change in demand for oil and gas. Besides this, the climate-related risks should be in the risk decision making, for example by using scenario analysis to create resilience strategies.

Oil and gas supply chain networks are complex and well-developed in terms of network construction. The infrastructure, including the transportation of oil and gas, is well-designed. Still, there should be certain possibilities for adjustments and changes in the infrastructure. The large numbers of supply lines could make it possible to compensate for flow from one node to another. This implies that if one facility is unable to deliver oil or gas to its connections, other facilities can assist (Tørhaug, 2006). The large storage capacities at the facilities should make it possible to deliver additional oil and gas for a period of time to compensate for the disrupted facility. By creating an agreement of mutual assistance, the reliability towards the customer is strengthened.

When the supply chain network has the capability of being flexible during a disruption that affects the network, there is a need for information sharing among the affected parts (Urciuoli et al., 2014). A close information flow between suppliers and customers can minimize and mitigate the negative consequences caused by the disruption. If information is shared at an early stage, the ripple effects can be minimized (Tomlin, 2006). Depending on the importance of the different parts of the network and the connections, specific information sharing can be set as a property of resilience. Several sections in the oil and gas supply chain network have high importance, and in case there is a disruption at, for instance, a specific field, the connected facilities should be warned as soon as possible. This way they can prepare and further convey the information to their connections and customers.

A strong oil and gas network with high resilience can be evaluated on the basis of different factors. Since oil and gas sectors have high prioritization on risk management and mitigation, the focus on strengthening the resilience can lay in the ability to bounce back quickly after disruptions, with minimal damages and ripple effects. This means that an understanding of the network behavior and its patterns can be seen as beneficial. In the context of network topology analysis, knowledge can be gained about vulnerabilities, dependencies and important, critical parts of the network.

4 Resilience-Based Importance Analysis

This chapter presents a methodology of resilience-based importance analysis. A framework, consisting of three main parts is developed and utilized for the purpose of this study. The three parts can be seen in figure 5 and include (1) network construction, (2) topology analysis and (3) resilience evaluation.

The function of this resilience-based importance analysis is to evaluate how different measures of a performance function, based on node disruptions, can be applied in order to calculate the performance and behavior of a supply chain network. The models are used based on a constructed network and its respective topological properties and analysis. Important nodes are identified by using a method that weights node degree, node flow and node betweenness. The nodes can then be compared, where a set of selected nodes with high criticality are chosen as failure nodes to evaluate how disruptions and loss of capacity at these nodes affect the network performance function. The outcome can then be evaluated and compared with the calculations of the important nodes, to reevaluate their importance in the network. The loss of performance and the network behavior, with importance analysis based on node indicators, can be used as a method to evaluate system resilience.

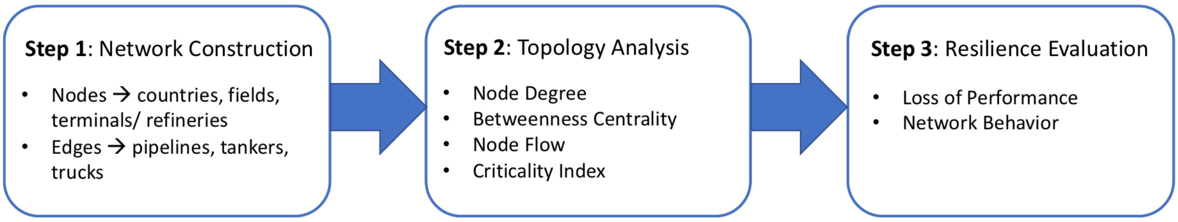

Figure 5: Framework with three main parts for resilience-based importance analysis.

4.1 Network Construction

Since the network of a supply chain can be an important tool when describing and analyzing the structure of a complex system (Cerqueti et al., 2019), the first step of evaluating the behavior of a system is how the supply chain network is constructed. A construction shows how the supply chain network is designed, and how the nodes and edges are connected together. The nodes represent important independent units, and the edges represent the connections between the nodes. The physical network shows dependencies and interactions in the network.

On the basis of the physical network, a logical network can be extracted, where the set of nodes (N) and edges (E) can be represented by $G = (N,E)$ (Nielsen, 2016). The set of edges is composed of pairs of nodes, such that $\{n_i, n_j\}$ is the edge connecting node n_i and node n_j. The nodes are usually given a number each, to distinguish between them. This sort of logical network gives a representation of the construction, making it easier to analyze topological properties.

4.1.1 Adjacency Matrix

To get an overview of how the supply chain network is connected and to see the degree of each node, an adjacency matrix A can be conducted based on the logical network. The adjacency matrix shows the relationship between all of the nodes in the network, indicating which nodes that are connected together with an edge. Equation 1 shows the relation between two nodes, where the value of a_{ij} is equal to 1 if the two nodes n_i and n_j have a connecting edge, and 0 if they are not connected. Equation 2 shows the adjacency matrix, which gives a mathematical expression of the network and its dependencies, as well as the degree of all of the nodes.

$$a_{ij} = \begin{cases} 1, & \text{if } \{n_i, n_j\} \in E \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1j} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & a_{i3} & \dots & a_{ij} \end{pmatrix} \tag{2}$$

4.2 Topology Analysis

Depending on how a supply chain network is constructed, the network topology, including topological properties, can be analyzed in order to identify critical nodes and gain knowledge about the system performance and behavior. Node degree, betweenness centrality and node flow are metrics that can be evaluated to measure the criticality of a node, which can be referred to as the criticality index (CI) of the node (Ding et al., 2020). Node degree and node flow analyze the node and its closest dependencies, while the betweenness centrality discovers the amount of influence a node has on the overall network (Barthelemy, 2004; Bellingeri et al., 2020). These three metrics can be combined with a specific weight each depending on their importance and correlations.

The criteria importance through intercriteria correlation (CRITIC) method is a method proposed by Diakoulaki et al. (1995), which determines the weight of a set of chosen metrics with the use of correlation (Fan et al., 2021). The CRITIC method creates a way of combining topological properties with node flow, and makes it possible to rank the nodes in the network. This can further be used to identify the nodes that are considered to have high importance (Ding et al., 2020).

4.2.1 Node Degree

The node degree refers to the number of edges linked to a certain node (Bellingeri et al., 2014). Different network structures have different system impacts, whereas node degree often is used as an indicator to point out important nodes (Annibale et al., 2010; Bellingeri et al., 2014). A high node degree can in many cases imply that the node is of high importance. Equation 3 shows the formula for calculating the degree of a certain node n_{ij}, with respect to the adjacency matrix. The formula is a summation of all of the edges connected to the node.

$$deg(n_i) = \sum_{i=1} a_{ij} \tag{3}$$

4.2.2 Betweenness Centrality

The betweenness centrality of a node shares information about the amount of influence the node has in the network (Gilsing et al., 2008). Although node degree gives a good representation of how important a node is, it only assesses the importance from a local perspective. Node betweenness, on the other hand, evaluates the node on a global scale, by measuring its influence on the overall network. A node can have a relatively low degree, but still be one of the most important nodes in the network because it might be the connection between two communities (Ding et al., 2020). Removal of a node with high betweenness centrality may lead to a high loss of performance. The node betweenness is calculated by using equation 4. N_{jl} is the number of shortest paths between node j and l, and $N_{jl}(i)$ is the number of shortest paths between node j and l passing through node i.

$$B_i = \sum_{i=1} \frac{N_{jl}(i)}{N_{jl}} \tag{4}$$

4.2.3 Node Flow

Each edge has a capacity that is determined by the flow of the nodes. The work flow of a node indicates the load of it, where in-flow is set as equal to out-flow. Depending on the network under consideration, the flow can have different units of measurement. During node disruptions, the capacity of the node can be reduced, which can cause a flow reduction. This can further lead to a loss of performance and changes in the network behavior. The loss of performance can be seen as a reduction in the total average flow in the network, meaning the total flow that reaches the end node(s).

4.2.4 Criticality Index

Node degree (deg), betweenness centrality (B) and node flow (F) can be combined and utilized to calculate the criticality index (CI) of each node in the network (Ding et al., 2020). This index evaluates the nodes and gives them values between 0 and 1, where high values imply high criticality. This method was used by Ding et al. (2020), and is based on the CRITIC method. It identifies nodes that are considered important in the network.

To calculate the criticality index, the three metrics deg, B and F are first normalized to obtain values between 0 and 1. The values are normalized by using formula 5, where x^*_{ij} is the normalized performance value of the ith alternative on the jth metric.

$$x^*_{ij} = \frac{x_{ij} - min(x_{ij})}{max(x_{ij}) - min(x_{ij})} \tag{5}$$

The three normalized metrics deg^*, B^* and F^* are then given a weight each by using formula 7 and 8, where the two variables i and j are set as equal to these metrics. The value of σ symbolizes the standard deviation of metric j, and r_{ij} is the correlation coefficient between metric i and j. C_j indicates the amount of information transmitted through the corresponding metric, where a higher value means a larger amount of information is transmitted. C_j is calculated by using the standard deviation and correlation coefficient, in order to find the weights. The correlation coefficient r_{ij} is calculated through formula 6, where i_n specifies the values of the i-variable in the sample, and $\bar{i}$ is the mean value of the i-variable. The same information is applied for the j-variable.

$$r_{ij} = \frac{\sum(i_n - \bar{i})(j_n - \bar{j})}{\sqrt{\sum(i_n - \bar{i})^2 \sum(j_n - \bar{j})^2}} \tag{6}$$

$$C_j = \sigma_j \sum_{i=1}(1 - r_{ij}) \tag{7}$$

$$w_j = \frac{C_j}{\sum_{i=1} C_j} \tag{8}$$

When the weights are determined, the criticality index can be calculated by using formula 9. CI_i is the score of node n_i, and x_{ij}^* is the normalized value of the selected metric, which in this study are chosen to be deg, B and F.

$$CI_i = \sum_{i=1} x^*_{ij} \times w_j \tag{9}$$

The proposal of combining deg, B and F was introduced by Ding et al. (2020), where the formula adds the three metrics, multiplied by their corresponding weight. This proposal can be seen in equation 10. With this method, each node obtains its own criticality index, which refers to its importance, and can be utilized to rank the nodes in the selected network.

$$CI_i = w_1 deg(n_i)^* + w_2 B^*_i + w_3 F^*_i \tag{10}$$

4.3 Resilience Evaluation

The resilience of a network can be evaluated based on different system performance functions. Several system performance functions can be studied, where usually the ones that affect the customer satisfaction are highlighted (Beamon, 1999; Gunasekaran et al., 2001; Bhagwat and Sharma, 2007). When a system is capable of delivering products to its customers while being disrupted, the resilience can be considered as high. Hence, measurement of performance functions can be utilized to evaluate the resilience of a supply chain network.

