Eindhoven University of Technology

MASTER

Using flexible hubs to manage uncertainty in tank container networks
a simulation tool

Cremers, D.B.C.

Award date:
2020

Link to publication

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Eindhoven University of Technology
Industrial Engineering & Innovation Sciences

Master Thesis

Using flexible hubs to manage uncertainty in tank container networks: a simulation tool

D.B.C. (Daan) Cremers - 0889098
November 2020
Final public version

Thesis in partial completion of master OML. Operations Management & Logistics. A project for Den Hartogh Logistics, Rotterdam.

1st Supervisor:	dr. Virginie Lurkin
2nd Supervisor:	dr. Tom van Woensel
3rd Supervisor:	dr. Sonja Rohmer
Company Supervisor:	ir. Luke van de Bunt

Keywords: *tank container industry, uncertainty management, simulation tool, decision support tool, flexibility, flexible hubs, empty repositioning, container imbalance*

$\boxed{\text{Numbers in this document are scaled for confidentiality reasons}}$

Abstract

This research proposes a simulation model that can be used as a decision support tool for flexibility investment decisions for the tank container operator industry. Tank container operators are faced with the challenge of tank container stock imbalances which are caused by global trade imbalances. When these imbalances are anticipated they can cost effectively be resolved. However, when faced with unexpected imbalances, these costs are much higher.

The proposed simulation tool can test disruption scenarios on a tank container network. Specifically, this research is focused on implementing more flexibility into the network which make use of flexible hubs. Flexible hubs are hubs from which empty repositioning to multiple locations is possible with relative small cost. The research shows that the use of flexible hubs has a positive effect on solving disruptions that increase a deficit. Primarily repositioning costs and lost sales could be reduced. The use of flexible hubs additionally increases the efficiency of the tank container network, which reduces inventory cost of the network.

Executive summary

Den Hartogh is tank container operator active in the liquid chemicals market. Tank container operators face the challenge that global trade is imbalanced. This means that in some regions there is more export than import or vice versa. This brings forth an operational challenge. Den Hartogh solves these imbalances by setting a fitting pricing strategy which tries to steer demand for tank containers into solving these imbalances and by empty repositioning of tank containers. When these imbalances are forecasted correctly these imbalances can be solved without high costs. However, there can be situations where the forecast is not correct and an unexpected imbalance occurs. An unexpected imbalance leads to high repositioning costs, lost sales costs and inventory costs.

Firstly it was investigated which uncertainty factors can be recognized. In order to map the sources of uncertainty, a conceptual model was formulated. In this model factors like customer base, external factors and procedures were recognized as sources of uncertainty. Following an illustrative example, the impact of such a unexpected imbalance was shown, hereby exhibiting the value that solving these unexpected imbalances can bring.

There are two main directions that can be specified in order to reduce the impact of unexpected imbalances; robustness and flexibility. Robustness is centered around making the network more predictable, so that the unexpected imbalances have a lower probability of occurring. Flexibility is centered around ensuring that the state of the network can be changed quickly and cost effectively. For this research it was chosen to focus on investigating flexibility. It is centered around answering the following research question:

How can flexibility be used to increase profitability for tank container operators experiencing uncertainty in demand and supply?

Next, a literature review was performed concerning flexibility in logistical networks to asses what kind of flexibility can be implemented. The literature review revealed that flexibility is an ambiguous concept that can interpreted in many ways. For this research, flexibility was defined as the ability to change the state of a logistical network to handle uncertainty, with the ultimate goal to improve profitability. Flexibility concepts share three characteristics. Firstly flexibility is multi dimensional, which means it cannot be measured by a single dimension. *Range* and *response* were recognized as the most common dimensions, were range is the set of possible states that can be realised and response measures how fast or cost effectively these different states can be realised. Secondly, the type of flexibility that is needed is dependent on the environment a company is in. Third, flexibility measures potential performance rather than demonstrated performance. What that means is that flexibility measures how many states a system can reach, as opposed to demonstrated performance indicator, like utilisation rate or service rate.

The different concepts of flexibility that were found in literature were applied to the tank container network. As flexibility should allow one to quickly change the state of the network, it was chosen to implement flexibility in empty repositioning. This means that empty repositioning can be used to cost effectively move tank containers. More specifically, this was investigated using so called flexible hubs. Flexible hubs are defined as hubs in the network that have multiple regions it can reposition tank containers to and can do so cost effectively. The range is defined as how many repositioning options a a hub has and response then as how fast and with what cost this can be done. It was chosen to build a simulation model in order to calculate the effect of using flexible hubs to increase profitability. The purpose of the model is to asses how much

can be invested in flexibility. This investment in flexibility can then be in the form of a rate discount for demand to the flexible hubs. This increases the flexibility of the network because more tank containers can be moved to multiple regions in the network without high cost.

Next, the relevant cost components were determined. These cost components were repositioning impact, lost sales impact and inventory impact. These costs are indicated as impact cost because they were assessed on a network level, meaning they measured the impact on the network as a whole instead of the physical cost.

Using the above impact costs as input, the simulation model was formulated. This simulation model allows the user to simulate a certain amount of periods. In each period, a number of operations are performed. Firstly it determines the inventory available for demand in all regions defined by adding the arrivals of tank containers to this starting inventory. Consequently, demand is observed and the model decides how much demand can be accepted. The orders that cannot be filled are treated as lost sales. Next it predicts the future inventory in all the regions using the forecasted demand and tank containers in transit. Based on this prediction, the model makes a repositioning decision. This repositioning decision is determined by a MILP, which aims to minimize the total repositioning impact cost while covering the deficits as much as possible. The execution of these repositionings is the final step in a single period.

The model could not be tested against historical data, as the assumptions that were formulated stated that the inputs to the model are deterministic. Also demand forecasts and cost inputs assumed to be fixed, whereas in reality they are updated monthly. However, because the purpose of the model is to correctly estimate cost differences between redesign options, the model was validated using face validity.

It was chosen to take a set of flexible hubs with similar geographical and cost properties and aggregate these into a flexible region. This region had the ability to reposition to 4 of the 7 regions that were defined at Den Hartogh. The simulation model is able to test different levels of demand stimulation, therefore testing different redesign options where more demand was sent to the flexible region. This simulates an increased amount of flexibility.

The uncertainty on the network was simulated using certain disruption scenarios. A disruption in this case was simulated as a sudden change in demand. The first two kinds of disruptions focused on changing demand from or to a single region. Scenario 1 was defined as a change in demand to a certain region (import disruption) and scenario 2 was defined as a change in demand from a certain region (export disruption). It is to be noted that in each of these scenarios, demand could be stimulated or reduced. For scenario 3, the demand on a single trade lane was considered, where a trade lane is defined as a lane on which demand is observed between two regions in the network. Again demand in this scenario could be increased or reduced.

The first two scenarios were tested on the regions where the flexible region could reposition to. It was found the disruptions had the largest effect on regions where a deficit was predicted. When the disruption intensified this deficit suddenly, higher cost was observed. It also showed that the use of flexible hubs had a positive effect on reducing these costs, as it was observed that in these cases the cost reduction with stimulation more demand to the flexible region was steeper. The same pattern was visible in the instances for scenario 3. It was also shown that lanes that were critical to the supply of a regions were more sensitive to disruptions,and flexible hubs had a positive effect on cost reduction there as well. In all scenarios, cost reduction to solve disruptions was primarily due to decreasing lost sales impact and less for repositioning impact.

An important observation is that the use of the flexible coincided with a very steep reduction in inventory impact cost. This indicated that the use of the flexible region improved the flow of tank containers through the network. It was proven that this was a direct effect of the use of the flexible region and not of introducing more demand into the network.

The main limitations of the simulation tool are the fact that cost components and inputs are largely assumed to be deterministic, while in reality these change over time. Due to the dynamic properties of the network, these values could not be validated. It was however validated that the model behaves as it should, meaning that the cost differences between flexible region usage options is valid.

Following the aforementioned conclusions, the following recommendations are given:

- The simulation tool results show a inventory cost reduction when there is an increased usage of flexible hubs. This is especially the case when it is certain that the tank container can be used in a region where the flexible hub can repositioned to, as this creates a better flow of tank containers through the network.
- Running the disruptions scenarios showed that the flexible hubs had most impact in reducing repo and lost sales impact in regions where already a deficit was predicted. When observing this deficit, a risk assessment can be made how probable certain disruption scenarios in this region are and how this effects the total cost impact using the simulation tool.
- It is recommended to test how the benefit of flexible hubs is calculated by the tool using a more balanced demand forecast. In this research the forecast is made under the assumption of enough tank containers. Correcting this demand forecast to more realistic patterns frees up capacity of the flexible hubs and can also better illustrate how many tank containers in flexible hubs is actually needed to cover disruptions.
- If a way can be found to test the model using historical validation, this can provide extra value. Then it can be tested if the model duplicates reality, including the accuracy of cost components. The way to realize more demand to the flexible hubs is on the one hand stimulating commercial managers to actively search for such demand, but also provide a discount to demand going to flexible hub. If the cost components resulting from the simulation tool can be validated with more certainty, the tool can also provide valuable information about how large such a discount can be invested in flexible hubs demand stimulation.
- The utilization of the flexible hubs was stimulated by the ratio of demand forecasted from all the regions that had demand to the flexible region. Using the simulation tool, it can be investigated from what regions demand stimulation is most beneficial to profitability.

The implementation plan of the model consisted of using the tool on monthly basis. Then based on the observed forecast, high risk scenarios can be run using the tool. In doing this, it can be made clear how the use of the flexible hubs can help in solving solving disruptions. Most importantly, it can be visualized how much savings can be realised by stimulating demand to flexible hubs. Consequently, this demand can be stimulated by setting a discount on demand to flexible hubs.

The findings in this research can be extended in the future through implementing more flexible hubs, improving the calculation time of the tool, performing a more extensive sensitivity analysis and testing other strategies than flexibility, like robustness, for mitigating uncertainty.

Preface

This thesis marks the end of my period as a student in Eindhoven. The previous months were some of the interesting, but also stressful times of my studies. A little more over 1 month into my time at Den Hartogh, the Covid-19 pandemic struck, which forced me (and everyone around me) to be isolated in their homes. At times, I did not find this easy. Being used to work away from home and really seeing home as a place to relax, this sudden change (or disruption) in the status quo made meant my work life and private life intertwined more and more. Always being in the place that I also worked in resulted in a lot of stress that was hard relieve. For a long time I struggled with the final form of my research and increased stress, to the point at which an extension to my project deadline was necessary. However in the end I do not regret needing this extension, as it got me to a point where I can say that I am pleased with the result in brought forth, this master thesis.

I would like to extent my gratitude to my supervisors. Firstly my 1st supervisor and mentor Virginie Lurkin, for guiding me through this process and for always open to help me with any trouble I had, including my increased feelings of stress. Secondly my Den Hartogh supervisor Luke van de Bunt, for always making me answer the hard questions which ultimately made my thesis better and for his always helpful tips and genuine support. Also a big thank you to all Den Hartogh colleagues who helped me to answer any questions I had. I would also like to thank Tom van Woensel for providing me with feedback in the final stages of my project and Sonja Rohmer for taking the time to evaluate my thesis.

I would also like to thank all the people that were there to support me throughout this process. Firstly my girlfriend Julie, which always provided me with support in stressful times and for proof reading the final version. I also thank my parents for supporting me throughout my study period. Lastly I would also like to thank my friends from Dispuut Pael for the fun stress relieving moments and making my studies exponentially more entertaining.

Daan Cremers
November 2020

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1 General Introduction

This master thesis was executed at the global business unit (BU) of Den Hartogh Logistics in Rotterdam. Den Hartogh is a logistics service provider (LSP) for the chemical industry. The purpose of this chapter is to provide an overview of the environment Den Hartogh operates in, therefore describing the context of the research.

1.1 Global Chemical Industry

According to the International Council of Chemical Association (ICCA), the chemical industry is defined as 'the manufacture of chemicals and chemical products' (ICCA, 2019). The chemical industry supports numerous other industries in the world. 95% of all manufactured goods rely on some type of chemical process.

Over the recent decade, chemical sales have increased substantially. According to a report from the European Chemical Industry Council (Cefic), from 2008 to 2018, the total value of global chemical sales increased from 1,998 billion euros to 3,347 billion euros. The market shares that the different global regions have, however, shifted. In 2008, the EU and North America had by far the biggest share in the market. Throughout the years however this has shifted more towards emerging markets, especially to China and the rest of Asia. Figure 1.1 on the next page shows the percentage in market share in global sales for 2008 and 2018 (Cefic, 2020).

The shift to emerging markets like China is indicative of the ongoing globalisation of the chemical industry. This is also reflected in the revenue generated in the European union (EU) by selling chemicals outside of the EU. From 2008 to 2018, revenue from selling chemicals in the EU to outside of the EU increased from 20% to 29%. Revenue from selling to the home country market in the EU decreased from 34% to 13% and revenue from selling chemicals inside the EU increased from 48% to 58% (Cefic, 2020). From these numbers it can be seen that international sourcing (at least in the EU) has increased in the recent decade.

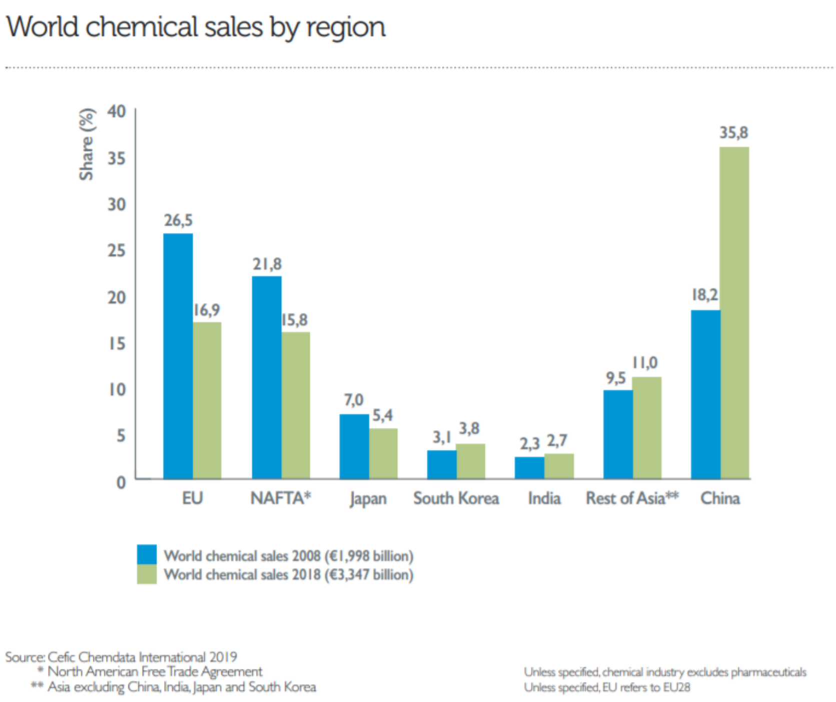

Figure 1.1: Market share chemical sales 2008/2018.

As mentioned before, Den Hartogh is a LSP for the chemical industry industry. It is solely focused on the transportation of chemicals, so their customer base exists of producers and buyers of these chemicals and chemical products. As the market for chemicals is global, Den Hartogh's customers are also scattered all over the world, meaning they offer logistical services on a global scale.

1.2 Chemical logistics

This section will discuss operations and dynamics in the chemical logistics field. More specifically, the transportation of liquid chemicals will be discussed, as this is the only type of chemical transported by the global BU of Den Hartogh.

1.2.1 Liquid chemicals logistics

There are a numerous methods for transporting chemicals and chemical products. The exact transportation method is dependent on the type of chemical. When considering liquid chemicals, there are five distinct methods of transportation : pipeline, bulk tankers, parcel tankers, tank containers or drums (Erera et al., 2005). The global BU of Den Hartogh can be seen as a tank container operator, which means that they manage a fleet of tank containers. Tank containers are designed for intermodal transport. The advantage of tank containers in international transportation of liquid chemicals is that they provide secure door-to-door intermodal transport of chemicals without need for special port-side infrastructure. Most tank containers are ISO tanks (International Organisation of Standardisation), which means they have globally standardized measurements. This makes them easy to handle for different modes of transportation (ship, barge, truck, rail etc). Another advantage is that tank containers can be cleaned after use. Typically tank container operators do not own the underlying modes of transportation to move these tank containers. Instead they maintain contracts with companies for all underlying transportation modes for the actual handling of the tank containers (for example container shipping companies and trucking companies)(Erera et al., 2005). This is also the case within the global BU of Den Hartogh.

1.2.2 Liquid chemical freight transportation pricing

For a customer to obtain service from a tank container operator, first a transportation rate must be agreed upon. This process is called quotation. There are two types of quotations, each specifically suited for different tank container business types:

1. *Spot business*
   This agreement locks in a transportation rate for a specific trade lane. A trade lane is defined as a given origin-destination pair (generally sea ports). The length of this agreement is dependent on the wishes of the customer. This kind of agreement is most used for demand on a short time horizon, for instance rush jobs or unexpected demand.

2. *Tender business*
   Tender business is where a customer asks the carrier to lock in rates for a collection of specific trade lanes. The customer provides the LSP with all the trade lanes it wants a price. The LSP does an offer for rates on all the trade lanes. After some rounds of 'bidding', a tender can lock in rates on certain trade lanes for a period of time with a maximum amount of loads that the customer can load for this rate. As Den Hartogh will not have been the only bidder, it could win 1st choice, 2nd choice etc. on certain trade lanes. The customer however is not obligated to load the maximum amount, and is also

not bound to when this will be loaded. Depending on the specific tender, there can be clauses to renegotiate the contract in certain situations. There also exist different lengths of tenders, ranging from a quarter of a year to several years.

Included in these rates are all costs covering the handling of the tank container (cleaning, transportation, equipment cost per day, etc.), overhead costs and a profit component. If a quote is accepted, then it will be valid for a predetermined number of days.

1.2.3 Tank container operations

If the quote is accepted, and order can be placed. This could be for one tank container or multiple tank containers. After checking if the tank containers are clean, they are sent from the closest tank container depot to the agreed upon loading location. From there the tank containers are transported to the agreed upon destination. The agreed upon destination is dependent on the INCO term. The INCO term is a predetermined commercial term, specifying the tasks, costs, and risks associated with moving goods internationally (Ramberg, 2011). In other words, it determines what leg of the total journey Den Hartogh executes and assumes risk for. After the tank containers are delivered, the customer has the opportunity to unload the tank containers and return it to the custody of the LSP at a prespecified location/depot. The customer has a beforehand agreed upon number of free handling days between delivery and return, and must pay a fee if the free handling period is exceeded. This overlay that starts at the end of the maximum number of free handling days until actual return is called demurrage. After the tank container is returned, possibly the tank containers are repositioned to another depot if necessary. The containers are cleaned at the original destination depot or at the depot they are repositioned to. After this, the tank containers can be used again. In Figure 1.2, this process is visualized.

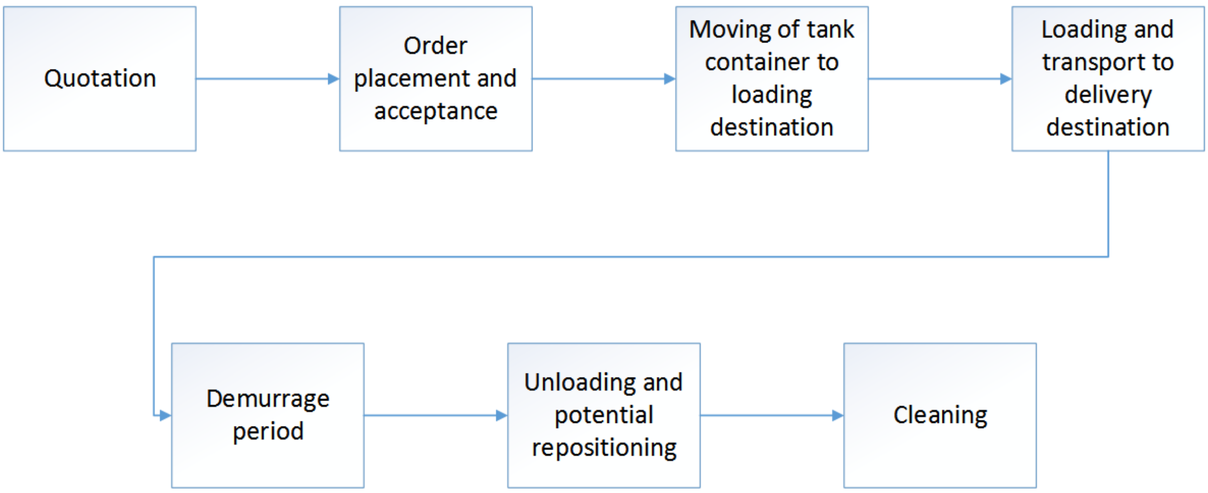

Figure 1.2: Flow chart of tank container operations

1.3 Den Hartogh Logistics and their position in the tank container market

Handling tank containers by the process visualized in Figure 1.2 is typical of a tank container operator, therefore the global BU of Den Hartogh can also be seen as such. The BU handles the global logistics of bulk liquid chemicals, with the exception of intra Europe demand. It has a fleet of 12.000 ISO tank container scattered all over the world. Roughly half of these tank containers are owned by Den Hartogh, while the other half is leased from a tank container leasing company.

Den Hartogh is not the only operator in the market. In a survey conducted by the International Tank Container Organisation (ITCO), it was stated that the industry is dominated on a global level by a relatively low number of tank container operators and leasing companies. The top 10 operators accounted for 56% of the global operators' fleet. In total, the global operators fleet consisted of 418.500 tank containers. In Figure 1.3, taken from this survey, it can be seen how the top 10 operators' fleets compare to each other (ITCO, 2020). Note that the numbers represent all tank containers operated by that operator (owned and leased) and that the number at Den Hartogh Logistics represents the fleet of the entire company (so not just the global BU), which is 20.000 tank containers (Den Hartogh, 2020).