A way of evaluating the performance function is by analyzing the loss of performance as how much the system has lost of a selected metric during the disrupted period. This can be done by comparing the system behavior during a normal state and disrupted state caused by node failure. When one, or several, nodes are disrupted, the node capacities can be reduced and the network behavior can change, which can further lead to a loss of performance. Based on the identification of critical nodes, important nodes can be used to measure and evaluate the outcome and consequences of node disruptions. The important aspect is to check how these nodes, and perhaps changes in these nodes affects the total network performance. The effect of the disruption can be analyzed and compared with the ranking of the node importance.

4.3.1 Loss of Performance

The network performance can be seen as a representation of the availability of the system, in terms of how much the network is able to deliver despite a disruption. When the performance is reduced, there is a loss of capacity, which can be seen as a loss of performance. The output is an important performance measure, since it is connected with the customer service (Beamon, 1999). When the output is below the expectations, the customer may turn to other suppliers, causing destruction in the network. Hence, the outcome of the performance after a disruptive event can be used to evaluate the resilience of a network.

The loss of performance can be seen in the context of the system performance function, and figure 4 from chapter 3.3.2. Without any disruptions, the system performance is in a normal condition, and in case of a loss of capacity, the performance function can be reduced. Depending on how fast the system can recover, and the consequences of the disruption, the outcome and loss of performance can be evaluated and compared based on different scenarios and nodes disruptions.

In order to check how different node disruptions, and their loss of capacities, affects the network performance, it can be useful to have a certain knowledge about their recoverability. A node that recovers at a high rate can cause less damage and consequences for the supply chain network than a node with a low recovery rate. However, if the nodes recover at the same rate, the outcome of the consequences can still differ. This is because of the different importance of each node, and it is therefore important to evaluate each node and their dependencies and interconnections to see how they individually influence the overall network.

4.3.2 Network Behavior

When a supply chain network is going through the different phase changes, from degradation to recovery, due to a disruption, the behavior of the system also changes. This behavior can be analyzed to gain knowledge about system resilience.

Based on a selected system performance function, such as the loss of performance, a resilience-based value on the basis of the network behavior can be calculated by using a deterministic approach given by formula 11 (Henry and Emmanuel Ramirez-Marquez, 2012; Hosseini et al., 2016). This formula is a function of time, and can be seen in the context of figure 4 from section 3.3.2. It gives a resilience-based evaluation of the network behavior at time t_r after a disruptive event e_j has occurred. This resilience-based value, $RE(t_r|e_j)$, is between 0 and 1, where higher value implies higher resilience. The minimum value of $RE(t_r|e_j)$ is equal to 0 and occurs when $F(t_r|e_j) = F(t_d|e_j)$. During this state, the recovery has not started yet, either because no resilience actions have been made, or because the action that has been made is ineffective. When the value of $RE(t_r|e_j)$ is equal to 1, the system has recovered fully.

$$RE(t_r|e_j) = \frac{F(t_r|e_j) - F(t_d|e_j)}{F(t_0) - F(t_d|e_j)} \tag{11}$$

5 Numerical Example

This chapter presents a case study with parts of the Norwegian oil and gas supply chain network as a numerical example. The network construction, as well as topological properties, are presented. Node disruption scenarios are made and important nodes are identified in order to evaluate the connection between important nodes and network performance and behavior.

5.1 Case Study: Norwegian Oil and Gas

Norway is the third largest exporter of natural gas in the world, where almost all the oil and gas produced on the Norwegian continental shelf is exported. It has one of the world's largest offshore markets, and the natural gas constitutes around half of the total value of Norway's exports. This makes the oil and gas industry one of the most important export products for Norway and a cornerstone in the Norwegian economy. The rapid development in subsea technology makes it possible to explore and extract oil and gas at longer depths and distances from land (Norwegian Petroleum, 2019).

The produced oil and gas on the Norwegian continental shelf is exported all around the world, and for certain countries this import is crucial for the country's energy supply (Norwegian Petroleum, 2021a). At the end of 2020, there were 90 fields in production, distributed in the North Sea, the Norwegian Sea and the Barents Sea (Norwegian Petroleum, 2021b). Many of the fields in these seas are connected, as seen in figure 6, where certain fields act as meeting joints before the oil and gas is further distributed to facilities onshore.

The oil and gas that is produced at the fields is either transported through pipelines or with tankers for delivery on land. This is an easy and efficient way to transport oil and gas, and especially oil, where the transport cost is low compared to the product price (Norwegian Petroleum, 2021b). The gas is mainly transported through pipelines, where gas transported with tankers is liquefied natural gas (Norwegian Petroleum, 2021a).

The delivery points on land include terminals and refineries, both in Norway and in other countries around the world. The onshore terminals and refineries in Norway are placed along the coast, where the oil and wet gas, also named gas condensate, is usually stored in rock caverns before they are loaded onto tankers for further export (Norwegian Petroleum, 2021d). Shuttle tankers are usually used when the delivery distance is relatively short, such as destinations in north-western Europe. For longer distances, like destinations in the Mediterranean countries, Asia or America, larger tankers are used as transportation method (Norwegian Petroleum, 2021a).

The terminals and refineries along the Norwegian coast transform crude oil and natural gas into everyday products such as petrol, diesel and heating oil (Equinor, 2021b). Among all the terminals and refineries in Norway, Mongstad in Nordhordland, is the largest one. It is also one of the largest in Europe, with around 1500 ships calling every year (Equinor, 2021a).

The pipeline system at the Norwegian shelf is big and complex, compounded by many large and long pipelines, with extremely large capacity. Since this study is limited to a small section of the Norwegian oil and gas supply chain network, only a few pipelines, including those that transport oil and gas condensate will be included. Figure 6 shows the pipeline system where oil and condensate from the fields are transported to facilities onshore. Since the main part of this numerical example is evaluated around the nodes, and not the edges, the pipeline system will not be explained in detail.

Figure 6: Representation of the pipeline system for oil and gas condensate. Figure derived from Norwegian Petroleum (Norwegian Petroleum, 2021d).

5.1.1 Network Topology

The presented oil and gas network is simplified and includes only a few fields, countries and facilities. However, fields, terminals and refineries that are considered as important in the Norwegian oil and gas network are included. Figure 7 gives a representation of the constructed network, with embedded upstream, midstream and downstream activities. It contains four echelons, which are fields, terminals/ refineries, first distribution, and second distribution. In the first echelon, there are four fields included; Ekofisk, Johan Sverdrup, Troll and Sleipner, where Ekofisk and Johan Sverdrup are among the biggest fields on the Norwegian continental shelf (Equinor, 2022), producing respectively around 140 000 and 440 000 barrels of oil each day.

As seen from figure 6, Ekofisk is the field directly connected to the main pipe that sends oil to Teesside in England. All the oil from the fields Ula, Gyda, Vallhall and Hod is transported through Ekofisk. Therefore, in the constructed network, Ekofisk is named as the main node since it works as an important hub in the North Sea, where the oil from the four other connected fields are embedded in this node.

The three terminals and refineries included are Teesside in England, and Mongstad and

Kårstø in Norway. Nearly all the oil from Ekofisk is transported to Teesside through a pipeline, as seen in figure 6. The oil from Johan Sverdrup and Troll is sent to Mongstad, while Kårstø receives gas condensate from Sleipner. Although all of the included nodes are considered important for this network, certain nodes can be evaluated as more critical than others. Their respective criticality index, as well as importance during nodes disruption scenario will be further analyzed and discussed in the upcoming sections.

The three onshore facilities all have large storage capacity, where the oil and gas usually is stored before it is further distributed. The largest facility, Mongstad, has a storage capacity of 9.44 million barrels (Equinor, 2021a). This storage option makes it possible to deliver custom-made orders, and creates a buffer for the facilities. Due to the importance of this, the storage at the different facilities is set as separate nodes from their respective facility, acting like individual units.

Based on the physical network, a logical network is extracted, which can be seen in figure 8. This logical representation of the network shows the 17 nodes, where each node is given a number as a reference. Hereafter, the nodes will be referred to by their respective given number.

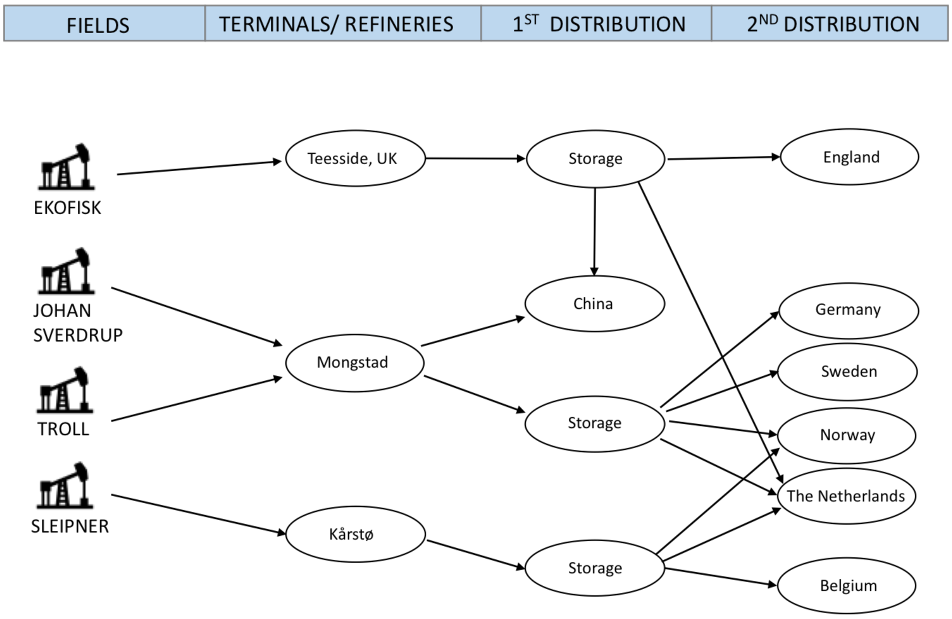

Figure 7: Physical network.

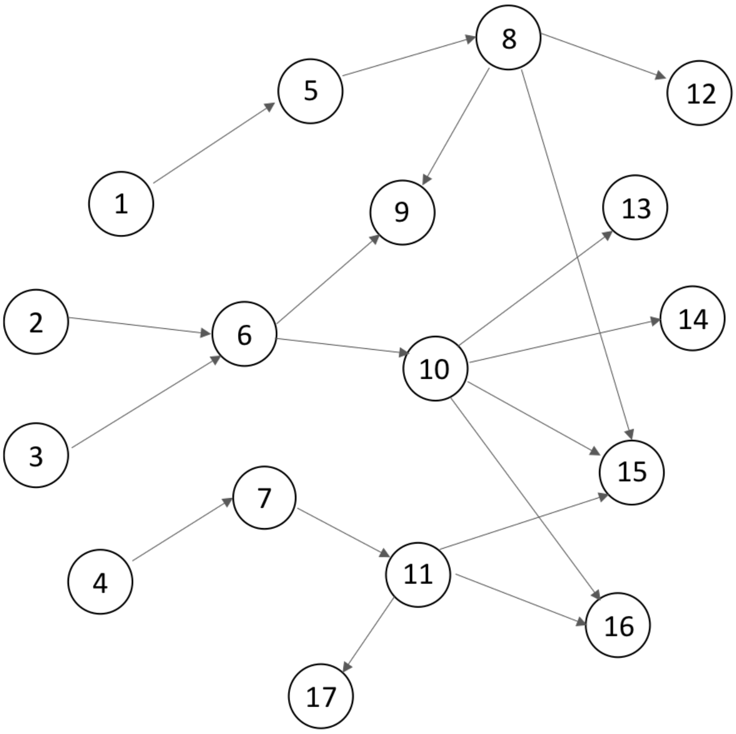

Figure 8: Logical network.