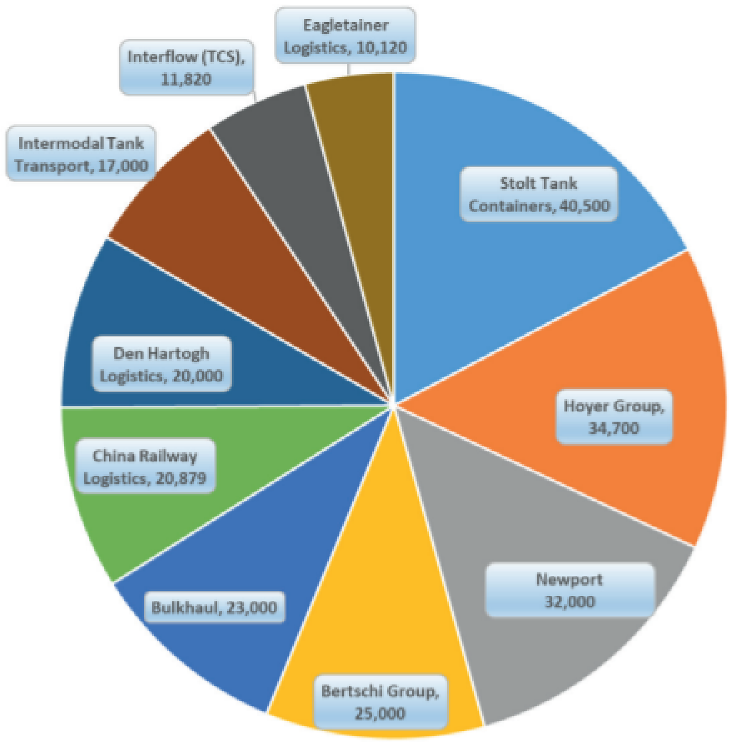

Figure 1.3: Top ten tank container operators (at 1st of January 2020)

To be competitive in the market, Den Hartogh needs to be able to offer its services at a competitive price. To be able to facilitate this, Den Hartogh needs to position their supply of tank containers in such a way that they are able to adequately respond to the market. This means getting their tank containers to the right place, at the right time, for the right price.

2 Project description

This section will provide a description of the problem that Den Hartogh is facing and wants to have resolved. Firstly an overview of the challenges faced in the network will be presented regarding the network imbalance, uncertainties in demand and supply, as well as the impact of the unexpected imbalance. This will lead to the problem statement and the research questions that will be handled in this thesis.

2.1 Network imbalance

The challenge that Den Hartogh faces is to plan its flows of tank containers as efficient as possible. This is a challenge because trade flows between global regions are imbalanced. However on the other hand, there is the influence of competition. Demand is split between multiple tank container operators and depending on how competitors price their business, a tank container can only acquire a certain amount of business. This has an effect on the supply of tank containers. Due to imbalance, some hubs/regions might have a natural deficit or oversupply of tank containers. This is the case because supply of tank containers moves with along with demand flows executed by Den Hartogh. In below Table 2.1, the magnitude of imbalance between global regions in 2019 is shown. Den Hartogh recognizes 7 distinct global regions, which have been numbered for confidentiality reasons.

Global Region	Orders to	Orders from	Imbalance
1	9.825	10.297	-472
2	3.574	3.755	-181
3	7.198	7.060	138
4	821	651	170
5	2.878	2.609	270
6	6.094	7.030	-936
7	3.689	3.303	386

Table 2.1: Imbalance per region over 2019

The challenge in managing the network of tank containers is that a lot or uncertain factors contribute to the fluctuations in demand and supply of tank containers. Therefore unexpected imbalances can occur. This can have substantial risk, for example in areas where tank container stock is suddenly cut short, lost sales may occur. On the other hand, in areas where tank container stocks are too high, unforeseen repositioning and storage costs can occur. Ensuring that the network planning is set up in such a way that it can cope with uncertain imbalances can therefore contribute to a optimal network margin. To prevent tank container stock to run out or increase too much in some regions or hubs, these imbalances have to be solved in order to ensure a stable supply of tank containers. Den Hartogh does this on two levels, one focused on long term imbalances and one on short term imbalances.

2.1.1 Balancing by pricing

This method is focused on solving long term imbalances. A component called the market correction is incorporated into the price. This market correction can be adjusted according to the current and predicted future state of the tank container supplies. If a certain region or hub is expected to run short of tank containers or experience a surplus of tank containers, this market correction can be used in order to try to steer demand in a way so that imbalances are solved. This correction is applied at the loading hub and destination hub separately. That means orders coming from a surplus area will be priced lower and orders going to a surplus area will be priced higher. For deficit areas this is the other way around.

To facilitate this decision, a forecast is made every month by the general manager of each region for the upcoming nine months. The function of a general manager is to oversee operations and commercial interests in a region. This forecast includes the forecasted tank container movements out of the region the general manager is responsible for. From this forecast, it can be predicted what the tank container stocks will be per region for the upcoming nine months. Based on this information, a market correction decision can be made. This happens on a regional level and on hub level once every month.

2.1.2 Balancing by empty repositioning

Above method cannot solve all imbalance in the network. Global trade imbalance is something that still exists and the pricing strategy strategy is not always 100% effective. Therefore on the short term, empty repositioning is used. Repositioning (repo) is the process of repositioning empty tank containers from a surplus area to a demand area. According to Theofanis and Boile (2009), empty container management is one of the most complex problems in the global logistics industry. Worldwide, 20% of all container movements are empty flows to account for global trade imbalance (Edirisinghe et al., 2016). The decision whereto repo's will be done is again decided with help of a demand forecast. These forecasts are produced by the commercial managers, who are responsible for a set of customers (typically in the same region). It is done on a hub-to-hub scope (demand on a trade lane per week) with a 13 weeks time horizon and is based on what demand the commercial manager thinks he/she potentially can execute with enough tank containers. With these forecasts as input, a repositioning model is used. The model tries to balance out the stocks by making use of a minimum cost flow objective. This kind of model maximises the total demand flow of the network with minimum cost. This results in suggested repo movements. After the results have been processed and evaluated, a repo decision is made, communicated to the regional managers/operations as a repo suggestion and where possible the suggestions are executed.

2.2 Uncertainty in demand and supply

Solving container stock imbalances in the ways described above is a challenge for Den Hartogh, however is manageable when supply and demand is known. Expected repo costs can namely be included in quotes Den Hartogh provides to its customers in the form of a repo contribution, partly covering these costs. How orders are priced and whereto repo's are executed is decided based on the forecasts by the general managers and commercial managers. However, forecasts are not always correct because demand is not deterministic. This is caused by different sources of uncertainty influencing supply and demand. Uncertainty occurs when decision makers cannot estimate the outcome of an event or the probability of its occurrence (Halldórsson et al., 2010). Therefore, uncertainty can induce increased supply and demand risk for Den Hartogh. This in turn increases the risk of sub optimal decisions, which is an inevitable consequence of uncertainty (Christopher and Lee, 2004). Therefore, actively dealing with uncertainty is something that can reduce supply and demand risk. In order to deal with uncertainty, first all sources of uncertainty should be identified and their effect explained. In Figure 2.1, a conceptual model with sources of uncertainty is given. In the next few subsections, the sources of relevant uncertainty sources influencing risk in demand and supply, as well as the interrelation between supply and demand uncertainty, are explained.

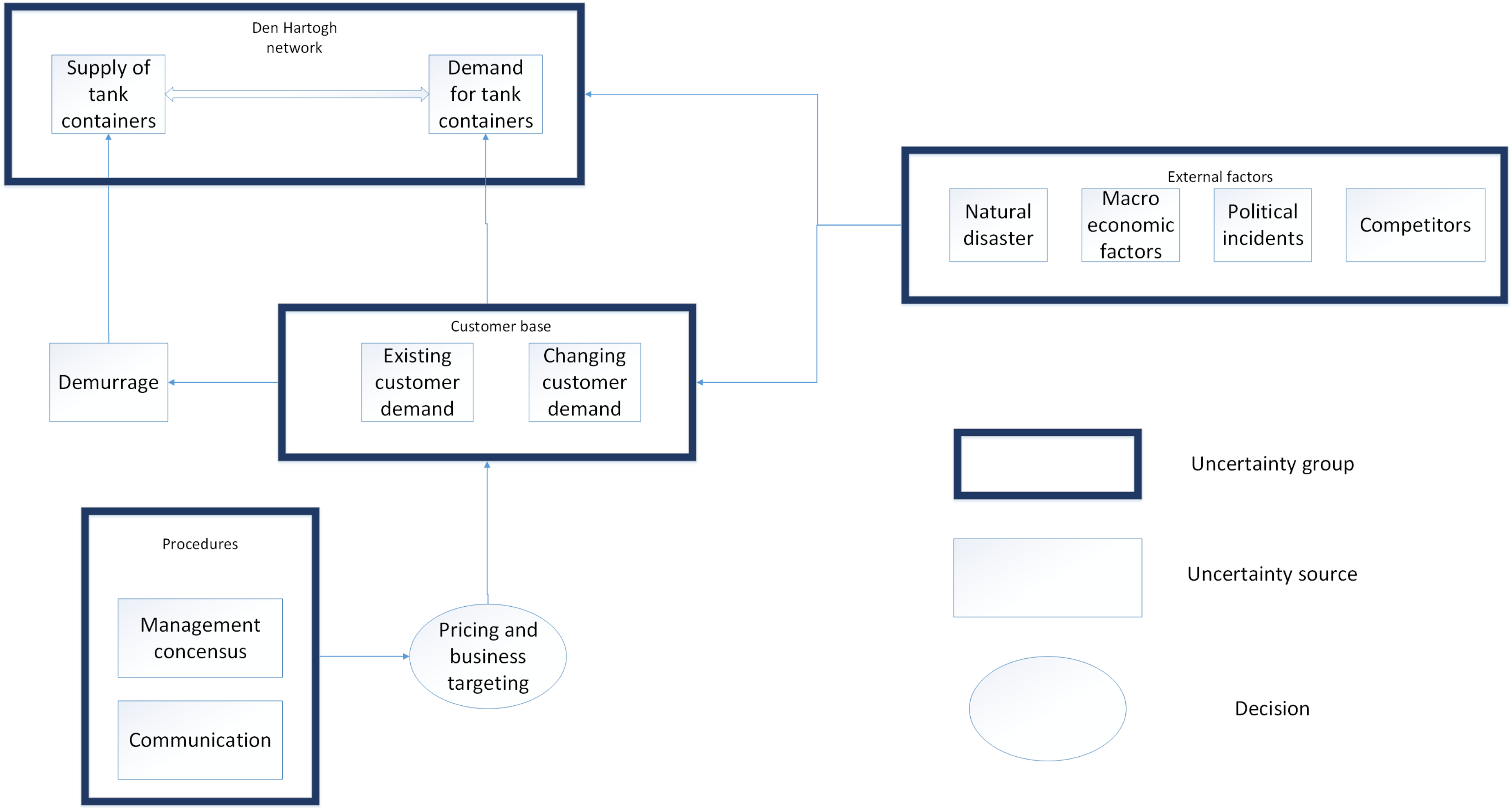

Figure 2.1: Conceptual model of uncertainty sources.

2.2.1 Den Hartogh network

The network of Den Hartogh can be defined by two important concepts. On the one hand there is demand for tank containers and on the other hand is supply of tank containers.

Demand for tank containers is defined as the demand that customers have for tank containers of Den Hartogh. Uncertainty in executed demand has three dimensions. The first dimension is the volume of demand. This defines the uncertainty in how much demand is executed. The second dimension is the temporality of the demand. This defines the uncertainty in when demand is going to arise. The third dimension is the location/allocation of the demand. This defines the uncertainty concerning where demand is executed and where demand is flowing to.

The supply of tank containers defines where supply of tank containers resides. The uncertainty in supply shares the three dimensions of demand. These are the volume of supply, when this volume is present and where in the network supply is. The location of the supply is determined by demand being executed or empty repo's.

Demand and supply also influence each other. Firstly there is the influence of supply on demand. The volume of the supply of tank containers in any point in time also determines when and how much demand actually can be executed. For example a deficit of supply naturally hinders possibility for demand execution. Also from where to where supply is moving determines where demand can be executed in the future.

On the other hand there is the influence of demand on supply. Because Den Hartogh moves chemicals by use of their tank containers, demand flows also largely determine all dimensions in the state of the global supply of tank containers, with exclusion of the effect of empty repo's. This makes demand and supply of tank containers highly interrelated, with the execution of demand leading in determining supply.

This interrelation is central to this research and Den Hartogh. Supply of tank containers should be matched with demand customers have and uncertainty in demand in supply has the potential to increase the gap between these two.

2.2.2 Demurrage

As mentioned before, demurrage is the time between the end of the free handling days after the delivery of the tank container and its return to Den Hartogh's control. Demurrage is something that occurs regularly at Den Hartogh and demurrage revenue is a large part of the total revenue of the global BU. There can be a number of reasons why demurrage occurs, but the leading reason lies with the customer. It could for instance be that customers use tank containers in demurrage as temporary storage for their chemicals. It could also be that they leave tank containers in demurrage to provide themselves with flexibly on when to retrieve the chemicals. This is partly dependent on the drivers of the customer and the organisation of their supply chain. The uncertainty in demurrage is however not only dependent on the demurrage period, but goes over the entire period the customers has to unload the tank container (free days + demurrage). This is because customers can also return tank containers earlier. Den Hartogh does however produce an expectation for the free handling and demurrage period by use of a prediction model. Uncertainty in the length of this period gives uncertainty in the temporality dimension of supply of tank containers, meaning that it is uncertain when supply is going to become available. The allocation and volume of the change in supply however is not influenced, as this is known just after the order is accepted.

2.2.3 Customer base

Customer uncertainty is the uncertainty in orders placed by Den Hartogh's customers. The uncertainty in orders placed can be divided into two distinct uncertainties:

- *Uncertainty in existing customers*
  This group of customers consists of customers that already have some business with Den Hartogh in the form of spot business or tender business. Rates specified in quotes for tenders and spot business are valid for a certain time for an estimated amount of tank containers. This means that for these customers it is easier to predict how much orders will be placed and where these orders flow to. It is however uncertain when these order will be placed, as this can be anytime in the period where the contract is valid.

  Existing business has therefore an effect on the temporality aspect of the demand, as it is unknown when orders are going to be placed. It is also uncertain how many orders are placed at one specific time. It could be all at once or spread out over the contract duration. It also has an effect on the demurrage uncertainty. Historical demurrage data from existing customers can be used as input to make a more accurate prediction of the demurrage period, making it less uncertain.

- *Changing customer demand*
  This is the demand that is either won or lost by Den Hartogh. On the one hand there is the risk of losing certain business after agreements expire. On the other hand there is the opportunity of winning new business.

  Winning or losing business has an effect on demand and is uncertain on every dimension of demand. This is the case because winning new business creates entirely new demand, so the direction, volume and time of demand is entirely not known beforehand.

  Winning new business also has an effect on how accurately the demurrage period can be predicted. With new business there is no historical data or past experience to base predictions on, which in turn makes demurrage more uncertain.

2.2.4 Pricing and business targeting

This aspect covers a decision variable for Den Hartogh. Den Hartogh has a choice as to what type of business it wants to focus on. This could for instance be to focus on long term business instead of short term business or spot business instead of tender business. Then after certain business is targeted, Den Hartogh can set their price accordingly. This can be done by for instance setting lower prices for targeted business.

This means that the business targeting and pricing has an effect on the customer base. Specifically it has an effect on any business that will be won or lost in the future. Setting a price in a certain way can win you certain business in the future, but can also cause existing customers to not continue business with Den Hartogh.

2.2.5 Procedures

Procedural uncertainty can be defined as the uncertainty in how decision makers actually act as opposed to how they are expected to act. Procedural uncertainty as defined in this research has two aspects:

- *Management consensus*
  This kind of uncertainty manifests itself if different parties have different decision drivers or differing priorities. The consequence that this could have is that surprising decisions are made that are not in line with current management objectives. An example for Den Hartogh could be that a commercial manager focuses on business that contributes to high sales of his specific customers, but is not in line with management objectives.

- *Communication*
  This kind of uncertainty is related to how the communication channels are set up. Unclear communication could for example lead to decisions being made lacking important knowledge or information. An example of this is in Den Hartogh's network in Asia. Almost all communication with customers goes via network partners, which are representative companies of Den Hartogh in that region. Because the connection with the customer is less direct, uncertainty can arise because communication with the customer is slower and it could be the case that information is passed along incorrectly or interpreted in the wrong way.

This kind of uncertainty has an effect on the business targeting and pricing. This is the case because misaligned objectives or misinterpreted information can lead to unexpected targeting or pricing decisions.

2.2.6 External factors

These are several external factors that Den Hartogh cannot influence directly. For Den Hartogh, the following outside factors where identified:

- *Natural disaster*
  This factor is related to natural phenomena which have a disruptive effect. Examples of this could be a tsunami, flooding, disease outbreak, earthquakes or a hurricane. These events have the potential to have a high impact on a the network, but are harder to predict and are generally less likely to occur.

- *Political incidents*
  This type of factor is related to legislation or behaviour of countries and/or global trade organisations. Examples of this could be increased tariffs between two countries, a trade ban, trade limitations between countries or war. These kinds of events are also hard to predict but can have a large effect on the network.

- *Macro economic factors*
  These kinds of factors are characteristics, trends or conditions that relate to the broad context of an economy. This could be for instance rate of inflation, buying power of customers or cost of operating in specific countries, which depends on economic factors in that country. These factors have potentially less impact than other outside factors, but could be predicted with more certainty.

- *Competitors*
  As mentioned in Section 1, Den Hartogh is not the only LSP in the chemical industry. The way that competitors offer their services is something that Den Hartogh has no knowledge of. For example, it is unknown how competitors price certain trade lanes or how their network is set up.

These external factors influence the network of Den Hartogh directly, and also indirectly through the customer base. A direct effect could for instance be natural disaster that prevents repo's out of a certain region. Because the customers of Den Hartogh operate in the same environment as Den Hartogh, they are also influenced by these factors. For instance, if a customer is hit with unexpected disruptions that stops their need for transportation, Den Hartogh loses this business.

2.3 Problem statement and impact of unexpected imbalance

Uncertainty in the network has the potential to cause unexpected tank container imbalances. To solve those imbalances, Den Hartogh has to perform certain recovery measures. The consequences of these imbalances can however be costly because of lost sales or expensive recovery operations. Setting up the network in such a way that Den Hartogh can deal with this uncertainty can give value by making sure Den Hartogh can make full use of business opportunities, is certain to deliver to its customers at a good price and can avoid expensive recovery actions. In recent literature, uncertainty in logistics is something that is widely investigated, especially in the context of supply chain management. Often robustness or flexibility are mentioned in this respect, with differing interpretations. For example, Trajanovski et al. (2013) define robustness in the context of networks as the maintenance of function under node or link removal and (Upton, 1994) define flexibility as the ability to change or react with little penalty in time, effort, cost or performance. A more detailed literature review is found in Section 3. For now, in order to show the value of such strategies for Den Hartogh, an illustrative example will be given.

The situation in the beginning of 2020 in region 1 will be used as an example. In this period, stock in the region dropped considerably. This can have two reasons. The first reason is because of more empty repo out of the region than into the region. In Table 2.2, the repo's that were executed out or into region 1 are shown. The individual repo's are placed in the months were the repo begins and indicates a repo of one tank container. Another reason for the dropping stock could be that orders to and from region 1 were imbalanced. These values are shown in Table 2.3. Note that these volumes indicate executed demand. This means that loaded tank containers out of the region go instantly out of the inventory and the loads to the region will arrive later, as they first will be in transit. Therefore a positive or negative balance has a direct and a future effect on the availability of tank containers. This is also the case for repo. Tables 2.2 and 2.3 below show that there is a relatively low import of tank containers in November 2019. This drop of demand into region 1 was not anticipated in the forecast. The combination of low imports and high exports caused the inventory to drop to a low level. This unexpected imbalance of tank containers had low stocks as a result. Consequently this had two major implications, namely lost sales and extra repo costs.

Month	Repo in	Repo out
January	0	106
February	2	112
March	13	35
April	56	10
May	99	5
June	10	26
July	9	25
August	5	19
September	18	24
October	47	29
November	43	16
December	112	7
January	65	0
February	149	2
March	47	16

Table 2.2: Monthly repo's from and to region 1 2019 and 2020.

Month	Loaded to	Loaded from	Balance
January	961	799	162
February	835	887	-52
March	805	926	-121
April	770	863	-93
May	826	930	-104
June	740	670	71
July	819	792	27
August	817	756	61
September	658	701	-43
October	649	736	-87
November	460	717	-257
December	700	740	-41
January	807	922	-116
February	761	844	-83
March	900	814	86

Table 2.3: Loaded tank containers to and from region 1 2019 and 2020 with balance indicator.

- *Lost sales*
  From order acceptance information, it was assumed that about 300 orders for tank containers could not be fulfilled due to insufficient tank containers. If one assumes a lost sales has a cost of about \$500, the lost sales are then estimated at \$150.000

- *Extra repo costs*
  A part of the repo's that were necessary to cover the deficit in region 1 were repo's that Den Hartogh usually never does. 243 of these expensive repo's were needed to reduce the deficit in region 1. If one assumes these expensive repo's cost \$750 each, the extra repo costs are then estimated at \$182.250.

Combining the estimated cost of lost sales and repo, this constitutes to extra repo costs and cost of lost sales of little over \$330.000. Therefore it can be concluded that uncertain imbalances in the network have a substantial impact.

2.4 Research directions and research questions

There are two main directions that can be specified in order to reduce the impact of unexpected imbalances: robustness and flexibility. The robustness option would imply an analysis into what kind of demand should be targeted in order to create more stable network flows. This demand can then be targeted using a fitting pricing strategy. The flexibility option would imply an analysis as to where flexibility in the network is needed and how this can be implemented. For this research it was chosen to focus on investigating flexibility and implementing more flexibility into Den Hartogh's network. The research will be centered around answering the following research question:

How can flexibility be used to increase profitability for tank container operators experiencing uncertainty in demand and supply?

In order to answer the research question, the following sub questions will be answered in consecutive order. With every sub question, the relevant section where this sub question is answered is stated.

1. *What types of flexibility can be implemented in logistics networks?*

   The purpose of this sub-question is to investigate what kind of flexibility measures for logistic networks are present in recent literature. This will lead to a review what kind of flexibility is possible and increases profitability for logistics networks. This sub question is covered in Section 3.

2. *What kind of flexibility can be implemented into the network of Den Hartogh?*

   The answer to this sub question will define what kind of flexibility can be introduced into the Den Hartogh's network. To determine this, first the characteristics of the network of Den Hartogh should be distinguished. This will be done through analyzing network flows along with existing management operations. This analysis will provide an understanding of what kind of flexibility characteristics are currently present in Den Hartogh's network. After this, a final scope can be defined as to what kind of flexibility will be introduced into the network. This sub question is covered in Section 4.