Adjacency Matrix

In order to see the relationship between all of the nodes in the network, an adjacency matrix is conducted, corresponding to equation 1 and 2 in section 4.1.1. This matrix can be seen in equation 12 and has a dimension of 17 × 17, representing all the nodes in the network. The nodes that are connected by an edge are indicated as 1, and non-connected nodes are indicated as 0. The adjacency matrix shows which nodes are connected together, as well as the degree of each node by adding the numbers in each row or column.

$$A = \begin{pmatrix}
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix} \tag{12}$$

Average Flow Per Day

The Norwegian oil and gas network is large, and the oil and gas production and export is high. Several barrels of oil and gas are transported every day, all around the world. Each edge has an average flow per day, where the values vary from 10 000 to 440 000 barrels of oil. The average flow values are collected from Norwegian Petroleum (2021a,d), and are slightly adjusted to get round numbers. These values can be seen in table 1, which shows the amount of average flow from node n_i to node n_j. Some nodes receive or send oil and gas to the same nodes, creating an interconnected network.

The total amount of flow in the network is 750 000 barrels of oil per day, or 31 250 barrels of oil per hour. This is calculated through summarizing the flow that reaches the end nodes, which are node 9, 12, 13, 14, 15, 16 and 17. This average flow per day for the network will be used as an indicator when comparing the reduced flow capacity with the normal flow capacity, indicating that an average flow of 31 250 barrels of oil per hour represent a stable state.

Table 1: Average flow per day in barrels of oil from node n_i to node n_j.

From (node n_i)	To (node n_j)	Average flow per day
1	5	140 000
2	6	440 000
3	6	90 000
4	7	80 000
5	8	140 000
6	9	200 000
6	10	330 000
7	11	80 000
8	12	70 000
8	9	30 000
8	15	40 000
10	13	10 000
10	14	80 000
10	16	100 000
10	15	140 000
11	15	40 000
11	16	30 000
11	17	10 000

5.1.2 Node Disruption Scenario

In order to evaluate the overall performance function of the network and the outcomes after a node disruption, a node disruption scenario is created, as well as a recovery plan. This scenario will be performed on the four highest rated nodes based on their criticality index, excluded the end nodes. Their node degree, betweenness centrality and amount of flow will be analyzed. Further, their respective criticality index will be compared with their importance in the network by evaluating their influence on the system performance, and their contribution to loss of performance during a disruption.

The created scenario will include an unforeseen node disruption, which will cause a reduction in capacity and flow at the four selected nodes. This disruption leads to a ripple effect, such that all the nodes that are connected to the certain disrupted node will receive less oil and gas. This will further affect some of the seven end nodes and the total average flow of the network, which normally is 31 250 barrels of oil per hour. The end nodes are node 9, 12, 13, 14, 15, 16 and 17.

The four nodes will be disrupted separately, with the same type of disruption. This disruption will not be a specified event, but it will be of the kind that can not be prevented, only mitigated. The four nodes will recover at the same rate, with the recovery percentages shown in table 2. Later on an alternative recovery plan for one of the nodes will be presented and performed for comparison.

The scenario will happen such that at the initial time t_0, there is no disruption, and the node flow is 100% and equal to 31 250 barrels of oil per hour. At the time t_e the disruptive event occurs, which causes the node flow to be reduced to 63%. The disruptive state, and also the phase with the lowest performance, lasts from time t_d to t_s, for approximately five hours. When a resilience action is initiated at time t_s, the system enters the recovery phase, and from this point on the flow is increasing again, first to 67%, then to 76%, 84%, 91% and finally to 100%. The final state occurs at time t_f after 20 hours, where the system again is stable.

The resilience action initiated at time t_s, which triggers the system to enter the recovery phase, may arise from different resilience and risk mitigation strategies, or as a result of the resilience properties that are embedded within the system. Regardless, the disruption scenario will show how the four selected nodes impact the overall network performance and behavior, and how they can be related to the vulnerability of the network.

Table 2: Node flow percentage at the disrupted nodes from original state to recovered state.

	t_0	t_e	t_d	t_s	t_1	t_2	t_3	t_4	t_f
Time (hours)	0	2	5	10	12	14	16	18	20
Flow (%)	100	100	63	63	67	76	84	91	100

Alternative Recovery Plan

In addition to the proposed recovery plan, a second scenario with a different recovery strategy and hence recovery rate will be examined for one of the nodes. This alternative recovery plan makes it possible to compare the behavior of the network, with respect to the recovery rate, and see how changes in recovery rate influences the network behavior and resilience.

The disruptive event will be the same as in the original scenario, and the time span from the original state to the stable state will also be the same. The only changed parameter is how the node recovers, meaning that the recovery rate and flow percentages will be different.

The purpose of this alternative recovery plan is to check and compare how the recovery rate influences the network resilience behavior, such that special actions or mitigation can be done at the nodes that are considered as important for the overall network performance. The alternative recovery percentages are shown in table 3. Where in this alternative scenario, the nodes has a lower flow during the disrupted state, time t_d to t_s. However, they manage to recover at a higher rate, such that the node flow percentages are higher at the different time sets.

During the stable state, the flow is equal to 100%, where it is reduced to 52% during the disrupted phase. After the resilience action has been initiated, the flow increases to 69%, 81%, 88%, 97% and finally to 100% again.

Table 3: Alternative node flow percentage at the disrupted nodes from original state to recovered state.

	t_0	t_e	t_d	t_s	t_1	t_2	t_3	t_4	t_f
Time (hours)	0	2	5	10	12	14	16	18	20
Flow (%)	100	100	52	52	69	81	88	97	100

5.2 Results

The results from the created disruption scenario are presented in this section. The topology analysis, including the values of the criticality index for each of the 17 nodes is calculated. Further, the disruption scenario is performed on the supply chain network, where the loss of performance due to disruption at each of the four nodes are presented in graphs and tables. Based on the original recovery plan and the alternative recovery plan, the resilience-based network behavior is calculated and presented in a graphs and tables. All the calculations are made in the program Microsoft Excel, and are shown in Appendix A.

5.2.1 Topology Analysis

In accordance with the CRITIC method and the formulas presented in section 4.2, the criticality index for each of the 17 nodes is calculated by first determining the node degree (deg), the total amount of node flow (F) and the betweenness centrality (B). These values can be seen in table 8. Further, the correlation coefficients r_{ij}, the standard deviations σ_j, the amount of information transmitted C_j, and the weights w_j are found based on the normalized values of deg, F and B. In table 4 the different correlation values between these three metrics are shown, and the values of σ_j, C_j and w_j can be seen in table 5, 6 and 7.

Table 4: Correlation matrix.

	r_{deg}	r_B	r_F
r_{deg}	1	0.86634	0.46047
r_B	0.86634	1	0.54383
r_F	0.46047	0.54383	1

Table 5: Standard deviation of the three metrics.

σ_j	σ_{deg}	σ_B	σ_F
$Value$	0.33080	0.33706	0.27117

Table 6: Amount of information transmitted.

C_j	C_{deg}	C_B	C_F
$Value$	0.22269	0.19881	0.27001

Table 7: Weight of the three metrics.

w_j	w_{deg}	w_B	w_F
$Value$	0.32204	0.28750	0.39046

Table 8 shows the values of deg, B, F and CI for each of the 17 nodes. The order of the nodes is based on their criticality index, where they are placed in descending order, with the highest value at the top. The flow F is equal to the total flow of the node in barrels of oil per day. Table 8 shows that the four highest ranked nodes are node 6, 10, 8 and 11. These will be further analyzed and used as reference nodes in the created disruption scenarios. The two nodes with the lowest criticality index value are node 13 and 17, where both had a value equal to zero.

Table 8: Values of deg, B, F and CI for the different nodes.

Node i	**deg**	**B**	**F**	**CI**
6	4	12	530 000	0.919
10	5	12	330 000	0.850
8	4	6	140 000	0.483
11	4	6	80 000	0.438
2	1	0	440 000	0.323
5	2	4	140 000	0.274
15	3	0	220 000	0.319
9	2	0	230 000	0.246
7	2	4	80 000	0.229
16	2	0	130 000	0.171
1	1	0	140 000	0.098
3	1	0	90 000	0.060
4	1	0	81 000	0.053
14	1	0	80 000	0.053
12	1	0	70 000	0.045
13	1	0	10 000	0.000
17	1	0	10 000	0.000

5.2.2 Loss of Performance

The loss of performance in the overall network is evaluated for each of the four node disruption scenarios. The calculations are made based on the average flow per hour for the whole network. It occurs, based on the criticality index, that node 6 is ranked as the most important one, and node 13 and 17 as the least important for the network. During the different disruptions, the non-affected nodes have a normal flow, and the normal average flow per hour, during normal state, is 31 250 barrels of oil per hour.

Node 6

Node 6 was ranked as the most important node with a criticality index of 0.919. It has a number of four connecting edges and a betweenness centrality equal to 12. The average node flow is 530 000 barrels of oil per day, where the flow is sent directly to node 9 and 10, where node 10 receives the most. From node 10 there are further connections.

A disruption at node 6 leads to a flow reduction, that affects node 9, 10, 13, 14, 15 and 16. This means five of seven end nodes will receive less oil and gas, which causes a decrease in the average network flow. During the disrupted state, the lowest flow is 23 079 barrels of oil per hour. Figure 9 shows the performance function from t_0 to t_f, according to the recovery plan and the recovery percentages. Table 9 shows the total average flow per hour for the network from the disrupted state to the recovered state.

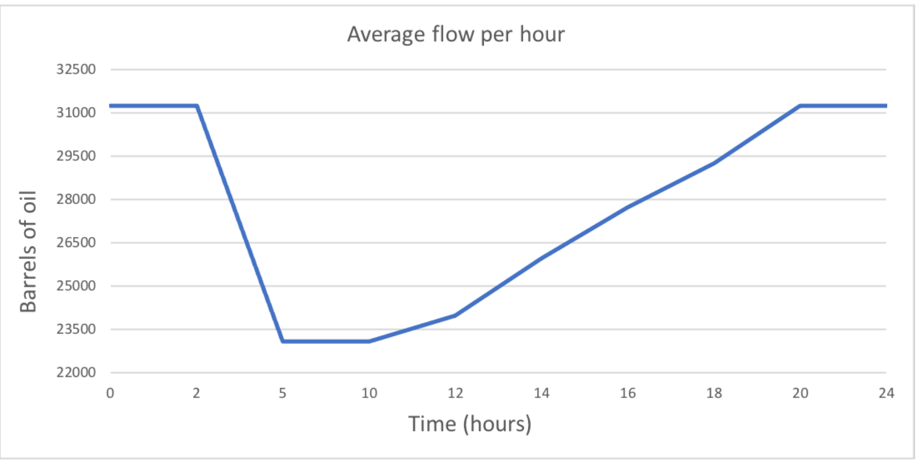

Figure 9: Network performance function during disruption at node 6.