3. *How can the relation between flexibility and profitability be quantified in terms of profitability?*

   In this stage, the effect of the proposed flexibility will be investigated on the profitability. This means that the flexibility will be translated into flexibility parameters, which will then be connected to profitability. This will result in a mathematical model where flexibility parameters are defined in relation to each other, the network characteristics and quantified profitability of the transportation network. This sub question is covered in Section 5.

4. *How can Den Hartogh change their flexibility parameters in order to increase profitability?*

   This sub question is focused on taking the flexibility parameters in the model as a result of answering sub question 3 and optimising these with the objective to increase profitability. This will lead to an optimal flexibility parameter setting that maximises the potential profitability of the network. This sub question is covered in Section 6.

5. *How can the information about optimal flexibility parameter settings be translated to decision making tools for Den Hartogh?*

   This sub question will make clear how the knowledge of optimal flexibility parameter settings can help Den Hartogh achieve more profitability through flexibility. This provides a basis for developing final management recommendations for Den Hartogh on how to achieve more profitability through flexibility, along with the limitations of the proposed model and future research directions. This sub question is covered in Section 7.

3 Literature review and flexibility implementation

In this section of the thesis a short overview of the available literature on flexibility will be provided. This will provide a theoretical basis for the definition of a final scope of a model for flexibility in logistical networks, which will then be connected to the operations of Den Hartogh.

3.1 Flexibility in operations literature

The concept of flexibility in operations is something that stems primarily from literature concerning flexibility in manufacturing. Sethi and Sethi (1990) for instance surveyed publications in the two decades before its publication, claiming the size of the literature was vast. However, Lau (1996) recognizes that flexibility is associated not only with manufacturing capabilities, but is also important for the linkages between manufacturing units and suppliers and customers, ergo the supply chain. Practically, a supply chain then is a network of nodes.

Flexibility is a tool that can be used primarily to handle uncertainty. Sreedevi and Saranga (2017) stated that high uncertainty in the supply chain leads to high supply chain risk, and therefore supply chain flexibility helps to reduce supply chain risk in uncertain environments. They also state that supply chain flexibility is typically considered as a key solution to the rising uncertainty and competitiveness in the market. Therefore uncertainty creates the need for flexibility.

3.2 Defining flexibility

Many publications on supply chain flexibility do not provide a clear definition of the term supply chain flexibility (Manders et al., 2017). There are however some characteristics of flexibility that can be recognized (Stevenson and Spring, 2007):

1. *Flexibility is multi dimensional*
   In a wide range of publications the two dimensions *range* and *response* are mentioned. These two dimensions were identified by Slack (1988) in the context of manufacturing flexibility. For example, a system that has a wider range of possible states it can be in would be more flexible. On the other hand there is response. If a system is flexible in the response dimension, it is able to adapt to another state in the range fast. This time factor however is not restricted to specifically time, but could also be interpreted as cost from changing states.

2. *Different elements of flexibility are more important in certain environments*
   This states the fact that flexibilities have a lot of different forms and what type of flexibility is needed is dependent on the environment. This can be seen by the different types of flexibility that can be defined by taking a broader or smaller perspective with respect to a supply chain.

3. *Flexibility measures potential performance*
   This indicates the characteristic of flexibility being a potential performance measure instead of a demonstrated one.

However, these characteristics do not give a definition of flexibility. The research question implies that flexibility will be used in order to tackle uncertainty and in doing so improve profitability. Morlok and Chang (2004) define flexibility as the ability of a system to adapt to external changes, while maintaining satisfactory system performance, which is close to a fitting definition. Specifically this thesis focuses on uncertainty in demand and supply and the effect on profitability. Therefore flexibility in the context of this research can best be defined as the ability to change the state of a logistical network in order to improve overall profitability by handling uncertainty. For Den Hartogh, this 'handling of uncertainty' with flexibility would be to influence flows of tank containers, as most of the network of Den Hartogh can be defined by tank container stocks. Having the ability to quickly and cost effectively move tank containers to places they are needed, gives flexibility in the network.

Another important property of flexibility is how it is measured. As said before, when describing the characteristics of flexibility, flexibility can be measured in dimensions. The two dimensions defined by Slack (1988), range and response, are widely accepted. However there is another view that can be recognized. Barad and Sapir (2003) state that flexibility can also be viewed in terms of sequential decision making. This defines a flexible decision as a decision that can be changed in the future when more information is available. As the availability of more information can lead to a mitigation of uncertainty, from this standpoint, it can be recognized that the decision making aspect is also relevant when defining flexibility. This is however viewing flexibility from a different standpoint than in dimensions range and response. Benjaafar et al. (1995) define flexibility in multi-stage decision-making as the degree of future decision-making freedom an action leaves, once it is implemented. This view means that the flexibility of a decision can be measured by a function of the number of actions that are possible at subsequent stages. Barad and Sapir (2003) state that it can be viewed as a device enabling decision-makers to respond effectively to future changes, by minimizing the degree of their future commitment. If one views this in combination with earlier called dimensions, one could say that a flexible decision is one that induces a situation that has enough range and response in the future, when receipt of new information is expected. Therefore it could also be argued that enabling range and response in the network, improves decision making flexibility. This can make decision making flexibility a mediator between the range and response dimensions and profitability.

3.3 Flexibility in logistical networks

When moving from supply chains to networks, first a network should be defined. A common way to denote the physical structure of a network is a set of nodes with corresponding connections between these nodes, the so called links or arcs (Murray-Tuite and Mahmassani, 2004). In general, two possible ways were recognized to enable flexibility into a network.

3.3.1 Network design problems

The first way to approach flexibility is the set up the network in such a way that the physical structure enables flexibility or that the structure is easily adaptable. This can be addressed as a network design problem. An example of this is how flexible the structure of a network is. Feitelson and Salomon (2000) for instance defined node and link flexibility. Node flexibility is defined as the ease with which new network nodes can be sited and link flexibility is the ease with which new links can be made between nodes. Another concept that is connected to this is network density. In a supply chain context, Falasca et al. (2008) define supply chain density as the quantity and geographical spacing of nodes within a supply chain. It stands to reason that a dense network would be more flexible. This is because more nodes are closer together, meaning that different links between nodes can be used more often and with less cost.

For Den Hartogh, this type of flexibility is possible, but not exactly in the way as defined above. Den Hartogh is a tank container operator, so has no ownership of underlying infrastructure. For instance places where tank containers can be kept in stock are fixed. Den Hartogh cannot decide to place a depot somewhere for instance. They do however have a choice to use this depot or not and in what way. So infrastructure cannot be influenced, and the structure of the network is more defined by tank container location.

3.3.2 Network planning problems

Network planning problems focus more on how flows are planned within a network. How flexibility can have a role in this can be approached in a number of ways. In the context of supply chain management this is often linked to supply chain risk management. Tang and Tomlin (2008) for instance investigated flexibility to mitigate supply chain risk. They cover three aspects of supply chain risk, namely supply risk, process risk and demand risk.

On the side of the supply there is supply risk. A measure of flexibility that is often addressed in combination with supply risk is multiple sourcing. Multiple sourcing is a way of hedging the risk of having supply from one supplier cut short by making sure supply is acquired via multiple channels. The other form of risk recognized by Tang and Tomlin (2008) is process risk. This is the risk associated with the internal processes within a network or supply chain. If the processes within a network of supply chain of network are not flexible, this process risk is high. Tang and Tomlin (2008) provide the example of manufacturing flexibility that can mitigate process risk. Imagine a network of manufacturing plants. If all plants can produce all types of material, then a network would be entirely flexible. If only one product can be manufactured, then there is no flexibility. In the event when a plant is disrupted, this type of flexibility would ensure continuation of operations. The third type of risk Tang and Tomlin (2008) identify is demand risk. Demand risk is associated with the uncertainty how much demand will be seen and in what location. One of the ways mentioned to reduce demand risk is product postponement. This means keeping products in a general state, with options to customize to a specific product later in the production process. This delays the decision what specific product will be produced, which allows flexibility in what product to produce in the end.

In the case of Den Hartogh, 'keeping products in a general state' could be interpreted as placing tank containers in locations where Den Hartogh has multiple choices in what to do with them. This makes sense as this would ensure flexible decision making. Sending a tank container to a location where there is only one possible choice to move it further in the network, would not be flexible.

Another view is given by Naim et al. (2006). They tackle flexibility more from a transportation view. They also recognize the types of flexibility defined by Feitelson and Salomon (2000). Naim et al. (2006) define flexibility types as mode, fleet and vehicle flexibility. Mode flexibility can be defined as the ability to use multiple modes of transportation, fleet flexibility is the ability to make changes in your transportation fleet and vehicle flexibility is the ability of vehicles in the fleet to handle different types of products. Another mention of mode flexibility is Ishfaq (2012). They explore the use of having two mode choices between certain origin destination pairs, with one mode serving as backup for the other mode. They found that using this strategy can improve resilience against unexpected disruptions in the network.

3.4 Conclusion on literature

Scientific publications recognize several types of flexibility for supply chains and logistical networks. These types of flexibility are necessary to maintain competitive in an uncertain environment, as uncertainty induces risk. Some characteristics of flexibility were defined, as well as the dimensions that flexibility can be measured by, namely range and response. The types of flexibility that are found in literature have a effect on these dimensions. An important note on this concept is that the dimensions range and response have a general definition, but are not a general representation of flexibility. What this means is that range and response can have a different representation depending on what kind of flexibility one considers. For example, node flexibility has another representation in range in response than multiple sourcing.

Another concept that was introduced was the viewpoint of flexible decision making. However there can be made a connection between this viewpoint and range and response. It could be the case that good range and response in some way enables flexible decision making. For example, a dense network enables more flexibility in where to source from. In general this type of flexibility enables decisions to be made final later in time. This can be addressed as decision postponement, and can be linked to product postponement from manufacturing literature.

Depending on how uncertain the environment of the network is, correct setting of flexibility dimensions has potential to mitigate risk and remain competitive in a dynamic environment.

3.5 Flexibility at Den Hartogh

In the previous subsections. a few things can become clear about flexibility at Den Hartogh. These are:

1. *The state of the network of Den Hartogh is dependent on where tank containers are situated, so the network design problem and planning have the same practical implementation.*

2. *Flexibility for Den Hartogh would be to ability to change the locations of their tank containers quickly and cost effectively.*

3. *As flexibility is increased when tank containers are in flexible positions, increasing flexibility for Den Hartogh can be achieved by stimulating demand to these locations.*

The most important observation is then that flexibility can be increased when tank containers are in locations that are flexible, but that raises the question when a location is deemed flexible. This flexibility has two possible interpretations, namely flexibility in demand in the form of alternative demand options (range) and this potential demand is high enough (response). Another interpretation could be in the sense of flexible empty repositioning. This second interpretation fits however better in the flexibility definitions. Having multiple demand could be tricky, as firstly there should be demand available where needed and this option should be attainable with current pricing settings of the network. Therefore it was chosen that this research will focus in flexibility in empty repositioning.

4 Flexibility in empty repositioning and impact on profitability

This section will answer the second research question and explain how flexibility in the Den Hartogh network will be implemented. It will explained how flexibility in empty repositioning can be increased at Den Hartogh in order to increase profitability. Firstly, the actual implementation will be discussed along with how this will be quantified. After that, the network pricing of Den Hartogh will be discussed in order to isolate the cost components that impact profitability and that are of influence when considering unexpected imbalances.

4.1 Flexible hubs

As mentioned in the previous chapter, the flexibility of Den Hartogh can be increased by stimulating demand to flexible locations. So it is important to identify these flexible locations where repo is cost effective and have multiple repo options. However that raises the question what repo options would be beneficial for solving unexpected imbalances. In this case, this would be a location where repo is possible to different regions, as an imbalance is costly when repo is needed between regions. Den Hartogh already recognizes these kinds of hubs, and calls them flexible hubs. These hubs have the potential to execute repo's to several regions cost effectively. Thus having tank containers in those locations, can increase the amount of tank containers Den Hartogh can move to locations where needed. In Figure 4.1, this concept is illustrated. On the left side is an example with the use of a flexible hub and on the right an example without the use of a flexible hub. On the left demand flows to the flexible hub, which has then the freedom to cost effectively reposition to all three regions in this example. On the right this demand goes to region three directly. However in region 3, it is only possible to reposition to region 1, which is also very costly.

Figure 4.1: Flexible hub example

As flexible hubs therefore have potential to be used to make a more flexible decision for repo, it was chosen that the use of flexible hubs will be investigated further. In order to recognize flexible hubs in the network, the definition of a flexible hub should be made clear. In this case, these properties are the following:

- *Repo to several regions should be possible.*
  As said before, Den Hartogh has several global regions in their network. A flexible hubs should be able to reposition to at least two of these regions to have a flexible decision.

- *Repo to the different regions should have similar cost and these costs should be (mostly) covered by repo contributions.*
  Den Hartogh aims to cover almost all of their repositioning movements with contributions in their pricing model. So repositioning movements from the flexible hub to the different regions should be (almost) fully covered by these contributions. What is however also important is that repositioning to these different regions should have similar cost. This ensures the decision is indeed flexible and not guided by cost.

4.2 Flexibility modeling

The question that is raised after recognition of these flexible hubs is how one can optimize the use of these flexible hubs and how one can quantify the benefit of these flexible hubs. The flexible hubs are theorized to guard against unexpected imbalances. However, it is hard to define the link of these flexible hubs directly with profitability. , because potential benefits can only be estimated, while the cost of implementing flexibility are known beforehand (Ivanov et al., 2014). However, because an unexpected imbalance is a sudden event in the network, one could depict this as a disruption in the network. Therefore using a method that can asses the impact of a disruption can be used.

A term that is often mentioned in disruption management literature is the Ripple effect. The Ripple effect considers how changes to some variables are rippling through the rest of the supply chain and impacts performance. As all the nodes and links in a network are connected, a disruption somewhere in the network can ripple throughout the rest of the network (Ivanov et al., 2014). In the case of Den Hartogh, this is also of importance, as the network of Den Hartogh is very dynamic. Ivanov et al. (2014) define three quantitative methods to measure the ripple effect. These are mathematical optimization, simulation and system dynamics and control theory. Mathematical optimization can be used for design of a network under uncertainty assumptions, but in this method it is harder to asses the downstream effects of a disruption and is therefore less suited for the current research problem. System dynamics and control theory focuses on automatic control, which does not fit in the method Den Hartogh uses to make decisions in their network. Therefore it was chosen that simulation will be used as the quantitative modeling method to asses the impact of unexpected imbalances.

4.3 Simulation model implementation and use

The big question with regard to flexible implementation is how much flexibility is needed. With regard to the research question, the flexibility should have a positive effect on the profitability of the network. However, investing in flexibility costs money. The implementation that was chosen focuses on stimulating demand to flexible hubs. However this stimulation of demand will most likely mean lowering prices to the flexible hubs. This would work in the same way as the market corrections Den Hartogh uses to solve long term imbalances. This can only be done in a sustainable way if Den Hartogh knows how much they can invest in flexibility to get satisfactory returns. Therefore the simulation model should be used in order to test certain disruption scenario's on the network. Most likely these disruption scenario's lead to recovery cost. The simulation tool can help in determining the extra cost of not having enough flexibility and compare this to the situation with increased flexibility. From this cost analysis, Den Hartogh can then determine how much they have available to invest in flexible hubs.

4.4 Pricing model structure

In order to make a cost analysis, it should first be made clear how the pricing model of Den Hartogh is structured, as this determines the impact certain decisions have to the network. The following pricing structure is used by Den Hartogh to quote their orders. This depicts the sales rate of single order that has a certain origin and a certain destination. This structure is used to determine the value of an order in the network.

Table 4.1: Pricing structure of a single order

+ Direct tank container handling cost
+ Tank hire
+ Overhead cost contribution
+/- Market correction origin
+/- Market correction destination
+ Repo contribution
+ Repo days contribution
- Repo saving
- Expected demurrage revenue
+/- Quoted network margin
= Sales rate single order

- *Direct tank container handling cost*
  These are the costs that are directly linked to all operations that are needed to move the tank container from origin to destination, for instance a leakage check, transportation costs etc.

- *Tank hire*
  These costs are quoted to the customer for the use of the tank container. This rate includes costs of leased tank containers, depreciation, maintenance and repair of tank containers. These costs are charged for every day the tank container is expected to be in use for a specific order.

- *Overhead cost contribution*
  These are the costs that cannot be linked directly to a specific order like personnel salary. This is a fixed amount charged at every order.

- *Market corrections*
  As stated in the introduction, the market correction is a steering mechanism for the expected or actual surpluses and deficits in certain areas. In a surplus area, orders to that surplus area receive a penalty cost on the quote and orders from that surplus area receive a discount on their quote. For deficit areas, this is the other way around. Orders to a deficit area receive a discount on their quote and orders from that area receive a penalty on their quote. This discourages demand that brings the network more out of balance and encourages demand that balances the network out. The origin and the destination corrections of a certain location also balance each other out, so for example if a discount is given to orders to a certain location than the penalty for orders from that location is the same amount. This means that on a single order, the origin market correction of the origin location and the destination market correction of the destination location is charged on one order. These markets corrections are re-estimated monthly.

- *Repo contribution*
  This is a contribution that is aimed at covering the direct repo cost that could be needed after completion of the order. Therefore this cost element is quoted based on the destination of the order. The contribution aims to cover the total average cost of all tank containers that are repositioned from that location. This is done by firstly determining the direct repo cost of the location that it is most likely to be repositioned to. Then depending on how much percent of the tank containers are expected to be repositioned, the repo contribution is also corrected with this percentage. So for example, if 80% of tank container in a certain location are expected to be repositioned, the repo contribution is equal to 80% the expected repo costs of a single tank container. This also means that if no tank containers are expected to be repositioned, the repo contribution is equal to zero.

- *Repo days contribution*
  Of course executing a certain repo takes a number of days. Therefore, these days are also quoted to the customer in the same manner as the tank hire to cover the use of the tank container. The number of days that is quoted is again based on the percentage that is expected to be repositioned. So if the percentage that is repositioned is again 80% and the repo is expected to take 30 days, then 24 repo contribution days are quoted to the customer. This 24 days is then multiplied with the daily contribution rate.

- *Repo saving*
  This component entails a discount if a specific order has an origin where tank containers are normally repositioned from. The cost of repositioning from that location has then been 'saved'. This saving is quoted as a discount for that order. Therefore this component is based on the origin of the order. The discount is equal the quoted repo contribution and days from that origin. This saving can also be zero if no repo costs are saved when executing a particular order.

- *Expected demurrage revenue*
  If the free handling days of a tank container are exceeded, the customer pays a daily penalty fee. The revenue that this creates is called the demurrage revenue. This expected revenue is discounted on the quote. However that does not necessarily mean that the customer pays less. The reason this is subtracted is because this then gives a clear image of the expected margin the order will generate on a network perspective.

- *Quoted network margin*
  This is the expected margin the order will generate on a network level. Of course this is not the actual revenue an order will generate, as this depends on the actual costs that are made and the demurrage revenue, which is now only an expectation. This margin is dependent on the final sales rate the commercial manager agrees on with the customer.

All of these elements combined determine the sales rate of an individual order. Herein is the quoted network margin the expected profit an order will generate. As mentioned before, this is only an expectation, since the actual costs or demurrage revenue might be different than what is expected.

4.5 Relevant cost parameters

In order to evaluate what cost parameters are relevant when dealing with unexpected imbalances, first there should be made clear what cost elements are important when considering unexpected imbalances. Firstly there is the option to reposition into a deficit area or out of a surplus area. Secondly there is the risk of lost sales, as a shortage in tank containers could force Den Hartogh to decline spot demand. Thirdly there is extra cost in operating tanks. If tank containers cannot be loaded from a surplus area or repositioned, the tank container stays idle. This costs Den Hartogh money as this tank container is not being covered by tank hire.

4.5.1 Repo cost impact

How much impact a repo move actually has, is of course dependent on how much repo contribution Den Hartogh has received. However the impact that a potential order has for that tank container also changes. From a network perspective there is certain amount of money that Den Hartogh can spend freely on a repo. Going over this limit essentially means investing extra money to move the tank container, which will most likely come out of the profit. So knowing how high the impact of repositioning a tank container is important in order to know if a repo is economically viable. In this regard, three distinctions can be made, which correspond to how much contribution Den Hartogh already has received, what the actual cost of the repo will be and what the costs/gains are.

In order to make this more clear, an illustrative example will be given. In this case, it will be evaluated how much the impact is of repositioning a tank container from hub A to hub B. The cost components in green are the ones of importance to the impact of the repo move on a network level.