Table 9: Average flow per hour in barrels of oil at time t_r during disruption at node 6.

	t_d	t_1	t_2	t_3	t_4	t_f
Time	5	12	14	16	18	20
Avg. Flow	23 079	23 963	25 950	27 717	29 263	31 250

Node 8

Node 8 was ranked as the third most important node in the network, with a criticality index of 0.483. It has four connecting edges and a betweenness centrality equal to 6. The average node flow is 140 000 barrels of oil per day, where the flow is sent directly to node 9, 12 and 15. These three nodes are all end nodes, and there is no further distribution from here, where node 12 receives the most.

A disruption at node 8 leads to a flow reduction that affects node 9, 12 and 15. This means that three out of seven end nodes are affected. Since these three nodes receive less flow during the node disruption, it causes a decrease in the average network flow. During the disrupted state, which is three hours after the disruptive event occurred, the lowest flow is 29 092 barrels of oil per hour. When the resilience action is initiated at time t_s, the node flow starts to increase, which also leads to an increase in the average network flow. Figure 10 shows the performance function from t_0 to t_f, according to the recovery plan and the recovery percentages.

Table 10 shows the total average flow per hour for the whole network at time t_r, corresponding to figure 10. The table includes the average flow from time t_d to time t_f, which means from the disrupted state to the recovered state.

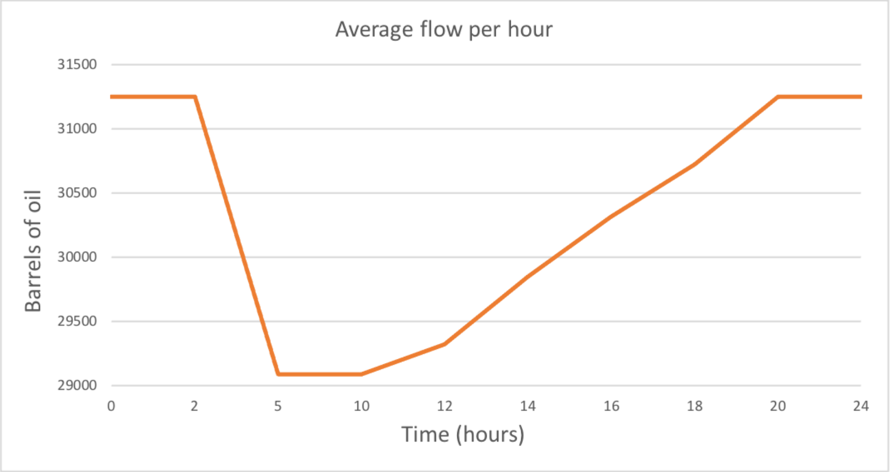

Figure 10: Network performance function during disruption at node 8.

Table 10: Average flow per hour in barrels of oil at time t_r during disruption at node 8.

	t_d	t_1	t_2	t_3	t_4	t_f
Time	5	12	14	16	18	20
Avg. Flow	29 092	29 325	29 850	30 317	30 725	31 250

Node 10

Node 10 was ranked as the second most important node in the network, with a criticality index of 0.850. It has five connecting edges and a betweenness centrality equal to 12. The average node flow is 330 000 barrels of oil per day, where the flow is sent directly to node 13, 14, 15 and 16. These four nodes are all end nodes, and there is no further distribution from here.

A disruption at node 10 leads to a flow reduction, that affects node 13, 14, 15 and 16. This means that four out of seven end nodes are affected. Since these four nodes receive less flow during the node disruption, it causes a decrease in the average network flow. During the disrupted state, which is three hours after the disruptive event occurred, the lowest flow is 26 163 barrels of oil per hour. Figure 11 shows the performance function from t_0 to t_f, according to the recovery plan and the recovery percentages.

Table 11 shows the total average flow per hour for the whole network at time t_r, corresponding to figure 11. The table includes the average flow from time t_d to time t_f, which means from the disrupted state to the recovered state.

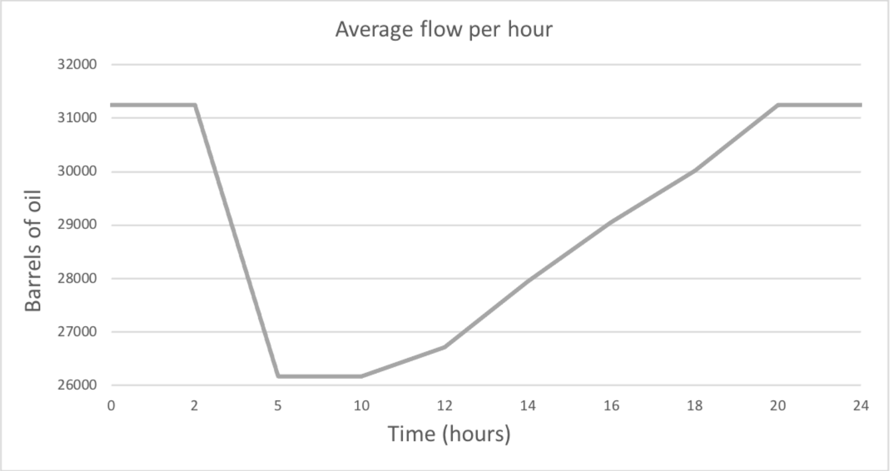

Figure 11: Network performance function during disruption at node 10.

Table 11: Average flow per hour in barrels of oil at time t_r during disruption at node 10.

	t_d	t_1	t_2	t_3	t_4	t_f
Time	5	12	14	16	18	20
Avg. Flow	26 163	26 713	27 950	29 050	30 013	31 250

Node 11

Node 11 was ranked as the fourth most important node in the network, with a criticality index of 0.438. It has four connecting edges and a betweenness centrality equal to 6. The average node flow is 80 000 barrels of oil per day, where the flow is sent directly to node 15, 16 and 17. These three nodes are all end nodes, and there is no further distribution from here.

A disruption at node 11 leads to a flow reduction, that affects node 15, 16 and 17. This means that three out of seven end nodes are affected. Since these three nodes receive less flow during the node disruption, it causes a decrease in the average network flow. During the disrupted state, which is three hours after the disruptive event occurred, the lowest flow is 30 017 barrels of oil per hour. Figure 12 shows the performance function from t_0 to t_f, according to the recovery plan and the recovery percentages.

Table 12 shows the total average flow per hour for the whole network at time t_r, corresponding to figure 12. The table includes the average flow from time t_d to time t_f, which means from the disrupted state to the recovered state.

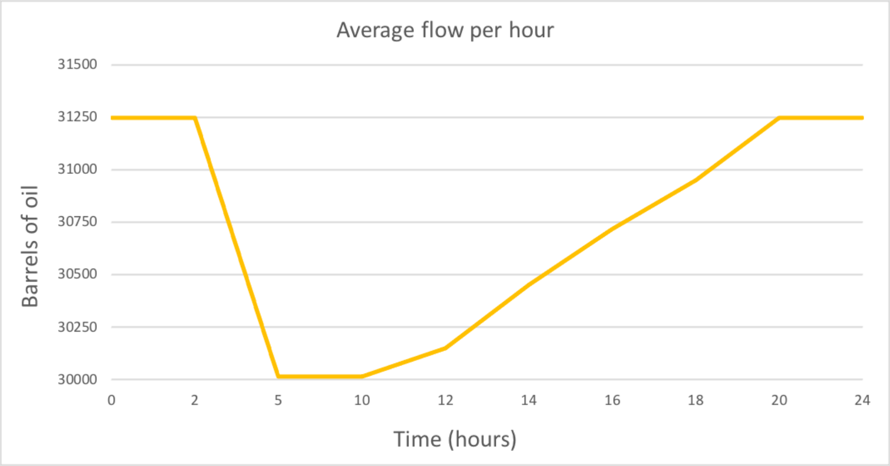

Figure 12: Network performance function during disruption at node 11.

Table 12: Average flow per hour in barrels of oil at time t_r during disruption at node 11.

	t_d	t_1	t_2	t_3	t_4	t_f
Time	5	12	14	16	18	20
Avg. Flow	30 017	30 150	30 450	30 717	30 950	31 250

Comparative Analysis

The four node disruptions, conducted on node 6, 8, 10 and 11, affected the performance function in different ways, with varying outcomes. To give a comparative view, these functions are plotted in the same diagram, seen in figure 13. The total average flow per hour for the network is changed from barrels of oil to flow percent. This flow percent represents the performance as a percentage of the normal flow, which is 100% during normal operation.

The flow percentages corresponding to figure 13 are presented in table 13. During the two first hours of the observation, the flow was normal and equal to 100%. The remaining flow values that are shown in the table represent the time period after the system has been disrupted, and during the recovery phase, until full recovery is achieved.

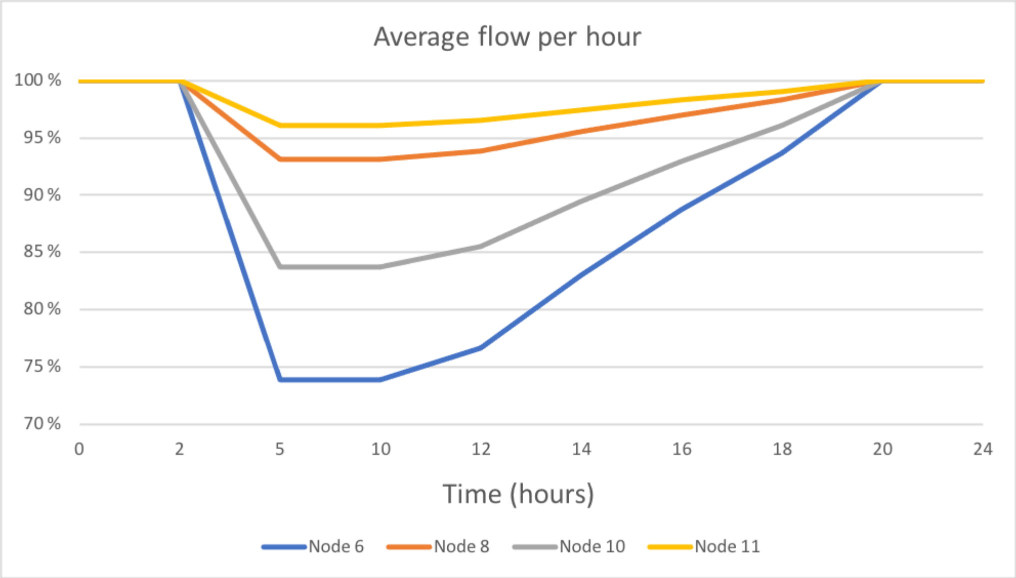

Figure 13: Network performance function based on disruptions at node 6, 8, 10 and 11.