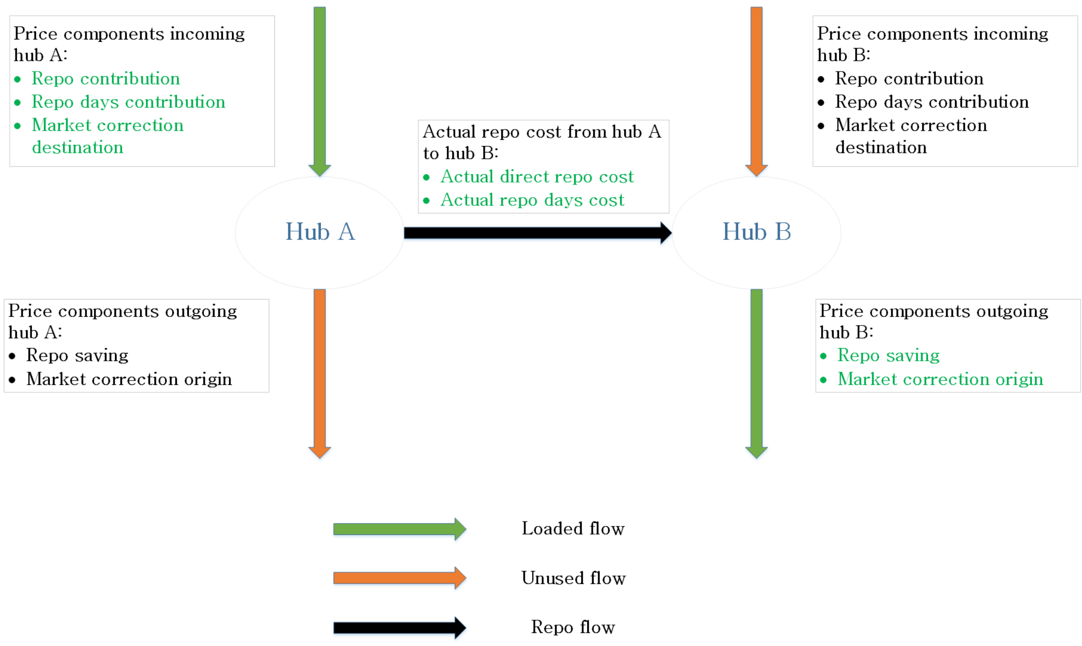

Figure 4.2: Repo impact flow chart

In Figure 4.2, a tank container is moved from hub A to B. This tank container was in the first place loaded to hub A. For this, Den Hartogh received a repo contribution and a contribution per day the tank container is expected to be repositioned and quoted a market correction. The decision was made to reposition from hub A to hub B, as in hub B there is demand for that tank container. That means that for the order in B, a market correction is quoted and, if applicable, a repo saving discount is quoted. The reason the market correction is included in this calculation is because when no repo takes place, the market corrections balance each other out. However when a repo takes place, this is not the case anymore. Therefore this change should also be incorporated, as it defines how the repo move impacts the network. For example, if an order takes place to hub A, a market correction of 500$ is quoted. If the tank container is not repositioned, the outgoing order will have a market correction of -$500, and the two balance each other out. However making the decision to reposition to hub B, which has an origin market correction of $200 means that Den Hartogh receives $700 in market corrections if the repo is executed, which can be used to cover the repo. Combining these costs, that means Den Hartogh has the following provision to cover the repo costs on a network perspective:

$$\begin{aligned} RepoProvision_{a,b} = {} & RepoContribution_a \\ & + RepoDaysContribution_a \\ & + MarketCorrectionDestination_a \\ & + MarketCorrectionOrigin_b \\ & - RepoSaving_b \end{aligned} \tag{4.1}$$

In this equation, the repo contribution and the repo days contribution are always zero or a positive number and the repo saving is subtracted from the provision. The market corrections however could be positive or negative, so depending on this property are added or subtracted from the provision. The actual repo costs of the movement are the following:

$$RepoCost_{a,b} = DirectRepoCost_{a,b} + ActualRepoDaysCost_{a,b} \tag{4.2}$$

The impact on the network can then be estimated by the following equation:

$$RepoImpact_{a,b} = RepoCost_{a,b} - RepoProvision_{a,b} \tag{4.3}$$

The impact is then defined as the extra costs that are made with repo movements. This value could also be negative, if the provisions turn out to be higher then the actual cost.

4.5.2 Lost sales impact

Den Hartogh strives to accept every order request if the customer agrees on the sales rate. If certain demand cannot be met, then one can view this as lost sales. In the first place, this means that the potential profit that that demand could have generated is lost. However there is another component that has impact. Most of the costs that are quoted are meant to cover costs that are directly linked to that specific order. So this revenue is not lost as this would have been used directly on the orders' transport operations. What revenue is lost however is the contribution to cover the overhead cost. This is fixed amount that for every order that cannot be met, is not used to cover the total overhead cost of the company. Therefore a single lost sale has the following impact in an arbitrary hub A:

$$LostSaleImpact_a = NetworkMargin_a + FixedOverheadCost \tag{4.4}$$

4.5.3 Inventory cost impact

The last component with relevant impact is the inventory cost. In case surplus exists somewhere and it is decided not to move these tank containers, that means this capacity is unused, while it could potentially be used for demand. Every day a tank container is not used, costs Den Hartogh money. These are the costs that the tank hire components in the pricing model aim to cover. Of course there is also the cost keeping the tank container in stock. Therefore the daily inventory cost of a single tank container in an arbitrary hub A is equal to:

$$DailyInventoryCost_a = DailyDepotStorageCost_a + DailyTankOperatingCost \tag{4.5}$$

5 Simulation model formulation

In this chapter the third research question is answered by providing a simulation tool that quantifies the relation between flexibility and profitability. Den Hartogh can use this simulation tool to simulate certain scenario's. In doing this, the user of the tool can estimate what the cost impact is of certain scenario's on the network, how the use of flexibility can reduce this impact and how much can be invested in flexibility.

This chapter will firstly discuss the general assumptions of the model. Secondly the variables of the model will be listed. Lastly, the steps of the simulation model are explained.

5.1 General model assumptions

Below are the general assumptions of the model:

1. *It is assumed that ports are aggregated into larger regions*
   The model allows the user to choose which ports are aggregated into regions, which form the nodes of the network.

2. *The demand is deterministic and based on the forecasted demand for tank containers*
   An important input to the simulation tool is the future demand. The difference between the forecasted demand and the observed demand is seen as an unexpected imbalance or disruption. In order for the model to isolate the impact of a disruption, the forecast input will be used as deterministic demand.

3. *The lead time of an order, that is composed of the demurrage time, transit time and cleaning time, is stochastic*
   The stochastic behaviour of order lead times is mainly due to the high variability of the demurrage time (e.g. it can span from 0 days to about 200 days). As a result, we assume a fixed transit time, a fixed cleaning time of 4 days and we simulate the demurrage time based on a distribution.

4. *Cleaning of tank containers is possible in all hubs*
   We assume that cleaning is possible at any hub. This simplifying assumption seems reasonable since we are dealing with demand at regional hubs.

5. *Storage cost in every hub is the same*
   Of course storage cost could be different from hub to hub. However for simplicity, this assumed to be equal everywhere. Compared to the daily cost of operating a tank container, this cost is small, therefore is expected to not have of big impact.

6. *All tank containers are homogeneous*
   Den Hartogh owns several types of tank containers with different specifications, such as size or product type restrictions. For simplicity, it is assumed that all tank containers have the same specifications and can be used for all demand.

7. *The amount of tank containers in the network remains constant*
   For sake of simplicity it is assumed that no tank containers are bought, leased or handed in and the amount of tank containers in maintenance remains constant during the simulation period, effectively keeping the amount of tank containers in the network constant.

8. *Repo decisions are made every period*
   This assumption is reasonable as Den Hartogh executes repo's continuously.

9. *Repo is only possible on probable lanes*
   While in theory repositioning is possible on any lane, some decisions are unrealistic because of the extremely high costs of the corresponding lanes. We therefore limit the repositioning options to a predefined set of realistic lanes.

10. *Tank containers that come out of demurrage in a region can be instantly used for demand*
    It is assumed that tank container can be used immediately after demurrage and cleaning. This assumptions is reasonable when the length of a single period and the number of regions is large enough, which will cause the internal repo lead times of regions to be short compared to the period length.

11. *Demand that cannot be met will be treated as lost sales*
    If demand cannot be met due to a lack of tank containers, the unsatisfied demand is considered as lost sales. This makes sense since Den Hartogh operates in a competitive market and customers will therefore turn to a competitor.

12. *The model operates on a 'fill all' principle*
    The model will always try to fill as much demand as possible and will never decide to not do a repo if doing so can fill potential demand. Consequently, this means no demand is rejected provided there are enough tank containers on stock. This makes sense, as declining orders harms customer relations with that specific customer. Also in case of a tender agreement, Den Hartogh is obligated to fill the demand.

5.2 Simulation parameters and variables

In Tables 5.1 and 5.2 the parameters and variables that will be used for the simulation model formulation are shown.

Parameter	*Description*
T	Number of simulation periods.
F	Number of forecasted periods.
R	Number of regions.
RPH	Repositioning prediction horizon.
$MinInv_i$	Minimal inventory in region i.
$d_{i,j,t}$	Forecasted demand from region i to region j in period t.
RA_i	Percentage of potential surplus available for repo per period in region i.
$RB_{i,j}$	Binary to indicate possibility of repo between region i and region j.
LSI_i	Lost sales impact of a single order lost in region i.
$RI_{i,j}$	Repo impact of any repo move from region i to region j.
IC	Inventory cost of holding a single tank container in stock per period.
$RLT_{i,j}$	Lead time of a repo move from region i to region j.
np	Number of runs for inventory prediction.
ns	Number of total simulation runs.

Table 5.1: Simulation parameters

Variable	*Description*
$e_{i,j,t}$	Executed demand from region i to region j in period t.
$r_{i,j,t}$	Number of initiated repo movements from region i to region j in period t.
$OLT_{i,j}$	Random variable for the lead time of an order from region i to region j.
$olt_{i,j}$	Random variate of $OLT_{i,j}$.
WIP	Set of orders in transit or in demurrage after executed order arrivals.
$o_{i,j,l,a}$	Single executed order from region i to region j beginning in period l and arriving in period a.
$INIT_{i,t}$	Initial inventory in region i at the start of period t.
$IBD_{i,t}$	Inventory available before demand in region i in period t.
$IAD_{i,t}$	Inventory available after demand in region i in period t.
$IADR_{i,t}$	Inventory available after demand and repo in region i in period t.
$SFA_{i,t}$	Scheduled amount of order arrivals in region i in period t.
$SEA_{i,t}$	Scheduled amount of repo arrivals in region i in period t.
$LST_{i,t}$	Total amount of lost sales of demand in region i in period t.
$LS_{i,j,t}$	Amount of lost sales of the demand from region i to region j in period t.
$DE_{i,t}$	Predicted deficit in region i predicted in period t.
$SU_{i,t}$	Predicted surplus in region i predicted in period t.

Table 5.2: Simulation variables

5.3 Pseudo code of single simulation step

In Algorithm 1, the pseudo code of the steps undertaken in a single simulation period is shown. After this, a more detailed explanation of the operations are given.

Algorithm 1 Single period simulation steps

Step 1: determine inventory available for demand

for every region $i \in R$ **do**
    $IBD_{i,t} = INIT_{i,t} + SFA_{i,t} + SEA_{i,t}$
end for

Step 2: determine lost sales

for every region $i \in R$ **do**
    if $\sum_{j=0}^{R} d_{i,j,t} > IBD_{i,t} - MinInv_i$ **then**
        $LST_{i,t} = \sum_{j=0}^{R} d_{i,j,t} - [IBD_{i,t} - MinInv_i]^+$
    else
        $LST_{i,t} = 0$
    end if
end for

for every pair (i, j) with $i \in R$, $j \in R$ **do**
    $LS_{i,j,t} = \frac{d_{i,j,t}}{\sum_{j=0}^{R} d_{i,j,t}} * LST_{i,t}$
    $e_{i,j,t} = d_{i,j,t} - LS_{i,j,t}$
end for

Step 3: execute accepted demand

for every pair (i, j) with $i \in R$, $j \in R$ **do**
  for every order in range $e_{i,j,t}$ **do**
    Draw random variate $olt_{i,j}$ from distribution $OLT_{i,j}$
    $SFA_{j,t+olt_{i,j}} \leftarrow SFA_{j,t+olt_{i,j}} + 1$
    Append $o_{i,j,t,t+olt_{i,j}}$ in WIP
  end for
end for

for every region $i \in R$ **do**
  $IAD_{i,t} = IBD_{i,t} - \sum_{j=0}^{R} e_{i,j,t}$
end for

Step 4: predict the inventory

$pr = 1$
while $pr < np$ **do**
  for all $o_{i,j,l,a}$ in WIP with $a > t$ **do**
    Draw random variate $olt_{i,j}$ from distribution $OLT_{i,j}$ given that $olt_{i,j} > t - l$
    if $olt_{i,j} \leq RPH$ **then**
      $IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,r} + 1$
    end if
  end for

  for every pair (i, j) with $i \in R$, $j \in R$ **do**
    for every order in range $d_{i,j,l}$ with l in $[t+1, t+RDH]$ **do**
      Draw random variate $olt_{i,j}$ from distribution $OLT_{i,j}$
      if $l + olt_{i,j} \in [t, t+RDH]$ **then**
        $IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} + 1$
      end if
    end for
  end for

  for every region $i \in R$ **do**
    $IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} - \sum_{l=t+1}^{t+RDH} \sum_{j=0}^{R} d_{i,j,l}$
    $IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} + \sum_{l=t+1}^{t+RDH} SEA_{i,l}$
    $IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} + IAD_{i,t}$
  end for

  $pr \leftarrow pr + 1$
end while

for every region $i \in R$ **do**
  $E[IAD_{i,t+RPH}] \approx \frac{\sum_{pr=1}^{np} IAD_{i,t+RPH,pr}}{np}$
end for

Step 5: determine surpluses and deficits

for every region $i \in R$ **do**
  if $E[IAD_{i,t+RPH}] < MinInv_i$ **then**
    $DE_{i,t} = MinInv_i - E[IAD_{i,t+RPH}]$
  else
    $DE_{i,t} = 0$
  end if

  if $E[IAD_{i,t+RPH}] > MinInv_i$ **then**
    $SU_{i,t} = (E[IAD_{i,t+RPH}] - MinInv_i)RA_i$
  else
    $SU_{i,t} = 0$
  end if
end for

Step 6: make repo decision and execute repo's

Execute repo model to get values for $r_{i,j,t}$

for every region $j \in R$ **do**
  $SEA_{j,t+RLTi,j} \leftarrow SEA_{j,t+RLTi,j} + \sum_{i=0}^{R} r_{i,j,t}$
end for

for every region $i \in R$ **do**
  $IADR_{i,t} = IAD_{i,t} - \sum_{j=0}^{R} r_{i,j,t}$
  $IADR_{i,t} = INIT_{i,t+1}$
end for

5.4 Model formulation of single simulation step

We consider a graph with a total of R nodes connected by a set of $2*R^2-R$ directed links. These nodes are considered regions in the network and consist of multiple hubs. The regions can hold stock of tank containers and are connected by two types of directed links Firstly there are the demand lanes, also called trade lanes. On these trade lanes, demand for tank containers exists. In this research, an order relates to demand for a single tank container, making the demand on a lane the total set of these individual orders, also making the demand an integer value. Demand is possible on every link, so this means the network can be seen as a fully connected graph, with every region having directed connections between each other. Demand within the region is also possible. In that case, the other type of flows are the repo flows or the empty flows. These are the executed repo's by Den Hartogh and also relate to the repositioning of a single tank container. These flows are also fully connected and directed between the regions. As it is assumed that tank containers in a region become instantly available for demand, this flow is not present from within the region itself. Figure 5.1 below depicts a graphical representation of these flows between 3 different regions.

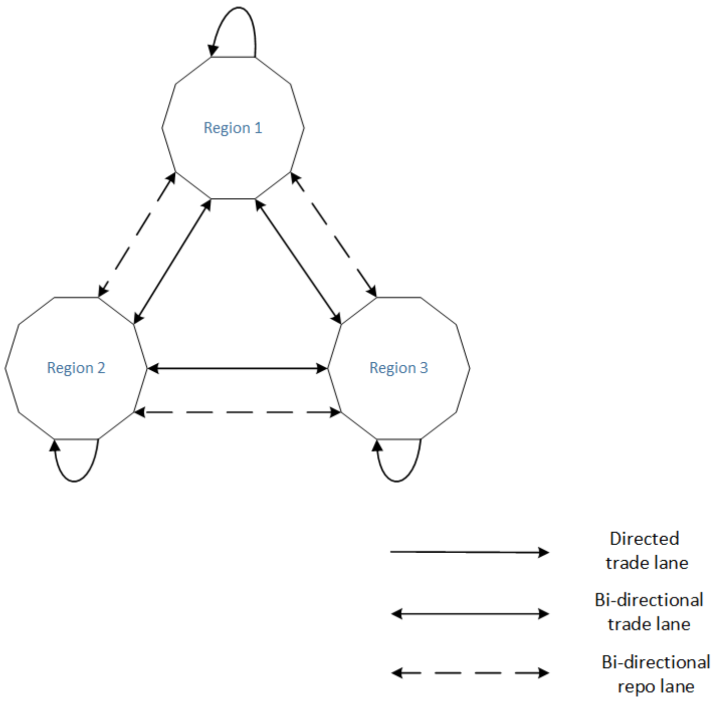

Figure 5.1: Visual representation of an example network

The simulation executes the following steps per period, as indicated in the pseudo code. These steps are explained in Sections 5.4.1 until 5.4.6.

The first step determines the amount of tank containers that are available for demand by adding the arrivals of tank containers to the beginning inventory. Then, depending on the size of the demand, it is determined how many orders can be accepted in all the regions and these are consequently executed. Then the model will predict the future inventory in all the regions. From this prediction, it can be determined what the expected surpluses and deficits are in all the regions. The expected surpluses and deficits serve as input for the repositioning model, where all the repo moves in that period are determined. After this is determined, the decided upon repo's are executed and the simulation moves to the next period. In the following subsections, these steps are explained in more detail with the corresponding mathematical formulas and lines in the pseudo code. Also with every equation, new variables or parameters that are introduced are explained.

5.4.1 Step 1: determine inventory available for demand

In following equations, t will be the current period in the simulation horizon T. The inventory available before demand in region i and period t is determined by Equation 5.1 (lines 1-3 of the pseudo code). The purpose of this calculation is to asses how much inventory is available for demand in the period.

$$IBD_{i,t} = INIT_{i,t} + SFA_{i,t} + SEA_{i,t} \qquad \forall i \in R \tag{5.1}$$

- $IBD_{i,t}$ is the inventory before demand in region i in the current period.
- $INIT_{i,t}$ is the initial inventory in region i in the current period.
- $SFA_{i,t}$ are the scheduled full arrivals in region i in the current period. This is the amount the tank containers that come out of demurrage and consequently have been cleaned.
- $SEA_{i,t}$ is the amount of scheduled empty arrivals in region i in the current period. These are the arrivals of repo's in the region.
- R is the amount of regions

5.4.2 Step 2: determine the amount orders that can be accepted

As it is assumed that a region has a minimal inventory, it is not possible to go below this inventory. Therefore, if the demand in a region is significantly high that the inventory drops below the minimum, lost sales occur. The amount of lost sales are calculated by (lines 4-10):

$$LST_{i,t} = \begin{cases} \sum_{j=0}^{R} d_{i,j,t} - [IBD_{i,t} - MinInv_i]^+, & if \sum_{j=0}^{R} d_{i,j,t} > IBD_{i,t} - MinInv_i \\ 0, & else \end{cases} \qquad \forall i \in R \tag{5.2}$$

- $LST_{i,t}$ is the total amount of lost sales in region i in the current period.
- $d_{i,j,t}$ is the forecasted demand from region i to region j in the current period.
- $MinInv_i$ is the minimal inventory in region i

After the total lost sales in every region are determined, these lost sales are divided over the specific lanes according to demand size of a lane compared to the total demand in that region, determining the lost sales per lane. This can be calculated by (lines 11-12):

$$LS_{i,j,t} = \frac{d_{i,j,t}}{\sum_{j=0}^{R} d_{i,j,t}} \cdot LST_{i,t} \qquad \forall i,j \in R \tag{5.3}$$

- $LS_{i,j,t}$ is the total amount of lost sales on lane (i, j).

Then after all the lost sales are determined, the executed demand can be calculated by (lines 13-14):

$$e_{i,j,t} = d_{i,j,t} - LS_{i,j,t} \qquad \forall i,j \in R \tag{5.4}$$

- $e_{i,j,t}$ is the amount of executed demand from region i to region j in the current period.

5.4.3 Step 3: execute accepted demand

Consequently, the accepted demand should be given a lead time. The lead time is defined as a stochastic variable. Therefore all individual orders for a single tank container should be assigned a lead time based on the distribution for that lane. This is done for every order in the total accepted demand $e_{i,j,t}$ on every lane in the current period (lines 15-21):

For every order in $e_{i,j,t}$, $\forall i,j \in R$:

$$draw\ random\ variate\ olt_{i,j} \in OLT_{i,j} \tag{5.5}$$

$$SFA_{j,t+olt_{i,j}} \leftarrow SFA_{j,t+olt_{i,j}} + 1 \tag{5.6}$$

$$o_{i,j,t,t+olt_{i,j}} \in WIP \tag{5.7}$$

- $olt_{i,j}$ is a random realisation of $OLT_{i,j}$
- $OLT_{i,j}$ is a random variable describing the leadtime for an order from region i to region j
- $o_{i,j,t,t+olt_{i,j}}$ relates to a single order from region i to j with loading period t and arrival period $olt_{i,j}$
- WIP is the list of individual orders, recording the loading and arrival period of the order. This list is needed later to predict the future inventory.

Then, the inventory after demand can be calculated by (lines 23-25):

$$IAD_{i,t} = IBD_{i,t} - \sum_{j=0}^{R} e_{i,j,t} \qquad \forall i \in R \tag{5.8}$$

- $IAD_{i,t}$ is the inventory after demand in region i.

5.4.4 Step 4: predict the inventory

In order to predict the inventory, the model simulates how much inventory after demand will be available at the end of the repositioning decision horizon. This is a rolling horizon that dictates how many periods in the future will be predicted for. For example, if the repositioning decision horizon is 3, then the inventory up until $t + 3$ will be predicted. It will do this for a predetermined amount of simulated prediction runs and consequently determine the expected inventory by taking an average value of the inventory in all the prediction runs. Firstly, pr is set as $pr = 1$ for the first iteration, where pr is an index for the current prediction run (line 26). Then the next step is to determine whether the orders currently in transit or in demurrage will arrive before the end of the repositioning decision horizon. This is done for all the orders in WIP and can be calculated by (lines 26-32):

$\forall$o$_{i,j,l,a}$ $\in$WIP *with* a>t:

$$draw\ random\ variate\ olt_{i,j} \in OLT_{i,j}\ given\ olt_{i,j} > |l-t| \tag{5.9}$$

$$IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} + 1 \qquad if\ l + olt_{i,j} \leq RPH \tag{5.10}$$

- l and a are indications for the loading and arrival periods of the specific order.
- RPH is the repositioning decision horizon.
- $IAD_{i,t+RPH,pr}$ is the inventory after demand in period $t + RPH$ in prediction run pr.