Table 13: Total flow percentage per hour at given times based on disruptions at the four nodes.

TIME (hours)	NODE 6	NODE 8	NODE 10	NODE 11
0	100.00	100.00	100.00	100.00
2	100.00	100.00	100.00	100.00
5	73.85	93.09	83.72	96.05
10	73.85	93.09	83.72	96.05
12	76.68	93.84	85.48	96.48
14	83.04	95.52	89.44	97.44
16	88.69	97.01	92.96	98.29
18	93.64	98.32	96.04	99.04
20	100.00	100.00	100.00	100.00

5.2.3 Network Behavior

According to the presented recovery plan, the network behavior was observed based on a resilience computation. This behavior can be seen in figure 14, with corresponding values presented in table 14. The calculation of this system resilience value was conducted with the use of the theory from section 4.3.2, and formula (11), where the network behavior and resilience value is calculated from time $t_d = 5$ hours.

During the disrupted state, which lasted for five hours, the system resilience was equal to 0. At the time $t_s = 10$ hours, the resilience action was initiated, and the system resilience started to increase. After 12 hours the value had reached 0.108. During the recovery phase, the system resilience continued to increase and when full recovery was achieved after 20 hours, the system resilience was equal to 1.

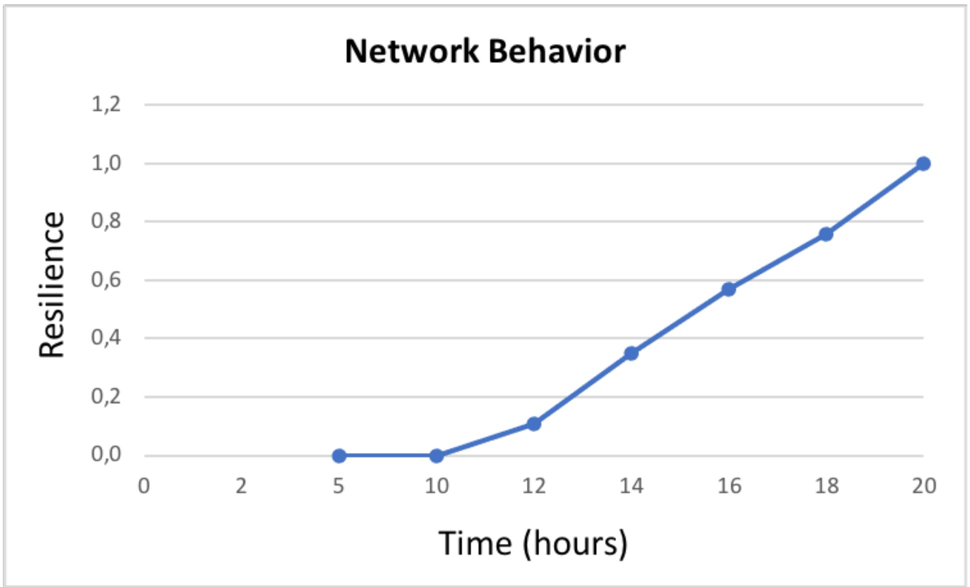

Figure 14: Resilience-based evaluation of network behavior based on flow.

Table 14: Resilience values based on network behavior.

	t_d	t_s	t_1	t_2	t_3	t_4	t_f
Time (hours)	5	10	12	14	16	18	20
RE $(t_r \mid e_j)$	0	0	0.108	0.351	0.568	0.757	1

Alternative Recovery Plan

In addition to the presented recovery plan, according to the created scenarios, an alternative recovery plan was conducted. This plan had different strategies, with a different recovery rate.

The results from this alternative recovery plan are presented in figure 15, with corresponding values presented in table 15. With different flow values, the network behavior also experienced changes. During the disrupted state, between time t_d and t_s, the capacity of the node was 52% and the resilience was equal to 0. When the node started to recover, the resilience increased, and after 12 hours, the value was 0.354.

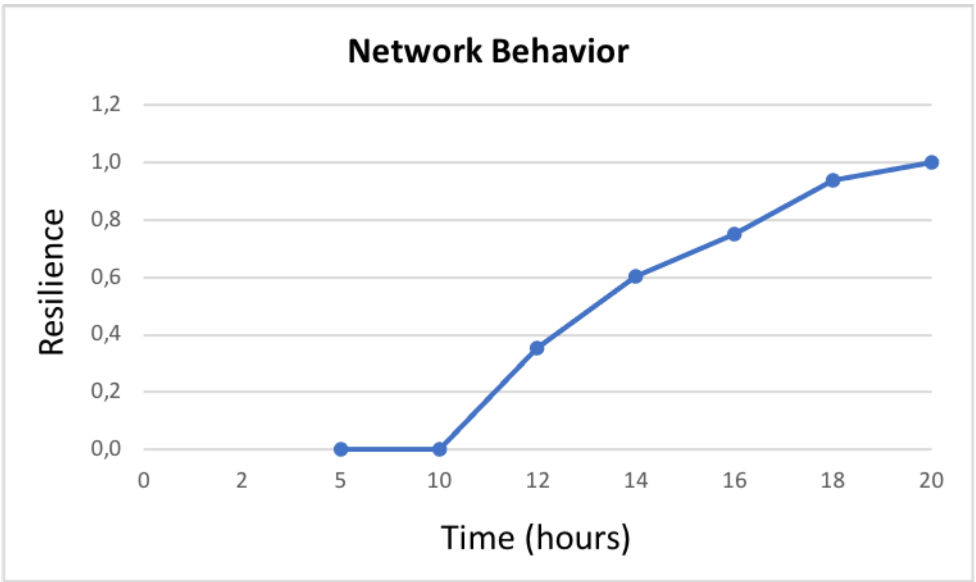

Figure 15: Resilience-based evaluation of network behavior based on flow, with alternative recovery plan.

Table 15: Resilience values based on network behavior, with alternative recovery plan.

	t_d	t_s	t_1	t_2	t_3	t_4	t_f
Time (hours)	5	10	12	14	16	18	20
RE $(t_r \mid e_j)$	0	0	0.354	0.604	0.750	0.938	1

6 Discussion

This section discusses the findings and the results from the numerical example in the context of the presented literature and theory.

The key findings from the results are summarized below.

1. Node 6 was ranked as the most important and critical node in the network, and it also had the highest negative impact on the network performance during disruption.
2. Flow had the highest weight when calculating the criticality index, followed by node degree and node betweenness.
3. A change of recovery rate lead to higher resilience in terms of network behavior.
4. There is a high correlation between the criticality index of a node and its effect on the network performance.
5. An evaluation of resilience, based on a performance function as a capacity of flow, has shown to be a good indicator.

6.1 Node Ranking

The importance of all the individual nodes in the network was determined based on their criticality index value, which was calculated with the use of the CRITIC method. In this network the chosen metrics were node degree, betweenness centrality and node flow, where each of these three was given a specific weight. The node flow had the highest weight value, which was $w_F = 0.39046$, followed by the node degree of $w_{deg} = 0.32204$ and the betweenness centrality of $w_B = 0.28750$. It can be discussed why node flow had the highest weight, where reasons such as network construction delimitations can be pointed out. Due to the small size of the network, many nodes only had one connected edge and zero betweenness centrality. The node flow, on the other hand, can be considered as a reliable metric, as it somehow can indicate the size of the node and its role in the network. All of the nodes had a certain node flow value that varied from 10 000 to 530 000 barrels of oil per day.

6.1.1 Correlations

The correlation matrix shows a high correlation between node degree and betweenness centrality, whereas the correlation between node degree and node flow is quite low. This indicates that nodes with a high degree also tend to have high betweenness centrality, and opposite. The low correlation between flow and degree can be explained by the network construction and the function of the end nodes. All of the start nodes only had one or two edges, however they all had a decent amount of node flow, which amplifies the low correlation. In this case, all of the start nodes were fields, which can be connected with the upstream activities of exploring and producing oil, making it natural that they have a high flow. Even though the production is high, the fields only send oil and gas to one or two other facilities, where they have the responsibility of further export.

6.1.2 Node Flow Impact

The four highest ranked nodes were node 6, 10, 8 and 11. All of these nodes had the highest node degree and betweenness centrality among the 17 nodes in the network. However, the metric that varied was the node flow, which was not in descending order. Only node 6 had the highest node flow among the 17 nodes, and the three others all had lower flow values than node 2. Node 11 even had a lower flow than, or equal to, several of the other nodes in the network, with an average node flow equal to 80 000 barrels of oil per day.

Even though node 2 had a higher node flow than node 8, 10 and 11, it was considered to have lower importance. Its criticality index was equal to 0.323, making it the fifth most important node. This is most likely due to its low degree and a betweenness centrality equal to zero. As briefly discussed, this node is a start node and its connections and betweenness centrality is therefore limited because of its location. Still, it has an important role in the network because of its high node flow. Both node 2 and 3 are start nodes connected to node 6, but the flow contribution from node 3 is low in comparison. This is also reflected in the node ranking, as node 3 has a relatively low ranking and a criticality index of 0.060.

6.1.3 Importance of Node 6

Node 6 was ranked as the most important node, with a criticality index equal to 0.919. It had the highest node flow, significantly higher than the other nodes, and was the only node connected to two start nodes. Node 6 also had the highest value of node betweenness, and a number of four connecting edges.

The high value of betweenness centrality for node 6 indicates that it is an important connection. Even though it only sends oil to two other nodes, node 9 and 10, node 10 has four further connections to node 13, 14, 15 and 16. This way, node 6 can be seen as the connecting node between two different communities, which was highlighted as an important consideration, besides node degree, by Ding et al. (2020).

Due to its location in the network, the oil from node 6 is transported to several long-distance nodes. Node 10, 13 and 14 only receives oil through node 6, where node 10 have further connections, but these receive oil from other nodes as well. A loss of connection will lead to node 10, 13 and 14 not receiving any oil at all. The connection to node 9 also highlights the importance of node 6, because node 9 receives more oil from node 6 than node 8, and loss of capacity at node 6 will have a greater negative impact on node 9 than a loss of capacity at node 8.

Besides the information given by the node degree, node flow, betweenness centrality and criticality index, node 6 can be considered as important because of its size. As pointed out in the case study, node 6 is the biggest refinery in Norway, and one of the largest in Europe

(Equinor, 2021a). It is also connected to node 2, which is one of the largest fields on the Norwegian continental shelf (Equinor, 2022). Only on the basis of this given information, node 6 can already be considered relatively important, where its high criticality index value can be seen as additional amplifying information.