These operations handle the orders currently in transit to all regions. However there is the possibility that orders executed in later periods also arrive before $t + RPH$. For this the forecasted demand is used, as it is assumed that all demand is satisfied as much as possible. This is done via following operations (lines 33-40):

For single order in range of $d_{i,j,l}$ $\forall i, j \in R$, $\forall$ l $\in$ [t+1, t+RDH] :

$$draw\ random\ variate\ olt_{i,j} \in OLT_{i,j} \tag{5.11}$$

$$IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} + 1 \qquad if\ l + olt_{i,j} \in [t+1, t+RDH] \tag{5.12}$$

The last step is to subtract the future demand from the inventory, add the scheduled repo's to the inventory and also add the inventory after demand in the current period. This is done by (lines 41-45):

$$IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} - \sum_{l=t+1}^{t+RDH} \sum_{j=0}^{R} d_{i,j,l} \qquad \forall i \in R \tag{5.13}$$

$$IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} + \sum_{a=t+1}^{t+RDH} SEA_{i,a} \qquad \forall i \in R \tag{5.14}$$

$$IAD_{i,t+RPH,pr} \leftarrow IAD_{i,t+RPH,pr} + IAD_{i,t} \qquad \forall i \in R \tag{5.15}$$

At the end of a prediction run, 1 is added to pr. The entire prediction run is repeated until pr is equal to np, which is the total amount of prediction runs (line 46-47). Then the expected inventory in all regions can be calculated by the following expression, and is then rounded to the nearest integer (lines 48-50):

$$E[IAD_{i,t+RPH}] \approx \frac{\sum_{pr=1}^{np} IAD_{i,t+RPH,pr}}{np} \qquad \forall i \in R \tag{5.16}$$

- $E[IAD_{i,t+RPH}]$ is the expected inventory after demand in region i in period $t+RPH$

5.4.5 Step 5: Determine surpluses and deficits

The deficit in a region is calculated by the following expression, rounded to the nearest integer (lines 51-56):

$$DE_{i,t} = \begin{cases} MinInv_i - E[IAD_{i,t+RPH}], & if\ E[IAD_{i,t+RPH}] < MinInv_i \\ 0, & else \end{cases} \qquad \forall i \in R \tag{5.17}$$

- $DE_{i,t}$ is the expected deficit of tank containers in region i.

This calculation creates a deficit in a region where the expected inventory is lower than the minimal inventory, and is zero otherwise. The surplus in a region can be calculated by (lines 57-62):

$$SU_{i,t} = \begin{cases} (E[IAD_{i,t+RPH}] - MinInv_i)RA_i, & if\ E[IAD_{i,t+RPH}] > MinInv_i \\ 0, & else \end{cases} \qquad \forall i \in R \tag{5.18}$$

- $SU_{i,t}$ is the expected surplus of tank containers in region i.
- RA_i is the percentage of a surplus that can be repositioned from region i.

The surplus follows the same principles as the deficit. However is assumed that not the entire surplus of a region can be repositioned, as not all tank containers are assumed to be in locations where repositioning is possible. Therefore, only a fixed percentage of the region is defined as the surplus.

5.4.6 Step 6: Make repo decision and execute repo's

After the surpluses and deficits are determined, a repo decision can be made. The model is based on a classical transportation problem where the deficits should be solved by the surpluses with the least amount of cost and can be formulated using a MILP. In expressions 5.19 until 5.24, this model is given (line 63 of the pseudo code).

$$Min \sum_{i=0}^{R+1} \sum_{j=0}^{R} (r_{i,j,t} \cdot RI_{i,j}) \tag{5.19}$$

s.t.

$$\sum_{i=0}^{R+1} r_{i,j,t} \leq SU_i, t \qquad \forall j \in R \tag{5.20}$$

$$\sum_{j=0}^{R+1} r_{i,j,t} = DE_i, t \qquad \forall i \in R+1 \tag{5.21}$$

$$r_{i,j,t} \leq M \cdot RB_{i,j} \qquad \forall i \in R+1, \forall j \in R \tag{5.22}$$

$$\sum_{j=0}^{R} r_{i,j,t} \leq IAD_{i,t} - MinInv_i, \qquad \forall i \in R \tag{5.23}$$

$$r_{i,j,t} \in \mathbb{Z}^{0+}, RB_{i,j} \in \{0,1\} \qquad \forall i \in R+1, \forall j \in R \tag{5.24}$$

- $r_{i,j,t}$ is the amount of repo movements from region i to region j in the current period. This is the main decision variable of the MILP.
- $RI_{i,j}$ is the cost of a repo movement from region i to region j.
- M is an infinitely large number
- $RB_{i,j}$ is a binary describing whether a repo from region i to region j is possible.

The expressions represent the following in the formulation of the MILP:

- Expression (5.19) defines the objective, which is to minimize the repo cost of all the repo movements. In this case, i is taken over $R+1$. This extra origin relates to a dummy source that is introduced. As the model constraints state that all deficits should be filled, this dummy source can be used when the deficits cannot be filled by the surpluses. The dummy source comes with unlimited supply but with very high cost, and will therefore only be chosen if no other options are available. Eventually, the model should provide values for all $r_{i,j,t}$, which indicates what repo movements will be conducted in the current period.
- Expression (5.20) and (5.21) ensure the deficits are covered by the surpluses.
- Expression (5.22) and (5.23) is the constraint that ensures only feasible repo moves are performed.
- Expression (5.24) defines that $r_{i,j,t}$ is zero or a positive integer and that $RB_{i,j}$ is a binary variable.

The MILP finds the optimal solution for the values of $r_{i,j,t}$. These repo's are then executed and the end inventory is set equal to the initial inventory by following operations (lines 64-70):

$$SEA_{j,t+RLTi,j} \leftarrow SEA_{j,t+RLTi,j} + \sum_{i=0}^{R} r_{i,j,t} \qquad \forall j \in R \tag{5.25}$$

$$IADR_{i,t} = IAD_{i,t} - \sum_{j=0}^{R} r_{i,j,t} \qquad \forall i \in R \tag{5.26}$$

$$IADR_{i,t} = INIT_{i,t+1} \qquad \forall i \in R \tag{5.27}$$

- $IADR_{i,t}$ is the inventory after demand and repositioning in region i in the current period. This ending inventory is equal to the initial inventory in the next period.

This marks the end of a simulation period and the model moves to the net period, in which all above steps in the current subsection are repeated.

5.5 Cost calculation

After the simulation is run the pre-specified amount of simulation periods T, the cost parameters are calculated. This will be done according to the cost parameters of interest defined in section 4.5, namely the repo impact, lost sales impact and inventory impact. The total repo impact is calculated by:

$$TotalRepoImpact = \sum_{t=1}^{T} \sum_{i=0}^{R} \sum_{j=0}^{R} r_{i,j,t} * RI_{i,j} \tag{5.28}$$

The total lost sales impact can be calculated by multiplied the total lost sales in all the regions multiplied by the impact of lost sale in that region, defined by LSI_i:

$$TotalLostSalesImpact = \sum_{t=1}^{T} \sum_{i=0}^{R} TLS_{i,t} * LSI_i \tag{5.29}$$

The total inventory cost is based on the $INIT_{i,t}$ in every period. During a period, there will be incoming and outgoing orders and incoming and outgoing repo's happening simultaneously, so the inventory will be around this initial value. Therefore summing all the beginning inventories and multiplying this with the inventory cost of a single tank container per period, denoted by IC which is assumed to be equal everywhere, will give the inventory cost over the entire simulation horizon.

$$TotalInventoryImpact = \sum_{t=1}^{T} \sum_{i=0}^{R} INIT_{i,t} * IC \tag{5.30}$$

After the cost parameters have been calculated, these are saved and the simulation is run again for the entire simulation horizon for a total of ns times, which is the amount of simulation runs. Then all the costs of every run are averaged against the total amount of simulation runs, which gives the total expected costs. The same is done for the repo decisions that were made, the inventory that was held in the regions and how many lost sales occurred in the regions.

5.6 Model testing

In order for the results of the simulation tool to be valid, the model should be tested. Of course an obvious way to test the model is to compare the simulation model output with real world data. That would mean checking if the the simulation model makes the same repo decisions as in reality. This is however hard to do, as the inputs of the model are static, whereas in reality these are dynamic. The most important example of this is the demand forecast. The demand forecast is made every month for the upcoming nine month and every month it is changed. However in the simulation model, a single forecast is used, as the simulation tool is designed to simulate the future. Also the forecast is based on what can be loaded with current pricing rules and enough tank containers, which often makes the forecast too optimistic. The pricing rules, like market corrections and repo cost and contributions also change, which could influence decision making. These facts make it complicated to do a historical data validation.

Sargent (2013) state that a simulation model should be tested with its purpose in mind. The purpose of the simulation tool is illustrate cost differences between different inputs, namely different disruptions and flexible hub usage strategies. Therefore, if it can be shown that these input-output relations are valid, it can also be assumed that the model simulates a valid representation of cost differences. Therefore it was chosen to validate the model using face validity, which tests if the model's input–output relationships are reasonable Sargent (2013).

5.6.1 Face validity setup

In order to show face validity, a test data set was created. This data set will serve as input for the simulation tool and will provide a base output. Then changing the parameters of the model one by one and establishing the difference in output will show what input-output relations exist. In the bullet points below the parameters that will be changed are listed along with the expected effect on the output, namely the $TotalRepoImpact$, $TotalLostSalesImpact$ and the $TotalInventoryImpact$. In Appendix A.1, the test data and how the data is altered for the cases below is provided.

- *Planned disruption and unplanned disruption*
  As the model should be tested for its intended purpose, it should be tested how the model reacts to changing demand, but more importantly suddenly changing demand. Therefore an anticipated disruption and a unanticipated disruption will be simulated. This will be done by introducing more imbalance in a single period. It is expected that an expected imbalance can be easily solved by repo, but with unexpected imbalance this will increase repo cost and lost sales.

- *Minimal inventory: $MinInv$*
  Decreasing the minimal inventory will decrease surpluses and deficits, and is therefore expected to decrease lost sales and repo costs. Increasing the minimal inventory will have the opposite effect.

- *Repositioning prediction horizon: RPH*
  Decreasing the prediction horizon without changing the lead times will in this case result in more lost sales. If the repo lead times remain the same, some repo's might come to late. These lost sales will then have less repo costs as a result. Increasing it will have the opposite effect, as repo's can be executed within the repositioning prediction horizon.

- *Percentage of surplus available for repo: RA*
  Increasing this percentage will free up more tank containers for repo and therefore decrease

the lost sales and increase the repo cost. Decreasing the percentage will have the opposite effect.

- *Cost parameters: RI, LSI and IC*
  Increasing and decreasing the cost parameters should show an equal reaction in the total cost output, and should not effect the decisions made or the other cost components.

- *Full and empty lead times: OLT and RLT*
  increasing the order lead time will result in more repo and lower inventory cost as orders are longer occupied in the system and decreasing the order lead times will result in less repositioning and more inventory cost. Increasing the repo lead times will increase lost sales and decreasing it will have the opposite effect.

5.6.2 Validation test result

The amount of runs, np for the inventory prediction runs and ns for the total simulation runs, is determined by the 95% confidence interval of the mean of the desired output. For np, the model will calculate how many runs are needed to so that every resulting expected DE or SU in a period has a 95% confidence interval with a half-width of at most 1.5 on each side of the mean. For ns, each of the cost elements (repo impact, lost sales impact and inventory impact) should have a confidence interval with a half width of at most 300. This was sometimes exceeded to limit the amount of runs and if the wider confidence interval had no impact on the conclusion. This usually coincided with the number of runs being about 350. In Table 5.3, the relative results of the test compared to the base case are shown and in Appendix A.3 the actual numbers and confidence intervals of the tests are given.

	Total repo impact	Total lost sales impact	Total inventory impact
Base	100%	100%	100%
Disruption planned	180%	46%	97%
Disruption unplanned	87%	1357%	101%
$MinInv$ increased	188%	789%	100%
$MinInv$ decreased	56%	3%	101%
RPH increased	114%	1%	100%
RPH decreased	46%	607%	102%
RA increased	82%	101%	100%
RA decreased	163%	127%	100%
RI increased	120%	103%	100%
RI decreased	80%	101%	100%
LSI increased	101%	154%	100%
LSI decreased	100%	57%	100%
IC increased	101%	106%	200%
IC decreased	100%	105%	50%
OLT increased	342%	194%	85%
OLT decreased	40%	1%	113%
ELT increased	87%	533%	99%
ELT decreased	101%	2%	102%

Table 5.3: Face validity test results

5.6.3 Test results discussion

As one can see, most of the expectations that were stated before the test are seen in the test results. However there were some deviations from the expectations. These can be explained by the following:

- Some test results led to a very small difference when no difference was expected, primarily in the lost sales. The most deviant case being IC increased, where the lost sales were 106% compared to the base. This occurred because the lost sales were already fairly low in the base test, meaning a slight difference resulted in a high percentage difference. As the confidence intervals of these results overlapped for a very large part, it was assumed these results were actually the same.

- Concerning the disruption, there is a slightly different outcome. Firstly, both cases are different from the base because the total demand in these cases was different from the base. For the planned disruption, repo costs went up but lost sales went down. This was because the extra demand generated in the disruption partly solved the deficit in another region, preventing these lost sales. When the disruption was unplanned, this extra demand could not be filled and resulted in more lost sales, and for these lost sales no repo was then performed, which dropped the repo costs also. This showed that an unexpected disruption has a different effect than a planned disruption.

- Increasing RA had less repo costs as a result, because more cheap repo availability became available, therefore decreasing the costs. Also, the lost sales did not change. This was the result of a value of ELT being equal to RPH. Because the model predicts an average inventory, sometimes less orders arrive than anticipated because of the variability of the order lead times. This in combination with long repo lead times sometimes still caused lost sales. Therefore the repositioning decision horizon RPH should be adjusted with consideration of the observed repo lead times ELT. If RPH is too short, repo's will be initiated too late and therefore also arrive too late and the variability of the order lead times might cause lost sales.

From these observations, it can be concluded that the model behaves as designed and with the right inputs can be used to test strategies on the Den Hartogh network.

6 Case studies

This chapter will provide the answer to the fourth research question, by setting up a case study where the simulation tool will be used and the use of flexible hubs investigated. The chapter firstly explains how exactly the model will be used in terms of regions and use of flexible hubs, followed by how the parameters have been determined and set. Next, the kind of scenario's that will be simulated will be discussed. This will be followed by an analysis of the results.

6.1 Implementation of flexible hubs

Firstly the implementation of flexible hubs will be discussed. As mentioned previously, the flexible hubs should have repo options to several regions in the network and also these repo's should be executed cost effectively. In order to investigate the use of these flexible hubs, it was deemed appropriate to define these then as separate regions. This makes it easier to run strategies on these regions and to isolate the effect of using flexible hubs. Den Hartogh themselves recognize about 35 hubs that have flexible properties, however adding all these hubs as their own regions exponentially increases the amount of connections in the network. Therefore it is beneficial to aggregate these hubs into their own regions to limit the complexity in the same way as the other global regions are aggregated. For this research, it was chosen to only incorporate 1 flexible region. This makes it easier to run strategies on this region and illustrate the effect of such a flexible region. This flexible region will serve as an illustrative example of how a flexible region can be used, so that Den Hartogh can add more flexible regions as they see fit following the same logic. It was chosen to aggregate 7 flexible hubs into 1 flexible region. These hubs have very similar characteristics in their network pricing, cost and lead time parameters and are geographically close together. They have the property that they can reposition their tank containers to regions 1, 2, 6 and 7, where the first three are mostly covered by repo contributions. The flexible region is depicted by region 8.

6.2 Model parameter settings

6.2.1 Deterministic parameters

In the bullet points below, the more general deterministic parameters of the model will be discussed.

- *Number of regions*
  It was chosen to incorporate all global regions defined by Den Hartogh including the flexible region. The hubs in the flex region are taken out of their original regions. This brings the number of regions R to 8.

- *Demand input*
  It was chosen to use the pricing forecast as input for the demand. This gives the monthly forecasted demand for tank containers for up to 9 months, which then makes the forecast horizon F equal to 9 and the length of a period equal to one month, with a month assumed to consist of 30 days. The forecast that was chosen was made at the end of March 2020 for April 2020 until December 2020. The demand for the flex region was estimated by analysing the short term forecast made by Den Hartogh. From this, a monthly average demand on all relevant lanes from and to the flexible region was calculated and put in the main input forecast. This demand was then adjusted accordingly with the main input forecast on the relevant lanes, so that this demand is not treated as extra demand.

- *Minimal inventory*
  The minimal inventory in the regions is an estimate made by Den Hartogh about what their minimal inventory is. The minimal inventory in the flexible region was estimated to be equal to the outgoing demand of the flexible region per month.

- *Repositioning lead times and impact*
  To asses the repositioning lead times and costs, all the repo's that where executed from January 2019 until March 2020 where analysed. This yielded how many repositioning were executed and from which to which region. Then, using the pricing as it was set in April 2020, a weighted average was calculated of the cost impact with use of the calculation described by equation 4.3 in section 4.5.1. The repo lead times where estimated by the weighted average of the historic repo's with the expected repo days.

- *Repo possibilities*
  To asses the repo possibilities RA, the values obtained in the previous bullet point were analyzed. Repo lanes that were not used in this period were also not included in the model. Also, some outliers where removed. These were repo's that where only done once, for instance from a hub where a single order was repositioned from and did not have any business with Den Hartogh whatsoever before or after the repo took place.

- *Repositioning decision horizon*
  In this case, RPH was set to the largest repo lead time defined. The validation test showed that RPH should be at least at large as the longest lead time to prevent repo's from arriving too late. It was also chosen to use this minimal value to prevent repo's to occur too early, as repo is a short term balancing method.

- *Repositioning percentage*
  It was chosen to take a repositioning percentage of 20% for the normal regions and 100% for the flexible region.

- *Lost sales impact*
  The lost sales of an order was dependent on the latest known calculated margins from orders out of all the regions plus the fixed overhead cost, as defined in equation 4.4. Therefore the lost sale was only dependent on the origin region and not on the margins on a specific lane.

- *Inventory impact*
  The inventory impact per day is the sum of the cost of operating a tank container estimated by Den Hartogh themselves plus hub storage cost, as defined by equation 4.5. To get the cost per period, this daily cost was multiplied by 30, as it is assumed that every month consists of 30 days.

6.2.2 Order lead times distributions

As the order lead times are assumed to be stochastic, a distribution will be provided for the lead times. This lead time will be estimated using a fixed transit time, a stochastic demurrage time and a fixed cleaning time. Therefore a distribution has to be found for the demurrage time. In the past, Den Hartogh has estimated these demurrage times with the lognormal distribution. In Figure 6.1, a bar graph of the number of days in demurrage from orders within region 1 that arrived in the three months before the 30th of March 2020 is shown. More demurrage times from different trade lanes exhibited this behavior. As the data in Figure 6.1 looks skewed, testing for the lognormal distribution for the number of demurrage days was deemed appropriate. However it is also possible that a gamma or weibull distribution can be fitted, considering the shape of demurrage distribution. These three distributions also have the property that no negative values can be taken, which is appropriate when considering lead times.

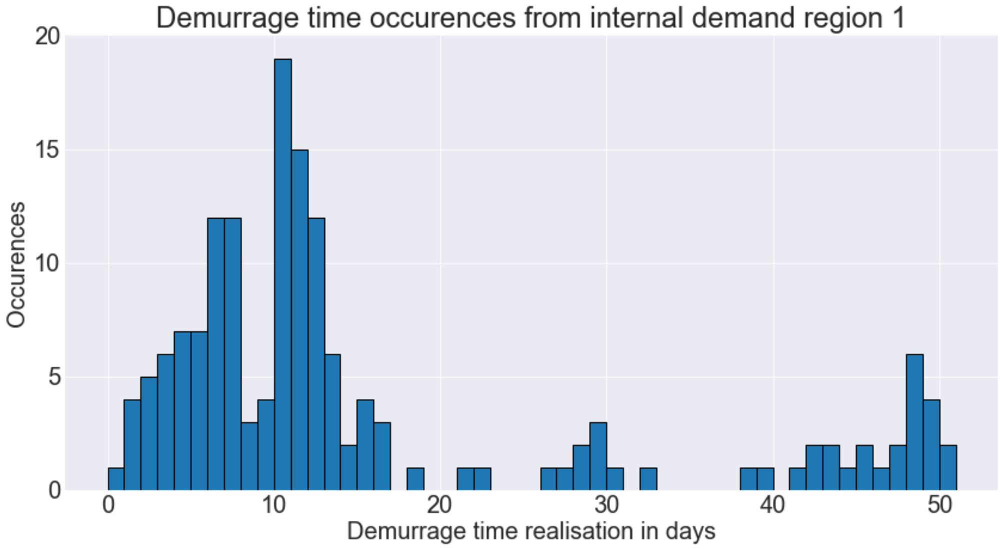

Figure 6.1: Bar graph demurrage times within region 1 January 2020 until March 2020

To test if the distributions fit the data, a Komolgorov-Smirnov test was used. This test can be used to test whether two samples come from the same distribution. The data that will be used is data collected by Den Hartogh which give the number of demurrage days for tank containers that have come out of demurrage. As the occurrence of long demurrage times is not uncommon and the data only included concluded demurrage times, it was chosen to not remove outliers, as this poses a risk that valid data points are removed. The decision for a distribution will be done in the following steps:

1. *Determine which of the three distributions gives the best fit*
   To determine the which of the three distributions can be fitted best, the demurrage data from January 2020 until March 2020 was used in order to reflect recent demurrage data. It was chosen to test demurrage data based on trade lane, so for every origin-destination pair. This means all three distributions will be tested on a total of 63 lanes. These distributions were fitted using maximum likelihood estimation (MLE). These fitted distributions were consequently compared with the actual sample to determine if a good fit can be established using a two-sample Komolgorov-Smirnov test, which tests if it is probable that two samples are taken from the same distribution. In Table 6.1 below, it is shown how many fitted distributions were accepted of the total of 63 lanes. There were 11 lanes that had no data available, as these were mostly rarely used lanes. This brings the total amount of distributions that were fitted to 52. A fit was accepted if the resulting p-value from the test was larger than 0.05.

Table 6.1: Accepted lognormal, gamma and weibull fitted distributions

Distribution	Lognormal	Gamma	Weibull
Accepted fits	35	26	17

It can be seen that the lognormal distribution scores best with about two-third of the distributions accepted by the test. Therefore it was chosen to investigate the lognormal distribution further.

2. *Which aggregation level will be used: lane specific demurrage distributions or region specific distributions*
   It was also investigated if aggregating the demurrage data on regional level provides a better fit than on a lane perspective. This means only factoring in the destination and not the origin. A region of course has the same set of customers, so this is possible. However fitting a lognormal demurrage distribution on all the regions resulted in only 2 of the 8 regions having an acceptable fit. This means there is more of a lognormal pattern within lane specific distributions than the regional distributions and therefore more to be gained by differentiating specific trade lanes. This makes sense because every lane represents a different set of customers.