6.2 Loss of Performance

To see how the different nodes affected the performance function of the network and the loss of performance during disruptions, a node disruption scenario was created. This was performed on node 6, 8, 10 and 11, since they had the four highest criticality index values. The performance function was set as the average total flow per hour for the whole network, and was equal to 31 250 barrels of oil per hour. A reduction in node capacity can affect the network in a negative way, and the results showed that all of the disrupted nodes somehow cause a loss of performance.

The different performance functions during node disruptions were displayed in the same figure and table, figure 13 and table 13, for comparison. It was clear that node 6 caused the biggest loss performance among the four nodes. During the disrupted state, before any resilience action had been initiated, node 6 caused a reduction in the total average flow corresponding to 73.85% of the original flow.

Node 10 also caused a noticeable loss of performance, reducing the total average flow per hour to 83.72% during the disrupted state. This had a high negative impact on node 15, since this node originally receives 140 000 barrels of oil per day from node 10, and only 80 000 barrels of oil per day in total from node 8 and 11.

Node 8 and 11 had the lowest negative impact on the network performance. This can be due to the network construction design. During the disrupted state, node 8 lead to a flow reduction of 93.09% and node 11 to 96.05%, where it increased after the resilience action had been initiated. The loss of capacity at node 8 had the highest negative effect on node 12, since node 9 and 15 both had other connections. The same yielded for node 11, where node 17 was the only node having one connection. In case of a shutdown at node 11, only node 17 will stand alone with no supplier. The other connected nodes, node 15 and 16, will receive from other nodes. In addition, the average node flow of node 17 is 10 000 barrels of oil per day, which is a low value compared to many of the other nodes. The same evaluation applies to node 8, but the supply to node 12, which is a single node with only a connection to node 8, has a significantly higher node flow.

This comparison gives a representation of how the four nodes affect the performance function, and it highlights the importance of node 6 and 10. The loss of performance caused by node 8 and 11 can be seen as minimal compared to node 6 and 10. This indicates that mitigation strategies should mainly be prioritized at node 6. However, node 10 also showed to cause a noticeable amount of loss, and since node 6 and 10 are directly connected, a strengthening in reliability can possibly be made by having close communication and collaboration among these two.

6.3 Node Criticality vs Performance Function

Importance analysis based on node indicators were highlighted by many researchers as a good way of measuring and evaluating system resilience and robustness (Barabási et al., 2000; Holme et al., 2002; Zheng et al., 2007; Gilsing et al., 2008; Annibale et al., 2010; Bellingeri et al., 2014; Cerqueti et al., 2019; Ding et al., 2020). In this case study, two methods were examined to evaluate, and possibly amplify, the importance of the nodes in the presented network. The results showed that the node ranking, based on a criticality index, matched well with the measures of the loss of performance caused by node disruptions. Node 6 had the highest criticality index and also caused the biggest loss of performance. The same yielded for node 8, 10 and 11, where they had the same order both in the node ranking and in their negative impact on the network performance.

By performing an importance evaluation of all the nodes, based on their topological properties and amount of work flow, an insight in their role in the network was gained before assessing their contribution to loss of performance. However, the measure of criticality index, based on the CRITIC method, mainly evaluated the nodes from a topological view, meaning that the end nodes, and especially start nodes, maybe were not given as much attention as they should have. Even though node flow was the highest weighted metric, nodes with zero betweenness centrality and low amount of edges were ranked as relatively low.

The evaluation of node importance based on how the nodes affected the network performance during disruption was measured on the basis of flow. This means that the performance was evaluated only as a measure of how much oil and gas the network was able to deliver to the end nodes despite a disruption, and other considerations were not included. However, since the outcome was analyzed as the total average flow for the whole network, the number of connections and locations of the nodes in the network were also indirectly evaluated. It appeared that nodes with high amount of flow also had a central role in the network.

Even though several performance functions can be evaluated for a single system under consideration, the flow is usually directly correlated with customer satisfaction, which makes it an important and reliable measure for resilience evaluation. Low customer satisfaction can lead to loss of connections, which can cause weaknesses in the network. Depending on the type of network, the performance function can be adjusted. For this case, where the system was an oil and gas supply chain network, the important aspect was flow and oil and gas delivery.

The two methods of evaluating node importance both have their strengths and weaknesses, but using them as a way to amplify each other seems to be a good strategy. The ranking, based on the criticality index, evaluates each node as an individual, as well as their role and importance in the network. While loss of performance evaluates their importance on a selected performance function that can be considered as important for the certain network. In this case, the performance function was flow, and the evaluation of loss of performance only weighted network flow as a parameter.

6.4 Resilience-Based Evaluation of Network Behavior

During the created node disruption scenarios, the network went through a different set of phase changes influenced by a predetermined recovery plan. This network behavior was evaluated on the basis of a deterministic resilience measure, where high values of $RE(t_r|e_j)$ indicated high system resilience. Two recovery plans were conducted, one original and one alternative. In the original plan, the flow percent during the disrupted state was 63%, while it was 52% in the alternative plan.

The comparison of the original recovery plan and the alternative recovery plan showed that the resilience increased with increasing recovery rate, independent of the flow percentage during the disrupted state. Since the resilience value is zero during the disrupted state, regardless of the flow percent, the important aspect is the increase of performance during the recovery phase, and until full recovery is achieved. This means the time period around, and after, t_s when a resilience action is initiated should be the focus during risk mitigation decisions. Even with a significantly lower flow percentage during the disrupted state, if the system is able to increase its performance capacity, the resilience will also increase.

The two different recovery plans were both conducted on the same scenario, and were measured during the same moments. The only changed parameter was the amount of flow. However, the resilience values were higher at every time measurement in the alternative plan. This indicates that it is more important to focus on the system recovery aiming to initiate a resilience action as soon as possible, rather than trying to prevent the occurrence of an unwanted disruption. The prevention may lead to less loss of performance during the disrupted state, but it might cause the system to recover at a slower rate. Hence, letting the system have a moment of low performance, in order to focus on the resilience action and recovery, may be beneficial.

6.5 Improvement of Resilience

When performing an importance analysis for the resilience of a system, the aim is to gain knowledge about network vulnerabilities and potential reliability improvements. Resilience can be measured in several ways, where in this study it was evaluated on the basis of importance analysis of nodes in the network. Since the results showed that node 6 and node 10 had high criticality, and also a high negative impact on the network performance during disruption, additional mitigation strategies should be implemented at these nodes. Node 6 was shown to have higher importance than node 10, but these two nodes are interconnected, such that a strengthening in reliability at one of the two nodes can affect the other in a positive manner.

The numerical example in this study included parts of the Norwegian oil and gas supply chain network. In general, the oil and gas industry can be seen as an important sector, with high risk prevention and mitigation focus. Still, strategies can be implemented to strengthen resilience, such as scenario analysis and delivery planning strategies during disruptions. The latter can be connected to storage options and capacity. Depending on the outcome of the disaster and the period of time the system is disrupted, storage of oil and gas can be beneficial, as it makes it possible to continue to deliver a decent amount of oil and gas to customers for a period of time. It can also be used as a buffer for other nodes, in case they have problems with their deliveries.

The node ranking, with respect to the criticality index, revealed vulnerabilities in the network in terms of topological properties, where a node is considered as critical for the network when it has a high node degree, high betweenness centrality and high amount of node flow. Analysis of node dependencies and their importance creates a picture of where the network reliability should be strengthened in order to obtain a strong network with high resilience. Since both the node ranking and the loss of performance showed that node 6 was considered the most important node. Risk mitigation strategies at this facility may contribute to higher system resilience, as the network can still stand strong even if there is an unforeseen disruption at this node.

The results from the alternative recovery plan showed that with a higher recovery rate, the system resilience also increased. This means that with an improvement of recovery rate at the most important nodes, here node 6 and 10, the system resilience can be considerably higher. Specific recovery plans for node 6 and 10 can be embedded within the system.

Node 6 is a facility located along the coast of Norway, prone to natural disasters and external attacks. Practice on specific disruption scenarios can be beneficial to gain knowledge about how the system reacts to certain disruptions, such as natural disasters, where the location can be analyzed in terms of climate change. Prediction of natural disasters can be difficult, but some areas are more prone to certain hazards than others. The potential impact, or a similar impact, can in some cases be identified and practiced to create a robust system.

Collaboration and information sharing is considered as a property of resilience. Even though the Norwegian oil and gas infrastructure is determined based on several factors, possibilities for flexibility should be an option. Node 6 and 10 can possibly make a mutual agreement with other nodes, where they assist with help in case there is a disruption. In case of such an agreement, the geographical distance and distribution should be considered. A mutual agreement of assistance have low benefits if the nodes are located in the same area and are struck by the same natural disaster or attacks.

Another alternative for resilience improvement is changes in the network construction design. Having a more evenly distribution of oil and gas will remove some of the high pressure on node 6, making other nodes less dependent on this node. However, this may not be a realistic change, as it can lead to a weaker supply chain, where benefits such as custom-made deliveries can be harder to accomplish.

6.6 Uncertainties

The performed method has most likely been affected by different uncertainty factors that may have influenced the outcome and results of the study. These uncertainties can mainly be related to the delimitations addressed in the introduction.

The presented supply chain network was simplified, and included only a few nodes and edges. This may have led to uncertainties in the node ranking, since some of the nodes lost their connections and were given lower node degree and betweenness centrality than they originally may have had. This may also be the reason why betweenness centrality was weighted as the least important metric among the three chosen metrics. With a more complex network, the betweenness centrality would most likely have gained more importance, and influenced the node ranking.

For the purpose of this study, only four nodes were investigated, where neither of the selected nodes was start or end nodes. This may have affected the outcome since some of the start nodes had a high node flow, and disruption at one of these nodes would probably have caused a significant loss of performance.

When analyzing the node importance, the focus area was on network topology and flow. Other factors such as collaboration and communication between suppliers and customers were not considered. Some connections in the network may have been more important than others due to various reasons, such as political or economical issues, and not only because of the amount of oil and gas delivery.

In the resilience-based importance analysis, only the recovery phase was evaluated. The degradation phase was left out, such that no measurements were included or examined during the degradation of the system. In a real case scenario, this phase is also a part of the system behavior, which has an influence on the system performance.

The four investigated nodes were set to have the same recovery rate. In practice, they most likely utilize different recovery strategies with dissimilar recovery rates. This may have affected the performance function, such that nodes with a higher recovery rate would have had less negative impact on the loss of performance, regardless of their high ranking.

7 Conclusions and Further Work

The following section presents the conclusions derived from the results, as well as recommendations for further work.

7.1 Conclusions

The purpose of this study was to investigate a resilience-based importance analysis in an oil and gas supply chain network during node disruptions. A research objective, including sub-objectives, was formulated to create the basis of the study, as well as scopes and delimitations.

To achieve the research objective, this study has identified critical nodes with the use of the CRITIC method, which weighted node degree, betweenness centrality and node flow based on correlations. In addition, node disruption scenarios were created and performed to evaluate the loss of performance caused by node disruption at the four highest ranked nodes, based on their criticality index. A resilience-based network behavior evaluation was analyzed with respect to a chosen recovery plan and an alternative recovery plan for comparison, where all of the selected nodes recovered within the same time period and with the same rates.

The results from the analysis showed that there is a high correlation between node criticality and impact on network performance during node disruption. The four investigated nodes had the same order of importance in the method based on their criticality index and in the method based on their impact on the network performance during disruptions, meaning that nodes with high criticality index value also had a high negative impact on the network performance during node disruptions.

The examination of the resilience-based evaluation of network behavior was conducted with a recovery plan which was equal for all four nodes. In addition, an alternative recovery plan was examined to see how differences in recovery rate, with respect to node flow, affected the resilience of the system. The comparison of these two recovery plans showed that a high recovery rate leads to higher resilience. This was regardless of the network flow during the disrupted state, which implicates that a system can have a relatively low flow during the disrupted state, but still have high resilience based on how it recovers and how fast it initiates a resilience action.

7.2 Recommendations for Further Work

The delimitations of this study create several options and recommendations for further work. An improvement of the results, and a more detailed evaluation, can be made by analyzing a more complex network with a higher amount of nodes and edges. The studied network in this case was parts of the Norwegian oil and gas network, which in reality is much bigger than presented. The evaluation can also be made by investigating the importance of all the nodes in the network, and not only four nodes. This would include the start nodes, which were left out in this study. Additionally, different recovery plans made specifically for each of the different nodes can be studied, where their influence on the network performance during node disruptions can be compared, as well as a resilience-based evaluation of the network behavior.

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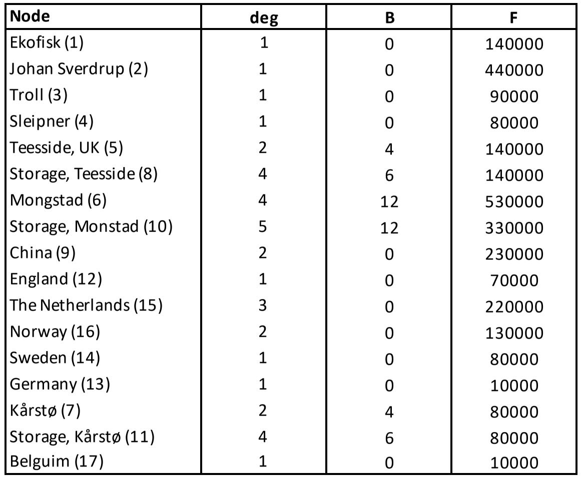
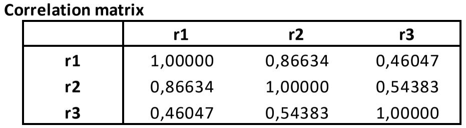
A Excel Calculations

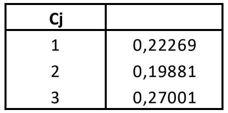


Node	deg	B	F
Ekofisk (1)	1	0	140000
Johan Sverdrup (2)	1	0	440000
Troll (3)	1	0	90000
Sleipner (4)	1	0	80000
Teesside, UK (5)	2	4	140000
Storage, Teesside (8)	4	6	140000
Mongstad (6)	4	12	530000
Storage, Monstad (10)	5	12	330000
China (9)	2	0	230000
England (12)	1	0	70000
The Netherlands (15)	3	0	220000
Norway (16)	2	0	130000
Sweden (14)	1	0	80000
Germany (13)	1	0	10000
Kårstø (7)	2	4	80000
Storage, Kårstø (11)	4	6	80000
Belguim (17)	1	0	10000

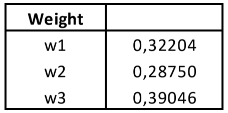


Correlation matrix

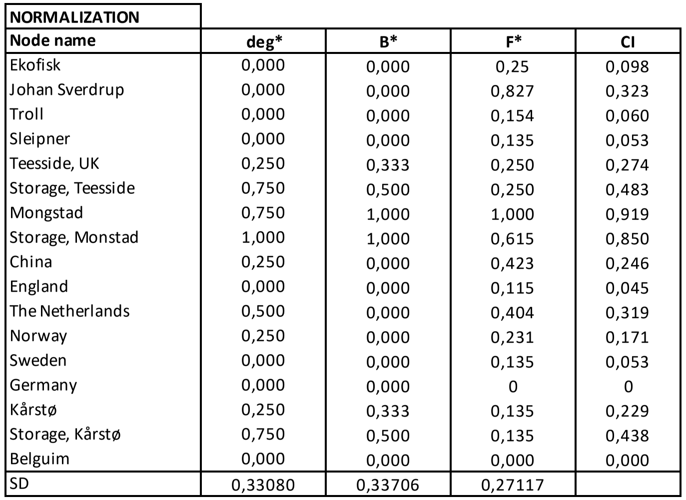
	r1	r2	r3
r1	1,00000	0,86634	0,46047
r2	0,86634	1,00000	0,54383
r3	0,46047	0,54383	1,00000



Cj	
1	0,22269
2	0,19881
3	0,27001



Weight	
w1	0,32204
w2	0,28750
w3	0,39046



NORMALIZATION

Node name	deg*	B*	F*	CI
Ekofisk	0,000	0,000	0,25	0,098
Johan Sverdrup	0,000	0,000	0,827	0,323
Troll	0,000	0,000	0,154	0,060
Sleipner	0,000	0,000	0,135	0,053
Teesside, UK	0,250	0,333	0,250	0,274
Storage, Teesside	0,750	0,500	0,250	0,483
Mongstad	0,750	1,000	1,000	0,919
Storage, Monstad	1,000	1,000	0,615	0,850
China	0,250	0,000	0,423	0,246
England	0,000	0,000	0,115	0,045
The Netherlands	0,500	0,000	0,404	0,319
Norway	0,250	0,000	0,231	0,171
Sweden	0,000	0,000	0,135	0,053
Germany	0,000	0,000	0	0
Kårstø	0,250	0,333	0,135	0,229
Storage, Kårstø	0,750	0,500	0,135	0,438
Belguim	0,000	0,000	0,000	0,000
SD	0,33080	0,33706	0,27117	

Disruption at node 6

Average flow per hour (b/h)			REDUCED FLOW									
			t0 = 0 hours	t01 = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
FROM	TO	FLOW	**Flow 100%**	**Flow 100%**	**Flow 63%**	**Flow 63%**	**Flow 67%**	**Flow 76%**	**Flow 84%**	**Flow 91%**	**Flow 100%**	**Flow 100%**
Ekofisk	Teesside, UK	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Johan Sverdrup	Mongstad	18333,33	18333,33	18333,33	11550,00	11550,00	12283,33	13933,33	15400,00	16683,33	18333,33	18333,33
Troll	Mongstad	3750,00	3750,00	3750,00	2362,50	2362,50	2512,50	2850,00	3150,00	3412,50	3750,00	3750,00
Sleipner	Kårstø	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Teesside, UK	Storage	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Mongstad	China	8333,33	8333,33	8333,33	5250,00	5250,00	5583,33	6333,33	7000,00	7583,33	8333,33	8333,33
	Storage	13750,00	13750,00	13750,00	8662,50	8662,50	9212,50	10450,00	11550,00	12512,50	13750,00	13750,00
Kårstø	Storage	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Storage, Teesside	England	2916,67	2916,67	2916,67	1837,50	1837,50	1954,17	2216,67	2450,00	2654,17	2916,67	2916,67
	China	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
Storage, Mongstad	Germany	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67
	Sweden	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
	Norway	4166,67	4166,67	4166,67	2625,00	2625,00	2791,67	3166,67	3500,00	3791,67	4166,67	4166,67
	The Netherlands	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Storage, Kårstø	Norway	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
	Belguim	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67

TOTAL FLOW / H		0	2	5	10	12	14	16	18	20	24
		t0 = 0 hours	t = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
NODE	FLOW / H	**Flow 100%**	**Flow 100%**	**Flow 63%**	**Flow 63%**	**Flow 67%**	**Flow 76%**	**Flow 84%**	**Flow 91%**	**Flow 100%**	**Flow 100%**
Ekofisk	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Johan Sverdrup	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33
Troll	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00
Sleipner	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Teesside, UK	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Storage, Teesside	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Mongstad	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33
Storage, Mongstad	13750,00	13750,00	13750,00	8662,50	8662,50	9212,50	10450,00	11550,00	12512,50	13750,00	13750,00
China	9583,33	9583,33	9583,33	6500,00	6500,00	6833,33	7583,33	8250,00	8833,33	9583,33	9583,33
England	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67
The Netherlands	9166,67	9166,67	9166,67	7008,33	7008,33	7241,67	7766,67	8233,33	8641,67	9166,67	9166,67
Norway	5416,67	5416,67	5416,67	3875,00	3875,00	4041,67	4416,67	4750,00	5041,67	5416,67	5416,67
Sweden	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Germany	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67
Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Storage, Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Belgium	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67
TOTAL	31250	**31250**	**31250**	**23079**	**23079**	**23963**	**25950**	**27717**	**29263**	**31250**	**31250**

Disruption at node 8

Average flow per hour (b/h)			REDUCED FLOW									
			t0 = 0 hours	t01 = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
FROM	TO	FLOW	**Flow 100%**	**Flow 100%**	**Flow 63%**	**Flow 63%**	**Flow 67%**	**Flow 76%**	**Flow 84%**	**Flow 91%**	**Flow 100%**	**Flow 100%**
Ekofisk	Teesside, UK	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Johan Sverdrup	Mongstad	18333,33	18333,33	18333,33	11550,00	11550,00	12283,33	13933,33	15400,00	16683,33	18333,33	18333,33
Troll	Mongstad	3750,00	3750,00	3750,00	2362,50	2362,50	2512,50	2850,00	3150,00	3412,50	3750,00	3750,00
Sleipner	Kårstø	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Teesside, UK	Storage	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Mongstad	China	8333,33	8333,33	8333,33	5250,00	5250,00	5583,33	6333,33	7000,00	7583,33	8333,33	8333,33
	Storage	13750,00	13750,00	13750,00	8662,50	8662,50	9212,50	10450,00	11550,00	12512,50	13750,00	13750,00
Kårstø	Storage	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Storage, Teesside	England	2916,67	2916,67	2916,67	1837,50	1837,50	1954,17	2216,67	2450,00	2654,17	2916,67	2916,67
	China	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
Storage, Mongstad	Germany	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67
	Sweden	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
	Norway	4166,67	4166,67	4166,67	2625,00	2625,00	2791,67	3166,67	3500,00	3791,67	4166,67	4166,67
	The Netherlands	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Storage, Kårstø	Norway	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
	Belguim	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67