3. *How much historic data will be used to fit the distribution*
   Until now three months of demurrage data was used to fit a distribution. It was chosen to also investigate how many fits are accepted if the training data for the model is increased. In Table 6.2, it is visualized how many fits were accepted with more months of data added.

   Table 6.2: Number of accepted lognormal fits with changing monthly data inclusion

Number of months data	3	4	5	6	7
Number of accepted fits	35	30	24	24	20

   It can be seen that with more months of data, the fit becomes increasingly worse. This is an indication that demurrage times can be better fitted with recent data to a lognormal distribution than with inclusion of less recent data.

4. *What fit works best to predict future demurrage observations*
   As it is established that fitting a lognormal can be done for certain lanes, the next step is to investigate how a fitted distribution could be used to predict future demurrage realisations. To test this, again a two-sample Kolmogorov-Smirnov test was used. This time the distributions were fitted using data from January 2020 until March 2020 and it was tested if the lognormal fitted distribution correctly predicted the demurrage data of April 2020 until June 2020. This yielded a result of only 7 fitted distributions that correctly predicted the upcoming three months. This casts doubt on using the lognormal to predict the demurrage times in this instance.

It was established that a lognormal distribution can be fitted on demurrage data, but that such a distribution not always correctly predicts future demurrage times. This could occur because the demurrage data often displayed a 'second peak'. This peak is also seen in Figure 6.1, which can be the result of the demurrage behaviour of a certain subset of customers. This kind of behaviour is hard to capture in a distribution. Therefore it was decided to use the empirical distribution as input for the simulation tool. However there were still trade lanes with missing or very little data. Therefore it was chosen to take two extra months of data, meaning that demurrage and transit times from November 2019 until March 2020 were used. For this period, there were 9 trade lanes with missing data and 21 of the 54 empirical distributions were accepted as coming from the same distribution when used to predict future demurrage times. The transit times of orders were estimated by taking a weighted average of the known transit times from all the origin destination pairs. Taking this weighted average of the transit time plus an empirical demurrage time plus 4 days of cleaning yields the lead time for an order. This final lead time is then rounded to the nearest month to get a lead time for the number of months. It was assumed a month consists of 30 days. The transit time of missing lanes was estimated manually and the demurrage time of these missing lanes was estimated by adding the empirical distributions of the corresponding destination region together.

6.2.3 Simulation starting state

In order to asses the initial location of all the tank containers, the location of the tank containers on the 30th of March 2020 was used. This data contains the information of the current status of all individual tank containers in the Den Hartogh fleet. Only the tank containers operated by the global business unit, were available and were not dedicated tank containers (allocated to one repeating standing order for a long period of time) were considered. The starting state has a fixed element that will not change for each simulation run. These are the tank containers which have the following statuses:

- *DEPOT CLEAN*
  These are the clean tank containers at the hubs. These were added to the initial inventory of the corresponding region.

- *DEPOT DIRTY*
  These are the dirty tank containers at the hubs. As it is assumed cleaning only takes 4 days, these are also added to the initial inventory of the corresponding regions.

- *DELIVERYWIP and REPOWIP*
  These are the repo's that are currently being executed. The tank status already has an expected end date, so the tank containers are added to the scheduled empty arrivals (SEA) in the corresponding period and region. So for example if the expected arrival time of a repo was 11th of May, it was added to the arrivals of the second period, as the month April is period 1.

Tank containers with the following statuses are reassessed for every run, as they can have a different realisation:

- *ORDERWIP*
  These are the tank containers that are in transit to a destination. These also have an expected arrival time. At this date, the tank containers will go demurrage. Consequently a random demurrage realisation is given plus the cleaning time and lastly the order is added to the scheduled full arrivals SFA in the resulting period. These tank containers are also added to the WIP list with the startperiod and endperiod, so that inventory prediction runs can be made in the simulation.

- *DEMURRAGEWIP*
  These are the tank containers that are currently in demurrage. Depending on how long these have been in demurrage, a random demurrage time is added with the fixed cleaning time and added to the corresponding SFA and to WIP. There were also however instances were the demurrage period already exceeded the maximal time in the empirical demurrage distribution. Instances that had been more than 50 days over the maximal demurrage time in the empirical distribution were assumed to stay in demurrage for the entire simulation period. Some of these were also tank containers at customers that made a deal with Den Hartogh to keep some tank containers for a long time. For other tank containers long in demurrage, no valid assumption can be made when they will come

available, so these are left out. These overdue tank containers consisted of 1.4% of the total fleet size. Tank containers that were less than 50 days over the maximum demurrage period in the empirical distribution were given a new value from the corresponding distribution independent of the already elapsed demurrage time. This assumption can be made because it is reasonable that these tank containers will become available somewhere in the simulation period. These were also added to SFA of the corresponding period and WIP with starting period 1.

6.3 Scenario types

The following three scenario types will be used to simulate disruptions on the network:

- *Scenario 1: import disruption*
  In this scenario, the import to a single region will be disrupted for a single period. This disruption manifests itself as a sudden import change to a region. This could be a sudden high import or a sudden low import. This means that all trade lanes going into a region will be affected. This simulates a market-wide disruption, as it affects all the customers in a region.

- *Scenario 2: export disruption*
  In this scenario, the export out of a region is altered for single period. This means a sudden high export or sudden low export from a region for a single period. This is also a market-wide disruption which affects all the customers in a region, and is primarily focused on spot demand.

- *Scenario 3: lane disruption*
  This is a disruption which is the result of unexpectedly winning or losing a big tender agreement. This means that on a specific trade lane, the demand will be suddenly higher or lower. This will be a disruption over multiple periods, as winning or losing a big tender is an effect that lasts for longer time.

6.4 Scenario disruption magnitude and justification

In scenario 1 and 2, there is a market-wide disruption, focused on a single region. The reason these scenarios were chosen is illustrated by the example given in Section 2.3. In the example given, the import to a region was unexpectedly low. In Table 6.3, the actual executed orders for tank containers are compared to the forecast from region 1 to all the other regions. The forecast in the current month indicates the forecast made in the month in which the orders were observed, for instance the forecast made in the month September for the September. This shows that the amount of orders dropped significantly with 25% in November compared to October, which was not forecasted beforehand. The forecast was however steadily too high, but did not show a downward trend.

Month	Loaded from	Forecasted in current month
September	658	1101
October	649	1055
November	460	1064
December	700	781
January	807	813

Table 6.3: Forecast compared to demand data region 1 2019 and 2020

It was chosen to scale this 25% drop in demand as the disruption percentage for scenarios 1 and 2. For this reason, in both scenarios the demand can be 25% higher or lower. Also the disruption will last for one month, as from Table 6.3 the demand levels also return to a higher level after the demand drop.

In scenario 3 the magnitude of the disruption depends on the lane considered. It was chosen to select the percentage of demand from the biggest customer on that lane. A large customer on a lane usually has a large tender agreement with Den Hartogh. Tender agreements always have the risk of not being renewed or being unexpectedly won, suddenly changing the demand on a lane for a longer period of time, as a tender agreement is a long term contract. Therefore in scenario 3 the disruption percentage is applied over multiple consecutive periods.

The disruption percentage of scenario 3 was calculated by taking the total demand from the largest customer and dividing this with the total demand on that lane. The period the demand was considered was in the three months before the simulation initialisation, so January 2020 until March 2020.

The scenarios will be denoted with a plus or a minus depending on whether the demand is stimulated or reduced. For example the scenario where the import is stimulated will be denoted as scenario 1+. The disruptions will be simulated in the third period of the simulation, hereby allowing for the mapping of the downstream effects of the disruptions.

As there are four regions that the flexible region can reposition to, scenario 1 and 2 will be tested on these regions. This means that there are four cases per region, as the import or export can be stimulated or reduced. For the scenario 3 the following lanes and disruption percentages were used, displayed in Table 6.4.

From	To	Disruption Percentage
Region 1	Region 2	17.2%
Region 2	Region 1	22%
Region 1	Region 3	9.5%
Region 3	Region 1	14%

Table 6.4: disruption percentages scenario 3

As there are 64 possible lanes on which demand can be stimulated or reduced to simulate a disruption, an exhaustive analysis is not feasible. The above mentioned lanes have much tender business and primarily the demand between region 1 and region 2 is dependent on large clients, so this kind of disruption is more realistic. It can also show some of the effects of disruptions that are not solely affecting the regions in the repo range of the flexible region, in this case region 3.

6.5 Flexible region strategy and savings quantification

As the purpose of the simulation model is to asses how much can be invested in flexibility, it was chosen that different levels of demand stimulation to the flexible region will be tested. This effectively increases the total demand in the system. Consequently it can be made clear how much the extra demand to the flexible regions brings in terms of solving the disruptions. Determining this will highlight how much flexibility is necessary and how much can be saved in terms of the relevant cost elements. The stimulation of demand will be done based on the current forecast to the flexible region and by boosting this demand by a set of stimulation factors. This stimulation factor will be denoted by p. For example, with p equal to 0, no demand to the flexible region will be executed, whereas with p equal to 2, twice as much demand will be forecasted to the flexible region than the original forecast. It is to be noted that using p

equal to 1 will give a analysis of the current situation and changing p would be possible redesign options for the network.

The use of the flexible region will be simulated by setting p to $[0, 0.5, ..., 3]$. In many cases, increasing p beyond 3 caused deficits in regions where demand to the flexible region came from. This indicates that at that point, the capacity of tank containers in the network becomes a problem. As extra lost sales is something that is aimed to be prevented, $p = 3$ was considered the maximum. This was also done to limit calculation time and also because such a sudden and sharp increase in demand is not realistic. With each step, it can be made clear what the cost savings are. From the cost savings per step in p, it can be made clear how much cost savings a tank container sent to the flexible region gives. This can be calculated by dividing the total cost savings of sending more tank containers to the flexible region divided by the total amount of extra tank sent to the flexible region over the entire simulation horizon.

6.6 Model results

In order to asses the actual impact of using the flexible region to solve a disruption, the results will be compared to a benchmark case. This benchmark case will have no disruptions on the network whatsoever. Comparing the cost effects of increasing p in the benchmark case with the effects seen in a case with disruptions will show what impact the use of the flexible region will have on the disruption solely. The reason this benchmark is done is because p can have underlying impact cost on the network that are irrelevant in soling the disruption. If, for example, increasing p reduces the costs regardless of any disruption, then this should not be attributed to solving the disruption but to the overall efficiency of using the flexible region. Firstly this benchmark case in Section 6.6.2, followed by the disruption cases on the region or lane the disruption case is focused on in Sections 6.6.3 until 6.6.7.

6.6.1 Number of runs ns

The number of runs were determined based on the confidence interval of the outputs: the repo impact, inventory impact and inventory impact. Taking ns equal to 100 for the benchmark run (so with no disruptions to the network and p equal to 1) meant the total width of the 95% confidence was 0.4% of the mean total repo impact. For the lost sales impact this was 0.9% of the mean lost sales impact and for the inventory this was 0.2% of the mean inventory cost. Therefore it was chosen to take 100 runs for all the instances. For np, the prediction runs, it was decided that the simulation will run until the half width of all surpluses and deficits confidence intervals was at most 5.5. This gave the deviation of the true mean of the most inaccurate deficit or surplus at most 3% for the benchmark case.

6.6.2 Benchmark case

The results with the cost impact components given is shown in Table 6.5. These results show the three cost components: repo impact, lost sales impact and inventory impact along with the total cost impact. Also difference in total cost as compared to $p = 1$ is shown.

p	Repo impact	Lostsales impact	Inventory impact	Total impact	Cost differences from $p = 1$
0	$ 3.159	$ 5.064	$ 45.200	$ 53.423	$ 2.604
0,5	$ 3.150	$ 4.702	$ 44.209	$ 52.062	$ 1.243
1	$ 3.129	$ 4.574	$ 43.116	$ 50.819	$ -
1,5	$ 3.211	$ 4.407	$ 42.098	$ 49.716	$ -1.103
2	$ 3.300	$ 4.236	$ 41.045	$ 48.581	$ -2.238
2,5	$ 3.217	$ 4.224	$ 40.203	$ 47.644	$ -3.174
3	$ 3.171	$ 4.216	$ 39.296	$ 46.683	$ -4.136

Table 6.5: Cost analysis benchmark case

From Table 6.5 it can be seen that more use of the flexible region decreased cost significantly, mostly due to decreased inventory impact. Also the total impact difference from $p = 1$ shows that increasing the use of the flexible region can bring cost savings compared to the current situation. The relative results for the benchmark case are provided in Table 6.6. This table shows the results relative to using the flexible region with p equal to 1. On the right hand side is the cost delta per extra tank container sent to the flexible region. For instance, increasing p from 0.5 to 1 meant that every extra tank container sent to the flexible region as compared to p equals 0.5 brought about a saving of $5.13 per tank container.

p	Repo impact	Lostsales impact	Inventory impact	Total impact	Delta per tank container
0	101,0%	110,7%	104,8%	105,1%	$ -
0,5	100,7%	102,8%	102,5%	102,4%	$ -5.63
1	100,0%	100,0%	100,0%	100,0%	$ -5.13
1,5	102,6%	96,3%	97,6%	97,8%	$ -4.55
2	105,5%	92,6%	95,2%	95,6%	$ -4.69
2,5	102,8%	92,3%	93,2%	93,8%	$ -3.87
3	101,4%	92,2%	91,1%	91,9%	$ -3.97

Table 6.6: Benchmark case results

In this benchmark case, region 1 is forecasted to have a large deficit of tank containers. However, the largest part of lost sales comes from region 4 and region 5, since there is also a high forecast there and there are no repo possibilities to these regions. These lost sales were 92.2% of the total lost sales at $p = 1$. It can be seen that gradually these lost sales are prevented due to the extra capacity of the flexible region. With increasing p, the repo impact fluctuates due to extra costs of repo from the flexible region and at the same time preventing more expensive repo's. At the same time, the inventory impact is reduced fairly constant with extra use of the flexible region. This occurs because a better utilisation rate of tank containers is realised. This has two reasons, the first being the realisation of more demand in the network, which ensures more tank containers are occupied. Secondly, in this case the tank containers that got to the flexible hub are also repositioned fast. This improves the flow of the network. This inventory impact is a substantial portion of the total cost impact. At $p = 1$, the total inventory impact was 85% of the total cost impact, while lost sales was 9% and repo was 6%. With more usage of the flexible region, the delta per tank container decreased due to the decreasing inventory impact, and less due to lost sales. This indicates that the inventory impact also has a large impact on the total cost impact.

6.6.3 Scenarios on region 1

In Table 6.7, the main results of the scenarios in region 1 are shown. These values are again relative to the total cost of the benchmark case at $p = 1$, along with the corresponding tank container deltas.

	Scenario 1+		Scenario 1-		Scenario 2+		Scenario 2-	
p	Cost impact	delta	Cost impact	delta	Cost impact	delta	Cost impact	delta
0	103,8%	$ -	107,0%	$ -	105,9%	$ -	105,1%	$ -
0,5	101,0%	$ -5.87	104,1%	$ -6.08	103,1%	$ -5.91	102,5%	$ -5.51
1	98,8%	$ -4.54	101,7%	$ -5.07	100,3%	$ -5.85	100,3%	$ -4.59
1,5	96,8%	$ -4.17	99,3%	$ -5.03	97,9%	$ -5.06	98,3%	$ -4.15
2	94,8%	$ -4.26	96,9%	$ -5.08	95,5%	$ -5.06	96,6%	$ -3.62
2,5	92,9%	$ -3.95	94,8%	$ -4.24	93,0%	$ -5.08	94,7%	$ -3.93
3	91,0%	$ -4.08	92,8%	$ -4.36	90,6%	$ -5.17	92,6%	$ -4.44

Table 6.7: Results region 1

The total cost at $p = 0$ decreased in scenario 1+. This occurred because this scenario decreased the forecasted deficit in the region. Also the impact of more demand in the network decreased the inventory cost. For scenario 1-, this was opposite. Less import meant more repo, lost sales and inventory impact cost, therefore increasing the total cost impact. For scenario 2+, the total impact increased slightly. In this case repo impact and lost sales impact increased significantly and inventory impact went down due to the extra demand. The opposite is true for scenario 2-, where reduction of export meant the deficit in the region was partly solved.

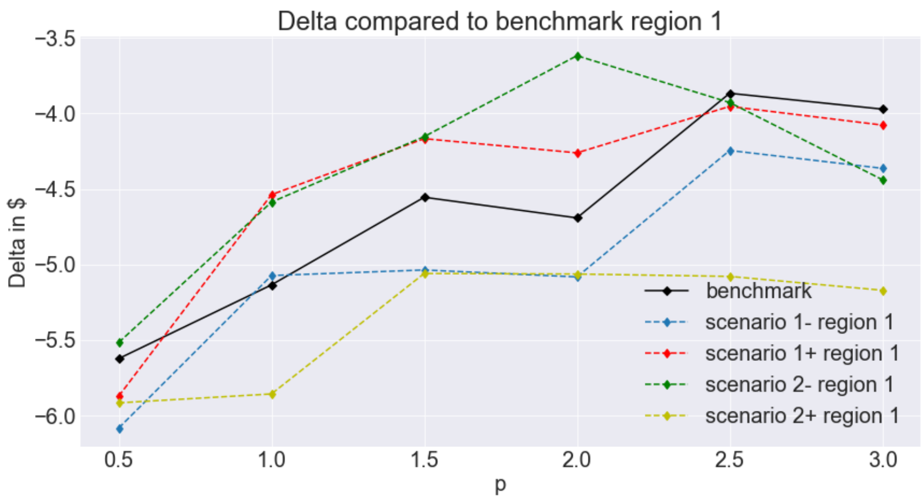

Figure 6.2: Delta to benchmark region 1

From these observations, scenario 1- and scenario 2+ actually impacted the network such that costs increased, while scenario 1+ and 2- actually solved a part of the deficit in the region. In Figure 6.2, the delta's compared to the delta in the benchmark is given. This shows that in scenario 1- and scenario 2+, the use of the flexible region resulted in the delta for these scenarios being more impactful than the benchmark. This indicates that the extra use of the flexible region had more cost impact reduction in these scenario's than the benchmark, meaning that the cost impact of the disruption was reduced faster. Also, this steeper curve is more visible in scenario 2+. That means that for the cases where the deficit was enlarged, the flexible region helped to decrease cost more rapidly.

As scenario 1- and 2+ increased the imbalance of the network, these will be discussed in more detail. In Table 6.8, the broken down results of scenario 1- and 2+ are shown.

	Scenario 1-			Scenario 2+		
p	Repo Impact	Lost sales impact	Inventory impact	Repo Impact	Lost sales impact	Inventory impact
0	110,9%	111,3%	106,3%	109,1%	120,7%	104,1%
0,5	110,5%	102,2%	103,8%	109,4%	112,2%	101,6%
1	110,0%	99,8%	101,3%	109,6%	107,8%	98,8%
1,5	112,2%	94,4%	98,9%	111,8%	103,5%	96,3%
2	116,4%	89,6%	96,2%	116,8%	97,2%	93,7%
2,5	120,7%	86,2%	93,9%	121,8%	92,0%	91,1%
3	115,2%	85,6%	91,9%	120,5%	88,7%	88,6%

Table 6.8: Broken down results region 1

In scenario 1- it can be seen that the primarily the repo cost is impacted. The reason for this being that a suddenly low import triggers more repo's from other regions to prevent lost sales. The repo impact therefore was higher than in the benchmark case. As p was increased, gradually more lost sales were prevented by repo's from the flexible region increasing the repo impact. As p was set to 3, also more expensive repo's could be prevented. Scenario 2+ is different from scenario 1- in that both lost sales and repo impact increased. In scenario 1-, the lower import is observed, but that lower import arrives later to the region itself because the tank containers are first in transit and in demurrage. This allows for more time to react. In scenario 2+, the effects in the region are instant, which allows for less time for the network to respond.

6.6.4 Scenarios on region 2

In Table 6.9, the results for the scenarios on region 2 is shown.

	Scenario 1+		Scenario 1-		Scenario 2+		Scenario 2-	
p	Cost impact	delta	Cost impact	delta	Cost impact	delta	Cost impact	delta
0	105,3%	$ -	105,2%	$ -	104,4%	$ -	106,2%	$ -
0,5	102,4%	$ -5.96	102,5%	$ -5.69	101,7%	$ -5.69	103,2%	$ -6.29
1	99,9%	$ -5.19	100,1%	$ -5.01	99,4%	$ -4.76	100,8%	$ -4.91
1,5	97,6%	$ -4.91	98,1%	$ -4.27	97,3%	$ -4.36	98,5%	$ -4.95
2	95,3%	$ -4.67	95,9%	$ -4.51	95,1%	$ -4.70	96,3%	$ -4.55
2,5	93,4%	$ -4.04	94,0%	$ -4.08	93,4%	$ -3.68	94,3%	$ -4.16
3	91,6%	$ -3.74	92,1%	$ -3.87	91,4%	$ -4.07	92,4%	$ -4.05

Table 6.9: Results region 2

With these scenario's there were less deviations from the benchmark cost impact at $p = 1$. The main reason being that at the time of the disruptions, there was a big enough buffer of tank containers to ensure the disruption had little effect. The main effects is due to the effect of the demand to region 2 being changed. In Figure 6.3, the deltas compared to the benchmark is shown. The deltas of scenarios 1+ and 2- tend to be lower than the benchmark delta, as a higher import and lower export in region 2 meant the deficit in region 1 was enlarged, and did not cause a problem in region 2 itself. Region 2 was not forecasted to have a deficit until the end of the simulation horizon. This indicates that the time of the disruption is also an important factor.