TOTAL FLOW / H		0	2	5	10	12	14	16	18	20	24
		t0 = 0 hours	t = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
NODE	FLOW / H	**Flow 100%**	**Flow 100%**	**Flow 63%**	**Flow 63%**	**Flow 67%**	**Flow 76%**	**Flow 84%**	**Flow 91%**	**Flow 100%**	**Flow 100%**
Ekofisk	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Johan Sverdrup	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33
Troll	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00
Sleipner	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Teesside, UK	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Storage, Teesside	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Mongstad	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33
Storage, Mongstad	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00
China	9583,33	9583,33	9583,33	9120,83	9120,83	9170,83	9283,33	9383,33	9470,83	9583,33	9583,33
England	2916,67	2916,67	2916,67	1837,50	1837,50	1954,17	2216,67	2450,00	2654,17	2916,67	2916,67
The Netherlands	9166,67	9166,67	9166,67	8550,00	8550,00	8616,67	8766,67	8900,00	9016,67	9166,67	9166,67
Norway	5416,67	5416,67	5416,67	5416,67	5416,67	5416,67	5416,67	5416,67	5416,67	5416,67	5416,67
Sweden	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Germany	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67
Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Storage, Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Belgium	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67
TOTAL	31250	**31250**	**31250**	**29092**	**29092**	**29325**	**29850**	**30317**	**30725**	**31250**	**31250**

Disruption at node 10

Average flow per hour (b/h)			REDUCED FLOW									
			t0 = 0 hours	t01 = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
FROM	TO	FLOW	**Flow 100%**	**Flow 100%**	**Flow 63%**	**Flow 63%**	**Flow 67%**	**Flow 76%**	**Flow 84%**	**Flow 91%**	**Flow 100%**	**Flow 100%**
Ekofisk	Teesside, UK	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Johan Sverdrup	Mongstad	18333,33	18333,33	18333,33	11550,00	11550,00	12283,33	13933,33	15400,00	16683,33	18333,33	18333,33
Troll	Mongstad	3750,00	3750,00	3750,00	2362,50	2362,50	2512,50	2850,00	3150,00	3412,50	3750,00	3750,00
Sleipner	Kårstø	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Teesside, UK	Storage	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Mongstad	China	8333,33	8333,33	8333,33	5250,00	5250,00	5583,33	6333,33	7000,00	7583,33	8333,33	8333,33
	Storage	13750,00	13750,00	13750,00	8662,50	8662,50	9212,50	10450,00	11550,00	12512,50	13750,00	13750,00
Kårstø	Storage	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Storage, Teesside	England	2916,67	2916,67	2916,67	1837,50	1837,50	1954,17	2216,67	2450,00	2654,17	2916,67	2916,67
	China	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
Storage, Mongstad	Germany	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67
	Sweden	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
	Norway	4166,67	4166,67	4166,67	2625,00	2625,00	2791,67	3166,67	3500,00	3791,67	4166,67	4166,67
	The Netherlands	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Storage, Kårstø	Norway	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
	Belguim	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67

TOTAL FLOW / H		0	2	5	10	12	14	16	18	20	24
		t0 = 0 hours	t = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
NODE	FLOW / H	**Flow 100%**	**Flow 100%**	**Flow 63%**	**Flow 63%**	**Flow 67%**	**Flow 76%**	**Flow 84%**	**Flow 91%**	**Flow 100%**	**Flow 100%**
Ekofisk	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Johan Sverdrup	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33
Troll	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00
Sleipner	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Teesside, UK	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Storage, Teesside	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Mongstad	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33
Storage, Mongstad	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00
China	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33
England	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67
The Netherlands	9166,67	9166,67	9166,67	7008,33	7008,33	7241,67	7766,67	8233,33	8641,67	9166,67	9166,67
Norway	5416,67	5416,67	5416,67	3875,00	3875,00	4041,67	4416,67	4750,00	5041,67	5416,67	5416,67
Sweden	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Germany	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67
Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Storage, Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Belgium	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67
TOTAL	31250	**31250**	**31250**	**26163**	**26163**	**26713**	**27950**	**29050**	**30013**	**31250**	**31250**

Disruption at node 11

Average flow per hour (b/h)			**REDUCED FLOW**									
			t0 = 0 hours	t01 = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
FROM	TO	FLOW	**Flow 100%**	**Flow 100%**	**Flow 63%**	**Flow 63%**	**Flow 67%**	**Flow 76%**	**Flow 84%**	**Flow 91%**	**Flow 100%**	**Flow 100%**
Ekofisk	Teesside, UK	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Johan Sverdrup	Mongstad	18333,33	18333,33	18333,33	11550,00	11550,00	12283,33	13933,33	15400,00	16683,33	18333,33	18333,33
Troll	Mongstad	3750,00	3750,00	3750,00	2362,50	2362,50	2512,50	2850,00	3150,00	3412,50	3750,00	3750,00
Sleipner	Kårstø	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Teesside, UK	Storage	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Mongstad	China	8333,33	8333,33	8333,33	5250,00	5250,00	5583,33	6333,33	7000,00	7583,33	8333,33	8333,33
	Storage	13750,00	13750,00	13750,00	8662,50	8662,50	9212,50	10450,00	11550,00	12512,50	13750,00	13750,00
Kårstø	Storage	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Storage, Teesside	England	2916,67	2916,67	2916,67	1837,50	1837,50	1954,17	2216,67	2450,00	2654,17	2916,67	2916,67
	China	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
Storage, Mongstad	Germany	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67
	Sweden	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
	Norway	4166,67	4166,67	4166,67	2625,00	2625,00	2791,67	3166,67	3500,00	3791,67	4166,67	4166,67
	The Netherlands	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Storage, Kårstø	Norway	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
	Belguim	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67

TOTAL FLOW / H		0	2	5	**10**	12	14	16	18	20	24
		t0 = 0 hours	t = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
NODE	FLOW / H	**Flow 100%**	**Flow 100%**	**Flow 63%**	**Flow 63%**	**Flow 67%**	**Flow 76%**	**Flow 84%**	**Flow 91%**	**Flow 100%**	**Flow 100%**
Ekofisk	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Johan Sverdrup	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33
Troll	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00
Sleipner	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Teesside, UK	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Storage, Teesside	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Mongstad	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33
Storage, Mongstad	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00	13750,00
China	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33	9583,33
England	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67
The Netherlands	9166,67	9166,67	9166,67	8550,00	8550,00	8616,67	8766,67	8900,00	9016,67	9166,67	9166,67
Norway	5416,67	5416,67	5416,67	4954,17	4954,17	5004,17	5116,67	5216,67	5304,17	5416,67	5416,67
Sweden	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Germany	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67
Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Storage, Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Belgium	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67
TOTAL	31250	**31250**	**31250**	**30017**	**30017**	**30150**	**30450**	**30717**	**30950**	**31250**	**31250**

Alternative recovery plan (node 6)

Average flow per hour (b/h)			REDUCED FLOW									
			t0 = 0 hours	t01 = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
FROM	TO	FLOW	**Flow 100%**	**Flow 100%**	**Flow 52%**	**Flow 52%**	**Flow 69%**	**Flow 81%**	**Flow 88%**	**Flow 97%**	**Flow 100%**	**Flow 100%**
Ekofisk	Teesside, UK	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Johan Sverdrup	Mongstad	18333,33	18333,33	18333,33	11550,00	11550,00	12283,33	13933,33	15400,00	16683,33	18333,33	18333,33
Troll	Mongstad	3750,00	3750,00	3750,00	2362,50	2362,50	2512,50	2850,00	3150,00	3412,50	3750,00	3750,00
Sleipner	Kårstø	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Teesside, UK	Storage	5833,33	5833,33	5833,33	3675,00	3675,00	3908,33	4433,33	4900,00	5308,33	5833,33	5833,33
Mongstad	China	8333,33	8333,33	8333,33	4333,33	4333,33	5750,00	6750,00	7333,33	8083,33	8333,33	8333,33
	Storage	13750,00	13750,00	13750,00	7150,00	7150,00	9487,50	11137,50	12100,00	13337,50	13750,00	13750,00
Kårstø	Storage	3333,33	3333,33	3333,33	2100,00	2100,00	2233,33	2533,33	2800,00	3033,33	3333,33	3333,33
Storage, Teesside	England	2916,67	2916,67	2916,67	1837,50	1837,50	1954,17	2216,67	2450,00	2654,17	2916,67	2916,67
	China	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
Storage, Mongstad	Germany	416,67	416,67	416,67	216,67	216,67	287,50	337,50	366,67	404,17	416,67	416,67
	Sweden	3333,33	3333,33	3333,33	1733,33	1733,33	2300,00	2700,00	2933,33	3233,33	3333,33	3333,33
	Norway	4166,67	4166,67	4166,67	2166,67	2166,67	2875,00	3375,00	3666,67	4041,67	4166,67	4166,67
	The Netherlands	5833,33	5833,33	5833,33	3033,33	3033,33	4025,00	4725,00	5133,33	5658,33	5833,33	5833,33
Storage, Kårstø	Norway	1250,00	1250,00	1250,00	787,50	787,50	837,50	950,00	1050,00	1137,50	1250,00	1250,00
	The Netherlands	1666,67	1666,67	1666,67	1050,00	1050,00	1116,67	1266,67	1400,00	1516,67	1666,67	1666,67
	Belguim	416,67	416,67	416,67	262,50	262,50	279,17	316,67	350,00	379,17	416,67	416,67

TOTAL FLOW / H		0	2	5	10	12	14	16	18	20	24
		t0 = 0 hours	t = 2 hours	td = 5 hours	ts = 10 hours	t1 = 12 hours	t2 = 14 hours	t3 = 16 hours	t4 = 18 hours	tf = 20 hours	t5 = 24 hours
NODE	FLOW / H	**Flow 100%**	**Flow 100%**	**Flow 52%**	**Flow 52%**	**Flow 69%**	**Flow 81%**	**Flow 88%**	**Flow 97%**	**Flow 100%**	**Flow 100%**
Ekofisk	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Johan Sverdrup	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33	18333,33
Troll	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00	3750,00
Sleipner	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Teesside, UK	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Storage, Teesside	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33	5833,33
Mongstad	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33	22083,33
Storage, Mongstad	13750,00	13750,00	13750,00	7150,00	7150,00	9487,50	11137,50	12100,00	13337,50	13750,00	13750,00
China	9583,33	9583,33	9583,33	5583,33	5583,33	7000,00	8000,00	8583,33	9333,33	9583,33	9583,33
England	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67	2916,67
The Netherlands	9166,67	9166,67	9166,67	6366,67	6366,67	7358,33	8058,33	8466,67	8991,67	9166,67	9166,67
Norway	5416,67	5416,67	5416,67	3416,67	3416,67	4125,00	4625,00	4916,67	5291,67	5416,67	5416,67
Sweden	3333,33	3333,33	3333,33	1733,33	1733,33	2300,00	2700,00	2933,33	3233,33	3333,33	3333,33
Germany	416,67	416,67	416,67	216,67	216,67	287,50	337,50	366,67	404,17	416,67	416,67
Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Storage, Kårstø	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33	3333,33
Belgium	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67	416,67
TOTAL	31250,00	**31250,00**	**31250,00**	**20650,00**	**20650,00**	**24404,17**	**27054,17**	**28600,00**	**30587,50**	**31250,00**	**31250,00**

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