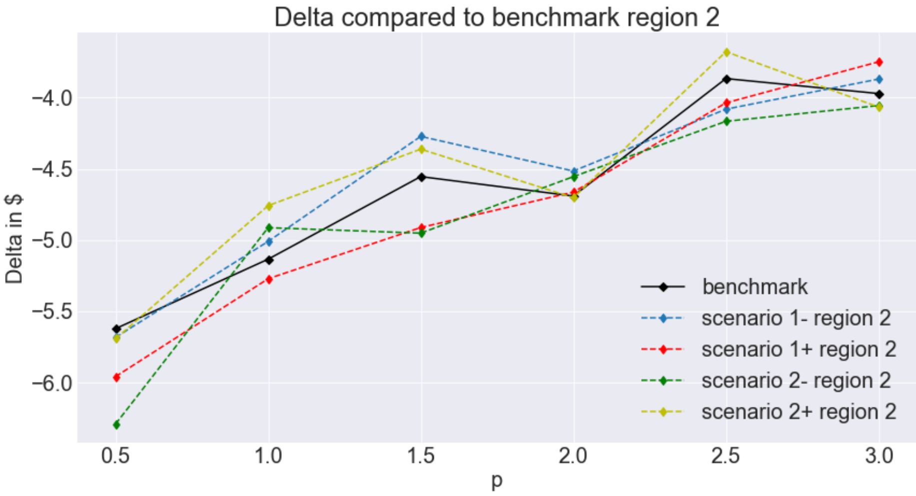

Figure 6.3: Delta to benchmark region 2

6.6.5 Scenarios on region 6 and 7

Just like in region 2, the scenarios had little effect on the total cost of the network. These effects were also primarily because the trade lanes to region 1 were effected. These regions were however forecasted to have a large surplus of tank containers. What can be illustrated is that due to the use of the flexible region, this surplus can be limited, also decreasing inventory impact. In Table 6.10, the total inventory impact of region 1 and 2 is given relative to the inventory impact in those regions at $p = 1$.

p	Inventory impact region 6	Inventory impact region 7
0	112,7%	107,9%
0,5	106,6%	104,2%
1	100,0%	100,0%
1,5	93,8%	96,4%
2	87,3%	92,2%
2,5	81,3%	88,5%
3	74,8%	84,2%

Table 6.10: Inventory impact region 6 and 7

The inventory cost in regions 6 and 7 dropped significantly with more use of the flexible region. This makes sense as demand to the flexible region also comes for a significant part from these regions.

6.6.6 Scenarios on lanes between region 1 and region 3

In Table 6.11, the result for the scenarios on the lanes region 1 to region 3 and region 3 to region 1 are shown.

	Region 3	to	Region 1		Region 1	to	Region 3	
	Scenario 3+		Scenario 3-		Scenario 3+		Scenario 3-	
p	Cost impact	delta	Cost impact	delta	Cost impact	delta	Cost impact	delta
0	103,5%	$ -	106,9%	$ -	106,5%	$ -	104,1%	$ -
0,5	100,8%	$ -5.77	104,1%	$ -6.04	103,6%	$ -6.05	101,4%	$ -5.61
1	98,3%	$ -5.25	101,7%	$ -5.04	101,1%	$ -5.22	99,1%	$ -4.91
1,5	96,1%	$ -4.58	99,5%	$ -5.57	98,9%	$ -4.52	97,2%	$ -4.07
2	93,8%	$ -4.82	97,4%	$ -4.41	96,4%	$ -5.23	95,2%	$ -4.09
2,5	92,1%	$ -3.59	95,8%	$ -3.31	94,3%	$ -4.58	93,3%	$ -4.01
3	90,2%	$ -3.87	93,6%	$ -4.73	92,2%	$ -4.42	91,5%	$ -3.74

Table 6.11: Results lanes between region 1 and 3

The scenarios which caused region 1 to have a larger deficit resulted in higher total cost impact at $p = 1$ compared to the benchmark. However, when comparing the deltas to the benchmark in Figure 6.4, only scenario 3+ of the region 1 to region 3 lane showed a more consistent higher total cost impact reduction than the benchmark. One would also expect more cost reduction in scenario 3- on the region 3 to region 1 lane. However, more cost reduction was only realised when increasing p to 3. This happened because in the benchmark case, a lot of repo's from region 3 were needed. Decreasing the demand from region 3 toregion 1 has a large effect on the deficit in region 1, but less on how much extra could be repositioned from region 3, because this only is a percentage of the total surplus in region 3. This, in combination with a large deficit in region 1, meant higher lost sales impact. It shows that only in the situation where a lot of demand is sent to the flexible region, the cost benefits start to decrease faster, because expensive repo's from region 3 are prevented. Until that point, the maximum amount of repos were executed to counter the deficit in region 1, and this maximum amount was almost equal to the benchmark case, keeping the repo costs fairly equal.

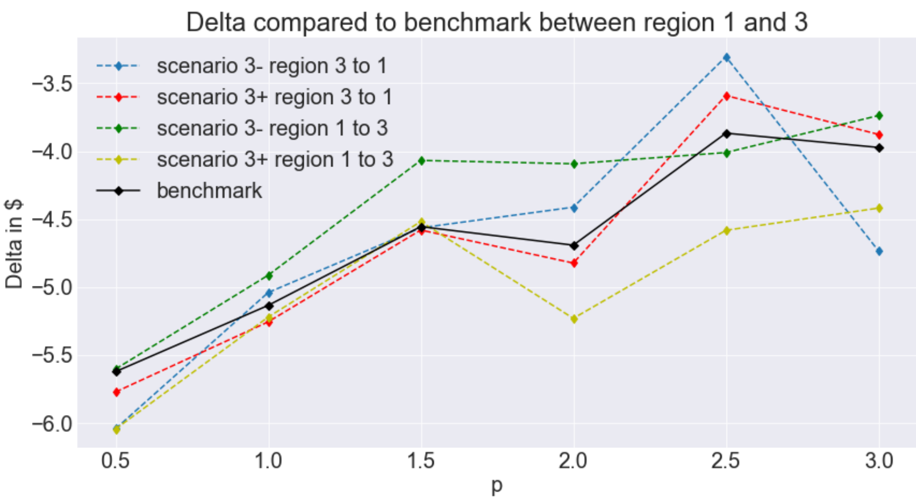

Figure 6.4: Delta to benchmark between region 1 and region 3

6.6.7 Scenarios on lanes between region 1 and 2

In Table 6.12, the results for the scenarios on the lanes region 1 to region 2 and region 2 to region 1 is shown.

	Region 2	to	Region 1		Region 1	to	Region 2	
	Scenario 3+		Scenario 3-		Scenario 3+		Scenario 3-	
p	Cost impact	delta	Cost impact	delta	Cost impact	delta	Cost impact	delta
0	104,3%	$ -	106,4%	$ -	106,0%	$ -	105,9%	$ -
0,5	101,6%	$ -5.56	103,5%	$ -6.06	103,1%	$ -6.10	102,9%	$ -6.18
1	99,5%	$ -4.46	100,6%	$ -6.10	100,3%	$ -5.99	100,2%	$ -5.70
1,5	97,5%	$ -4.17	98,6%	$ -4.20	97,9%	$ -4.93	97,9%	$ -4.87
2	95,1%	$ -5.13	96,3%	$ -4.74	95,6%	$ -4.96	95,5%	$ -4.92
2,5	93,3%	$ -5.12	94,3%	$ -4.18	93,7%	$ -3.80	93,8%	$ -3.75
3	91,3%	$ -2.07	92,3%	$ -4.24	91,9%	$ -3.83	91,8%	$ -4.14

Table 6.12: Results on lanes between region 1 and region 2

As can be seen from Table 6.12, in almost all scenarios the total cost impact increased at $p = 0$ compared to the benchmark case. What is interesting to see is that for the region 1 to region 2 lane, both scenarios resulted in a higher cost impact. In scenario 3+ a larger deficit was created in scenario 3- and deficit was created in region 2. This is an indication of a large dependency of region 2 on region 1. In Figure 6.5, the deltas compared to the benchmark is again shown. This shows that for the scenarios where the cost impact increased, the flexible region helped in reducing these cost impact faster.

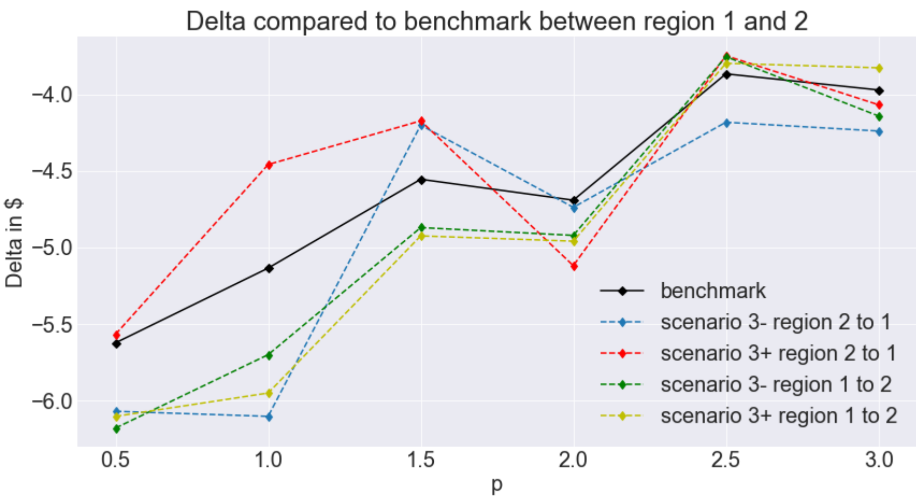

Figure 6.5: Delta to benchmark between region 1 and region 2

6.7 Alternate flexible region strategy

In the scenarios in Sections 6.6.2 until 6.6.7, the flexible region was utilized with different levels of demand stimulation. This means that more demand was introduced into the network. This alternate strategy tests how much impact a flexible region would have when keeping the total demand in the network the same. This was done by taking a percentage of the demand out of the lanes between the regions to which the flexible region can reposition. The percentage that was taken out of the respective lanes was instead rerouted to the flexible region. However this rerouting initially caused significantly more lost sales as instantly changing demand pattern meant a part of the demand going to the regions first had to go through the flexible region, which increases lead time. This caused that tank containers going to the flexible region could not be repositioned in time to other regions. After a certain warm-up period, the flexible region had enough tank containers to cover deficits. To correct for this warm-up period, a small part of the tank container stock was already moved to the flexible region, effectively simulating a situation where this flexible region usage was adopted earlier. In Table 6.13, the results for this scenario is shown. It was chosen to simulate this on the scenario 1- situation on region 1, as this is also congruent with the example in Section 2.3. The percentages are relative to the impact at 0% of demand to the flexible region, to see how the impact changes when increasing the percentage.

Percentage to flexible region	Repo impact	Lost sales impact	Inventory impact	delta
0%	100,0%	100,0%	100,0%	$ -
4%	98,7%	91,6%	98,7%	$ -2.96
8%	100,4%	88,2%	97,4%	$ -1.62
12%	94,6%	87,5%	96,7%	$ -1.55
16%	102,9%	87,6%	95,6%	$ -0.66
20%	114,6%	87,4%	94,6%	$ -0.29

Table 6.13: Results alternate flexible region strategy

It can be seen that using this kind of strategy gives diminishing returns. Firstly, the repo impact shows that a minimum at 12% demand to the flexible region is reached, and then the repo impact steadily increases, as more tank containers to the flexible region means more repositioning costs. When increasing the percentage from 0% to 8%, expensive repo's could be prevented, causing the repo impact to remain relatively stable. The lost sales impact also remains fairly constant after 12%. The inventory impact also decreases, however diminishing.

6.8 Discussion results

The results in this section can be used to draw some important observations. Not all scenarios had more cost savings compared to the benchmark. There is also clear distinction between inventory impact and repo and lost sales impact. However in all cases, the inventory impact went down when increasing p. For the repo and lost sales impact this was not always the case. Also, it was mentioned in Section 5.6 that the main goal of the tool is to illustrate cost differences in redesign options. This means that, with the assumptions made, it cannot be assumed that the calculated cost at each setting of p reflect reality.

6.8.1 Comparison of scenarios results

From the results it was clear that not all scenarios had a steeper cost impact reduction than the benchmark. More cost reduction was realised on scenarios where a deficit was increased, as opposed to where a deficit was partly solved by a disruption. On a regional level, in scenario 1 and 2, the cost reduction was mainly realised by preventing lost sales in region 1 and preventing expensive repositioning from region 3. The results also illustrate that use of the flexible region can mitigate disruptions on a specific lane, especially when this lane was critical to both regions, for example the region 1 to region 2 case in Section 6.6.7. This shows that the effect of the flexible region is positive in many scenarios. Even when the cost reduction is less than the benchmark case, there is still a reduction, albeit through inventory impact reduction.

6.8.2 Reduced inventory impact through flexible region use

It was shown that the element with the most impact on total cost impact reduction was the inventory impact. This is surprising considering the fact that it was hypothesized that the repo impact and lost sales impact were the most important aspects regarding the use of flexible hubs. Although this is also partly explained by the fact that increasing demand in the network also increases the utilisation rate of tank containers. This raises the question as to whether this reduced inventory impact is a direct result of the usage of flexible region. However, the alternate strategy described in Section 6.7 proves that this is also the result of the flexible region, as in that case the total demand in the network remained constant. This is an interesting observation, as a risk averse strategy like incorporating more redundancy usually leads to much higher inventory cost. In this case, flexibility improves the efficiency of the network by ensuring that tank containers are better utilized. Sheffi and Rice Jr (2005) also recognize this by stating that flexibility can also give benefits and operational efficiency in the 'normal' business operating situations, which these observations confirm.

6.8.3 Impact of lost sales and repo

The discussion point in Section 6.8.2 recognizes that the use of flexibility in the manner proposed in this thesis can give operational efficiency. However this is separate from the ability of flexible hubs to prevent deficits. The main cost elements of a deficit are the repo and lost sales impact. It was shown that in some cases, the use of a flexible region had a positive effect on solving a disruption, primarily when a disruption occurred in regions were a deficit of tank containers was forecasted. However this benefit was lower than expected. For example, one would expect the benefit of preventing a lost sale in region 1 to be the difference in cost between a lost sale in region 1 and a repo to prevent this lost sale from the flexible region. However this was usually only 15-20% of this expected value. There could be various reasons for this. One being that the deltas were calculated by dividing all tank containers sent to the flexible region in the simulation horizon. Tank containers that were sent at the end of the simulation period have not yet been used for a repo to prevent a lost sale, so the benefit of this tank container has not been realised in the total cost impact. Also, repo's that are executed at the end of simulation period increase the repo impact, but the lost sale impact is never incorporated. Also, lost sale impact is larger than defined in this research, at it does not incorporate the cost of damaged customer relations.

Another reason the benefit of preventing lost sales and expensive repo is the fact that the deficit in region 1 was predicted to already be large. This means that most of the repositioning from the flexible region already would go mostly to region 1. In a more balanced demand forecast case the cost reduction could be more visible.

6.8.4 Validity of cost impact results

As defined in Section 5.6, the model is primarily tested on validity of cost difference rather than reflecting reality. Therefore it is important to discuss that, given how the assumptions now are formulated, the simulation tool does not reflect reality in a sense that it can be tested against real data, which Sargent (2013) call historical data validation. Parameters, such as forecasts which are renewed each month and rates and cost components that change over time, change constantly. This results in the fact that the user should not use the tool to accurately predict total costs, but should only look at what the cost difference is between certain design options. Additionally, the pricing process at Den Hartogh does not stop, therefore predicted deficits are partly solved by this as well, which hard to model. Nevertheless, a validation that the model behaves as it should and makes decisions that are realistic was performed.

7 Conclusions and recommendations

In this section a conclusion will be drawn regarding the main research question based on the findings within this thesis. This conclusion will be drawn through initially summarising the main findings presented in this paper. These will be followed by limitations and suggestions for future research. Lastly, recommendations are provided, which will also provide an answer to the final sub question regarding how Den Hartogh can use the simulation tool to increase profitability.

7.1 Conclusions

The purpose of this research was to investigate how additional flexibility can lead to more profitability for Den Hartogh's the tank container network. The need for flexibility was illustrated by explaining the effects of uncertainty on a network such Den Hartogh's.

An investigation into the causes of uncertainty in Den Hartogh's network led to the development of a conceptual model that mapped these causes and their relation to each other. These effects indicated that uncertainty in a tank container network can have a significant cost impact. The reason as to why this cost impact is significant is due to uncertainty causing unexpected imbalances in the network. It was chosen to investigate the concept of flexibility further and how flexibility can be used to mitigate uncertainty and increase profitability.

The literature review revealed that flexibility is a broad topic in supply chain literature. Two measuring dimensions, range and response, were recognized. These concepts were connected to Den Hartogh via flexible hubs, which are hubs with flexible properties. These flexible properties were recognized in the context of range and response. Range was defined as the repo possibilities the hub has and response as the cost and time it took to execute these repo possibilities. It was hypothesized that moving more tank containers through these hubs can improve the responsiveness of the network to disruptions. The three cost components that were recognized were repo cost, lost sales cost and inventory cost. It was determined how these cost factors impacted the network in event of certain operations. This resulted in repo impact, lost sales impact and inventory impact components that were consequently used as the cost impact components of the tank container network.

The simulation tool that was developed was designed to simulate the network of Den Hartogh. Most importantly it correctly indicated the difference in cost impact of varying disruption scenarios and usage of flexible hubs. Using face validity, it was established that the model behaves as it should. The utilization of flexible hubs was increased by generating more demand to these hubs. These disruption scenarios simulated the effect of uncertainty on the network.

The main results of the case study provided insights on how use flexible hubs to mitigate disruption scenarios. It was found that for scenarios where a forecasted deficit was increased, the use of a flexible region resulted in steeper cost impact reduction. This was most visible in scenarios where the export of a certain region was suddenly increased. It was also shown that lanes that were critical to the supply of the regions were more sensitive to disruptions, and flexible hubs had a positive effect on cost reduction. Another important observation is that the use of the flexible hubs in the case study had a large effect on the inventory impact. This indicated that the use of flexible hubs gives an increased level of operational efficiency. The use of flexible hubs namely created an improved flow of tank containers, preventing idle tank containers. It was proven that this is largely an effect of a flexible hub and not only due to extra demand in the network.

7.2 Limitations

The proposed simulation tool has the following limitations:

- The network was aggregated on a regional level and with time periods of one month. This meant that assumptions had to be made for cost components within and between regions based on historical data causing the cost components to be only an approximation of the actual cost components.

- It was assumed that the cost components stay constant over time. In practice, these cost components also change depending on the state of the network. The same is true for the monthly demand forecast. This means that the total cost of each use of the flexible region is not validated. However the differences between these flexible region stimulation factors are valid under static pricing rules.

- Only one flexible region was considered in this research to limit complexity. This does not give a total image of how Den Hartogh can use flexible hubs in their entire network, as the flexible region in this research can only reposition to 4 of the 7 global regions defined by Den Hartogh.

- The effect of the pricing process of Den Hartogh was not incorporated. The pricing process will most likely already partly solve predicted deficits. In this research, this did not occur, and all deficits that were forecasted actually came to pass.

- Hub storage costs were assumed to be the same in every part of the network, whereas in reality this is not the case. This can influence the inventory impact cost.

- The fleet of tank containers was assumed to be similar, whereas in reality this is not true. This means that not all demand can be transported using all tank containers. This sometimes creates operational difficulties not reflected by the model. The same is true for the the cleaning of tank containers, as this is not possible in every location.

7.3 Directions for future research

The following directions for future research are proposed:

- The use of more flexible hubs implemented in the model can be tested. This will give a more complete image of flexible hubs in the entire network. It can also be investigated how the range and response of flexible hubs relate to profitability. For example, does a flexible hub that has three repo possibilities have a significantly stronger relation to profitability than a flexible hub with two repo possibilities.

- The calculation time of a simulation run is very long (up to 12 hours per single scenario under high accuracy requirements). The main reason for this are the prediction runs for the inventory. Each simulation period, a prediction run is done, therefore exponentially increasing the amount runs necessary to make a prediction that is accurate enough. Developing a heuristic that can accurately predict future inventory will greatly decrease the amount of time needed to run the scenarios.

- A more extensive sensitivity analysis of the model could be done. For example, it could be investigated how much impact changing input parameters has on the result. This was however also tested on a testing instance, but not on a real instance.

- At the start of this research, using robustness instead of flexibility to handle uncertainty was mentioned. This simulation tool can also be used to test robustness strategies instead of flexibility strategies.

- It can be investigated in what parts of the network flexibility has the most value. It is for instance reasonable to assume that parts of the network where there is mostly spot demand, a quick reaction to surging spot demand is possible with use of flexible hubs.

7.4 Recommendations and implementation

This last subsection provides the answer to the last sub question, namely how the tool can be used as a decision making tool for Den Hartogh. Firstly, general recommendations are given, followed by an implementation plan.

7.4.1 Recommendations

- The case study results indicate an inventory cost reduction is realised with more use of flexible hubs. Especially when it is certain that the tank container can be used in a region where the flexible hub can repositioned to, this creates a better flow of tank containers throughout the network.

- The case study results also illustrated the flexible hubs had most impact in reducing repo and lost sales impact in regions where already a deficit was forecasted. When observing this deficit, a risk assessment can be made how probable certain disruption scenarios in this region are and how this effects the total cost impact using the simulation tool.

- It is recommended to test how the benefit of flexible hubs is calculated by the simulation tool using a more balanced demand forecast. Now the forecast is made with the assumption that there are sufficient tank containers. Correcting this demand forecast to more realistic patterns frees up capacity of the flexible hubs and can also better illustrate how many tank containers in flexible hubs is actually needed to cover disruptions.

- If a way can be found to test the model using historical validation, this can provide extra value. Then it can be tested if the model duplicates reality, including the accuracy of cost components. The way to realize more demand to the flexible hubs is on the one hand stimulating commercial managers to actively search for such demand, but also provide a discount to demand going to flexible hub. If the cost components resulting from the simulation tool can be validated with more certainty, the tool can also provide valuable information about how large such a discount can be invested in flexible hubs demand stimulation.

- In this research, the utilization of the flexible hubs was stimulated by the ratio of demand forecasted from all the regions that had demand to the flexible region. Using the simulation tool, it can be investigated from what regions demand stimulation is most beneficial to profitability.

7.4.2 Implementation plan

Lastly an implementation plan will be discussed on how to use the simulation tool:

1. Den Hartogh uses a monthly cycle of pricing in which they adjust their market corrections. They do this based on a monthly demand forecast. It is recommended to use the simulation

tool also on a monthly basis, as this gives renewed insights in the marketplace and cost components.

2. Every month, based on the demand forecast, it can be made clear where deficits of tank containers can be expected. As it was shown that disruptions have the most impact in such parts of the network, a risk assessment should be made on what scenarios could come to pass.

3. These scenarios can be simulated using the simulation tool. In doing this, it can be made clear how demand stimulation to the flexible hubs can help in reducing disruption impact.

4. Using the cost impact information of demand stimulation to the flexible hubs, it can be made clear how much can be invested in flexible hubs. The savings per tank container indicate how much can be invested by dropping prices. If extra demand can only be realised by dropping the rates more than the savings per tank container, extra investment in flexibility is not necessary.

5. Combining all information above can be condensed into a market correction for demand going to flexible hubs, a sort of flexibility correction, as the information from the tool can visualize how far rates can be dropped in order for the flexibility correction to be profitable.

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Appendix A Face validity dataset

A.1 Base test data

T	7
F	9
R	4
RPH	2
IC	30

Table A.1: Base general parameter test setting

		Period								
RegionFrom	RegionTo	1	2	3	4	5	6	7	8	9
0	0	10	10	10	10	10	10	10	10	10
0	1	70	70	70	70	70	70	70	70	70
0	2	50	50	50	50	50	50	50	50	50
0	3	20	20	20	20	20	20	20	20	20
1	0	45	45	45	45	45	45	45	45	45
1	1	4	4	4	4	4	4	4	4	4
1	2	35	35	35	35	35	35	35	35	35
1	3	15	15	15	15	15	15	15	15	15
2	0	45	45	45	45	45	45	45	45	45
2	1	30	30	30	30	30	30	30	30	30
2	2	20	20	20	20	20	20	20	20	20
2	3	8	8	8	8	8	8	8	8	8
3	0	35	35	35	35	35	35	35	35	35
3	1	5	5	5	5	5	5	5	5	5
3	2	15	15	15	15	15	15	15	15	15
3	3	40	40	40	40	40	40	40	40	40

Table A.2: Base demand test

$MinInv_0$	$MinInv_1$	$MinInv_2$	$MinInv_3$
150	100	100	100

Table A.3: Base minimal inventory test

RA_0	RA_1	RA_2	RA_3
0,3	0,3	0,3	0,3

Table A.4: Base repo percentage test

Region i	$INIT_{i,1}$
0	200
1	90
2	130
3	160

Table A.5: Base initial inventory test

RegionFrom	RegionTo	$P(OLT_{i,j} = 2)$	$P(OLT_{i,j} = 3)$
0	0	0,66	0,33
1	0	0,2	0,8
2	0	0,6	0,4
3	0	0,2	0,8
0	1	0,2	0,8
1	1	0,66	0,33
2	1	0,2	0,8
3	1	0,2	0,8
0	2	0,6	0,4
1	2	0,2	0,8
2	2	0,66	0,33
3	2	0,2	0,8
0	3	0,6	0,4
1	3	0,2	0,8
2	3	0,2	0,8
3	3	0,66	0,33

Table A.6: Base test lead time distributions

	Period								
Region	1	2	3	4	5	6	7	8	9
0	145	96	54	15	0	0	0	0	0
1	124	103	63	21	0	0	0	0	0
2	123	73	40	10	0	0	0	0	0
3	77	45	19	6	0	0	0	0	0

Table A.7: Base SFA test data

Note: the values in table A.7 are based on the order arrivals in steady state as a result of the lead time distributions. The list of orders in transit (WIP) has also been created using this principle. These values where not altered when lead times are altered for testing.

To/From	0	1	2	3
0	0	1	1	0
1	1	0	1	0
2	1	1	0	0
3	2	1	2	0

Table A.8: Base ELT test

RegionTo/Period	1	2	3	4	5	6	7	8	9
0	20	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	11	11	0	0	0	0	0	0	0

Table A.9: Base SEA test data

To/From	0	1	2	3
0	0	1	1	0
1	1	0	1	0
2	1	1	0	0
3	1	1	1	0

Table A.10: Base RB test data

To/From	0	1	2	3
0	0	300	1800	0
1	1000	0	2000	0
2	800	1800	0	0
3	850	700	600	0

Table A.11: Base RI test data

LSI_0	LSI_1	LSI_2	LSI_3
800	800	800	800

Table A.12: Base lost sales impact test data

A.2 Test data altered

	increased	decreased
RPH	3	1
IC	45	15

Table A.13: Base parameters altered

		Period								
RegionFrom	RegionTo	1	2	3	4	5	6	7	8	9
0	0	10	10	12	10	10	10	10	10	10
0	1	70	70	87	70	70	70	70	70	70
0	2	50	50	62	50	50	50	50	50	50
0	3	20	20	25	20	20	20	20	20	20
1	0	45	45	45	45	45	45	45	45	45
1	1	4	4	4	4	4	4	4	4	4
1	2	35	35	35	35	35	35	35	35	35
1	3	15	15	15	15	15	15	15	15	15
2	0	45	45	45	45	45	45	45	45	45
2	1	30	30	30	30	30	30	30	30	30
2	2	20	20	20	20	20	20	20	20	20
2	3	8	8	8	8	8	8	8	8	8
3	0	35	35	35	35	35	35	35	35	35
3	1	5	5	5	5	5	5	5	5	5
3	2	15	15	15	15	15	15	15	15	15
3	3	40	40	40	40	40	40	40	40	40

Table A.14: Demand disrupted test

$MinInv_0$	$MinInv_1$	$MinInv_2$	$MinInv_3$
165	110	110	110

Table A.15: $MinInv$ increased

$MinInv_0$	$MinInv_1$	$MinInv_2$	$MinInv_3$
135	90	90	90

Table A.16: $MinInv$ decreased

RA_0	RA_1	RA_2	RA_3
0,50	0,50	0,50	0,50

Table A.17: Repo percentage increased

RA_0	RA_1	RA_2	RA_3
0,10	0,10	0,10	0,10

Table A.18: Repo percentage decreased

RegionFrom	RegionTo	$P(OLT_{i,j} = 2)$	$P(OLT_{i,j} = 3)$
0	0	0,33	0,66
0	1	0,1	0,9
0	2	0,2	0,8
0	3	0,1	0,9
1	0	0,1	0,9
1	1	0,66	0,33
1	2	0,1	0,9
1	3	0,1	0,9
2	0	0,2	0,8
2	1	0,1	0,9
2	2	0,66	0,33
2	3	0,1	0,9
3	0	0,2	0,8
3	1	0,1	0,9
3	2	0,1	0,9
3	3	0,33	0,66

Table A.19: Test lead time distributions increased

RegionFrom	RegionTo	$P(OLT_{i,j} = 2)$	$P(OLT_{i,j} = 3)$
0	0	0,8	0,2
0	1	0,6	0,4
0	2	0,8	0,2
0	3	0,6	0,4
1	0	0,6	0,4
1	1	0,8	0,2
1	2	0,6	0,4
1	3	0,6	0,4
2	0	0,6	0,4
2	1	0,6	0,4
2	2	0,8	0,2
2	3	0,6	0,4
3	0	0,6	0,4
3	1	0,6	0,4
3	2	0,6	0,4
3	3	0,8	0,2

Table A.20: Test lead time distributions decreased

To/From	0	1	2	3
0	0	2	2	0
1	2	0	2	0
2	2	2	0	0
3	3	0	3	0

Table A.21: ELT increased

To/From	0	1	2	3
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	1	0	1	0

Table A.22: ELT decreased

To/From	0	1	2	3
0	0	360	2160	0
1	1200	0	2400	0
2	960	2160	0	0
3	1020	840	720	0

Table A.23: RI increased

To/From	0	1	2	3
0	0	240	1440	0
1	800	0	1600	0
2	640	1440	0	0
3	680	560	480	0

Table A.24: RI decreased

LSI_0	LSI_1	LSI_2	LSI_3
1200	1200	1200	1200

Table A.25: Lost sales impact increased

LSI_0	LSI_1	LSI_2	LSI_3
400	400	400	400

Table A.26: Lost sales impact decreased

A.3 Test results with confidence intervals

	Repo impact	CI	Lost sales impact	CI	Inventory impact	CI
Base	43776	[-237, +237]	1283	[-212, +212]	128602	[-79, +79]
Disruption planned	78908	[-302, +300]	594	[-125, +125]	125033	[-60, +60]
Disruption unplanned	68529	[-611, +611]	8063	[-429, +429]	126020	[-67, +67]
MinInv increased	82147	[-291, +291]	10128	[-205, +205]	128427	[-61, +61]
MinInv decreased	24297	[-102, +102]	40	[-47, +47]	129464	[-127, +127]
RPH increased	49720	[-727, +722]	10	[-14, +14]	128078	[-105, +105]
RPH decreased	20126	[-327, +327]	7787	[-406, +406]	130674	[-55, +55]
RA increased	35858	[-334, +334]	1299	[-192, +192]	128568	[-64, +64]
RA decreased	71315	[-386, +386]	1629	[-239, +239]	128878	[-64, +64]
RI increased	52708	[-261, +261]	1316	[-211, +211]	128623	[-76, +76]
RI decreased	35035	[-199, +199]	1300	[-247, +247]	128531	[-82, +82]
LSI increased	43996	[-160, +160]	1974	[-263, +263]	128508	[-63, +63]
LSI decreased	43983	[-270, +270]	737	[-144, +144]	128591	[-83, +83]
IC increased	44136	[-237, +237]	1366	[-235, +235]	257029	[-156, +156]
IC decreased	43828	[-277, +277]	1343	[-219, +219]	64298	[-166, +166]
OLT increased	149524	[-238, +238]	2485	[-219, +219]	109540	[-55, +55]
OLT decreased	17508	[-84, +84]	8	[-15, +15]	145801	[-117, +117]
ELT increased	38256	[-435, +435]	6839	[-467, +467]	127864	[-64, +64]
ELT decreased	44154	[-253, +253	20	[-23, +23]	130781	[-79, +79]

Table A.27: Test results with confidence intervals

Appendix B Simulation tool model code

```python
#import packages
import pandas as pd
import warnings
from pandas.core.common import SettingWithCopyWarning
warnings.simplefilter(action="ignore", category=SettingWithCopyWarning)
import itertools
import numpy as np
import matplotlib.pyplot as plt
import datetime as dt
import math
import gurobipy as grb
from tqdm import tqdm
import random
plt.style.use('seaborn-darkgrid')
from pylab import rcParams
rcParams['figure.figsize'] = 14, 7
rcParams['font.size'] = 20
import os

#Define regions and flexible hubs
regions = ['CONFIDENTIAL']
flexiblehubs = ['CONFIDENTIAL']

#simulation parameters
T = 7
F = 9
R = len(regions)
cleaningtime = 'CONFIDENTIAL'
RPH = 2
RA= ['CONFIDENTIAL']
predictacc = 5.5
np = 30
ns = 100
IC = 'CONFIDENTIAL'

lostsalesinputs = np.array(['CONFIDENTIAL'])
LSI = {}
for i in range(len(lostsalesinputs)):
    LSI[i] = lostsalesinputs[i]

#disruption paramaters
#scenario 1: region import change, scenario 2: region export change , scenario 3
    tender change

scenario = 'input'
disperiod = 'input'
dispercentage = 'input'

#scenario 1 and 2 parameter
disregion = 'input'

#scenario 3 parameters
dislane = 'input'

#use of flex region in p
plist = [0, 0.5, 1, 1.5, 2, 2.5, 3]

#Week to month allocation
```

```
wtom = pd.read_excel("Weeks To Months.xlsx", sheet_name='Normal Allocation')
wtom.YearWeek = wtom.YearWeek.apply(str)
wtom.YearMonth = wtom.YearMonth.apply(str)
for i in range(len(wtom)):
    wtom.YearWeek[i] = wtom.YearWeek[i][:4] + 'W' + wtom.YearWeek[i][4:]
    wtom.YearMonth[i] = wtom.YearMonth[i][:4] + '-' + wtom.YearMonth[i][4:]
wtom.YearMonth = pd.PeriodIndex(wtom.YearMonth, freq='M')
wtom = wtom.set_index('YearWeek').to_dict()['YearMonth']

forecastmonth = pd.Period('2020-04')
testday = pd.Timestamp('2020-03-31')
repodf = []
LSdf = []

comb = [x for x in itertools.product([y for y in range(R)], repeat=2)]

#rounding function
def MonthRound(days):
    return max(1, round(days/30))

#Minimal inventory
MinInv = np.array(['CONFIDENTIAL'])

#coding of regions
regiondict1 = {'CONFIDENTIAL'}

regiondict2 = {'CONFIDENTIAL'}

#import tank location file
tank = pd.read_excel('Tank Location April.xlsx', sheet_name='Tank Location 30-03'
    , usecols='A, B, E, H, W, Y, AB, AC, X')
tank = tank[(tank['PlanningDestinationDescription'] == 'Global')]
tank = tank[(tank['Dedicated'] == 0)]
tank['AMonth'] = tank['EndDate'].dt.to_period('M')
tank = tank.reset_index(drop=True)
for i in tqdm(range(len(tank))):
    for j in flexiblehubs:
        if tank['HubFrom'][i] == j:
            tank['RegionFrom'][i] = 'flex'
        if tank['HubTo'][i] == j:
            tank['RegionTo'][i] = 'flex'
tank = tank.replace(regiondict2)

#Initial inventory region coding
init = tank[(tank['TankStatus'] == 'DEPOT CLEAN')]
init = init.groupby(['RegionTo']).count()['Dedicated']
init = init.reset_index(level=[0])

#input repo cost and possibility
repocost = pd.read_csv('repo input.csv')
RI = pd.DataFrame(np.zeros(shape=(R, R)))
RB = pd.DataFrame(np.zeros(shape=(R, R)))
RLT = pd.DataFrame(np.zeros(shape=(R, R)))
for i in range(R):
    RI[i][i] = 1000000000
for i in range(len(repocost)):
    f = repocost['RegionFrom'][i]
    t = repocost['RegionTo'][i]
    RI[f][t] = repocost['Repo incurred'][i]
    RLT[f][t] = round(MonthRound(repocost['transit days'][i]))
```

```
        if repocost['Repo incurred'][i] < 5000 and repocost['Repo incurred'][i] != 0:
            RB[f][t] = 1

#Full leadtimes distributions import
OLT = pd.read_pickle('leadtimes.pkl')
OLT = OLT.set_index(['RegionFrom', 'RegionTo'])

#results lists
repograph = []
lsgraph = []
inventorygraph = []
totalgraph = []

#begin loop for simulation at different p settings
for p in plist:

    #results dataframes
    totalcostindicatorlist = []
    reporesults = []
    lostsalesnr = []
    lostsalescost = []
    inventory = []

    #Simulation loop
    for runid in range(ns):
        #demand forecast import
        os.chdir(r'C:\Users\s148741\Google Drive\Studie\Master OML\Thesis\Data
            thesis\April')
        demand = pd.read_excel('demand_longterm.xlsx', usecols='C, D, E, G')

        demand = demand.replace(regiondict2)

        demand['Month'] = demand['Month'].str.replace('M', '-')
        demand['Month'] = pd.PeriodIndex(demand['Month'], freq='M')
        demand['Month'] = demand['Month'] - forecastmonth + 1

        demand = demand.pivot_table(index=['RegionFrom', 'RegionTo'], columns='
            Month', values='Global Demand Forecast - Use in Tool', fill_value=0)

        #incorporate zero demand lanes
        for i in range(len(comb)):
            if comb[i] not in demand.index:
                demand.loc[comb[i], :] = [0 for x in range(F)]

        #flexhubs values import and export

        #demand export
        demand.loc[(1,0)] -= int('CONFIDENTIAL')
        demand.loc[(7,0)] += int('CONFIDENTIAL')

        demand.loc[(0,2)] -= int('CONFIDENTIAL')
        demand.loc[(7,2)] += int('CONFIDENTIAL')

        #demand import
        demand.loc[(1,1)] -= int('CONFIDENTIAL')
        demand.loc[(1,7)] += int('CONFIDENTIAL')

        demand.loc[(0,1)] -= int('CONFIDENTIAL')
        demand.loc[(0,7)] += int('CONFIDENTIAL')

```

```
        demand.loc[(5,0)] -= int('CONFIDENTIAL')
        demand.loc[(5,7)] += int('CONFIDENTIAL')

        demand.loc[(0,0)] -= int('CONFIDENTIAL')
        demand.loc[(0,7)] += int('CONFIDENTIAL')

        demand.loc[(1,0)] -= int('CONFIDENTIAL')
        demand.loc[(1,7)] += int('CONFIDENTIAL')

        demand.loc[(6,0)] -= int('CONFIDENTIAL')
        demand.loc[(6,7)] += int('CONFIDENTIAL')

        demand = demand.clip(lower=0)

        #prepare dataframes with aggregated demand info

        demand = demand.reset_index()
        aggdemand = pd.DataFrame(index=range(R), columns=range(1, F+1))
        aggdemand = aggdemand.fillna(0)
        iaggdemand = pd.DataFrame(index=range(R), columns=range(1, F+1))
        iaggdemand = aggdemand.fillna(0)
        for i in range(len(demand)):
            for j in range(1, F+1):
                aggdemand[j][demand['RegionFrom'][i]] += demand[j][i]
                iaggdemand[j][demand['RegionTo'][i]] += demand[j][i]

        demand = demand.set_index(['RegionFrom', 'RegionTo'])

        print('start run ' + str(runid+1) + ' of '  + str(ns) + ' initial runs')
        op = 0
        totalrepo = pd.DataFrame(index=range(R), columns=range(R))
        totalrepo = totalrepo.fillna(0)
        executed = demand.copy()
        exaggdemand = aggdemand.copy()
        AvailableInventoryMatrix = pd.DataFrame(index=range(R), columns=range(T+1))
        AvailableInventoryMatrix[0] = init['Dedicated']

        #create arrival dataframes
        SFA = pd.DataFrame(index=range(R), columns=range(1, T+1))
        SFA = SFA.fillna(0)
        SEA = pd.DataFrame(index=range(R), columns=range(1, F+1))
        SEA = SEA.fillna(0)

        #initial inventory
        init = tank[(tank['TankStatus'] == 'DEPOT CLEAN')]
        init = init.groupby(['RegionTo']).count()['Dedicated']
        init = init.reset_index(level=[0])

        #plan arrivals
        #Cleaning Arrivals
        cleanWIP = tank[(tank['TankStatus'] == 'DEPOT DIRTY')]
        cleanWIP = cleanWIP.groupby(['RegionTo']).count()['Dedicated']
        cleanWIP = cleanWIP.reset_index(level=[0])
        for i in range(len(cleanWIP)):
            SFA[1][cleanWIP['RegionTo'][i]] += cleanWIP['Dedicated'][i]

        #repo arrivals
        repowip = tank[(tank['TankStatus'] == 'DELIVERYWIP')|(tank['TankStatus'] == 'REPOWIP')]
```

```
    repowip = repowip.groupby(['RegionTo', 'AMonth']).count()['Dedicated']
    repowip = repowip.reset_index(level=[0,1])

    for i in range(len(repowip)):
        reg = repowip['RegionTo'][i]
        if repowip['AMonth'][i] == forecastmonth-1:
            period = 1
        else:
            period = repowip['AMonth'][i] - forecastmonth + 1
        try:
            SEA[period][reg] += repowip.Dedicated[i]
        except KeyError:
            pass

    #variable initial state components
    #Demurrage arrivals
    loc = tank[(tank['TankStatus'] == 'DEMURRAGEWIP')]
    loc = loc.groupby(['RegionFrom', 'RegionTo', 'EndDate']).count()['Dedicated']
    loc = loc.reset_index(level=[0,1,2])

    DWIPlist = []
    overdue = []
    demtimedis = []
    lsn = pd.DataFrame(index=range(R), columns = range(1, T + 1))
    lsn = lsn.fillna(0)
    lsc = pd.DataFrame(index=range(R), columns = range(1, T + 1))
    lsc = lsc.fillna(0)

    for i in range(len(loc)):
        f = loc.RegionFrom[i]
        t = loc.RegionTo[i]
        wipdays = (testday - loc['EndDate'][i]).days
        nr = loc.Dedicated[i]
        dis = np.array(OLT.Demurrage[f,t])
        dis2 = dis[(dis > wipdays)] - wipdays
        if len(dis2) == 0 and max(dis) - wipdays < -50 and t != 1:

            overdue.append({'lane': (f,t), '#tanks': nr, 'Maximum sample value': max(dis),'elapsed demurrage days': wipdays, 'days past max sample days': max(dis) - wipdays})
            lead = random.choices(dis, k=nr)
            for x in range(len(lead)):
                period = pd.Period(testday + dt.timedelta(days = int(lead[x]) + cleaningtime), freq='M') - forecastmonth + 1
                DWIPlist.append({'lane':(f,t), 'startperiod': 1, 'arrival': period})
                try:
                    SFA[period][t] += 1
                except KeyError:
                    pass
        elif len(dis2) != 0:
            lead = random.choices(dis2, k=nr)
            for x in range(len(lead)):
                period = pd.Period(testday + dt.timedelta(days = int(lead[x]) + cleaningtime), freq='M') - forecastmonth + 1
                DWIPlist.append({'lane':(f,t), 'startperiod': pd.Period(loc['EndDate'][i], freq='M') - forecastmonth + 1, 'arrival': period})
                try:
```

```
                        SFA[period][t] += 1
                    except KeyError:
                        pass

        #order arrivals
        orderwip = tank[(tank['TankStatus'] == 'ORDERWIP')]
        orderwip = orderwip.groupby(['RegionFrom', 'RegionTo', 'StartDate', 'EndDate']).count()['Dedicated']
        orderwip = orderwip.reset_index(level=[0,1,2,3])
        for i in range(len(orderwip)):
            f = orderwip.RegionFrom[i]
            t = orderwip.RegionTo[i]
            nr = orderwip.Dedicated[i]
            dis = np.array(OLT.Demurrage[f,t])
            lead = random.choices(dis, k=nr)
            date = orderwip.EndDate[i]
            if date.month == forecastmonth.month - 1:
                ap = 1
            else:
                ap = date.month - forecastmonth.month + 1
            for x in lead:
                period = pd.Period(date + dt.timedelta(days = int(x) + cleaningtime), freq='M') - forecastmonth + 1
                DWIPlist.append({'lane':(f,t), 'startperiod': ap, 'arrival': period})
                try:
                    SFA[period][t] += 1
                except KeyError:
                    pass

        #run simulation for specified periods
        #define how much inventory will be available in the period after orders and repo come in
        for cPeriod in tqdm(range(1, T+1)):
            #define if dispruption period is reached and change demand dataframes
            if cPeriod == disperiod:
                for ii in range(R):
                    for jj in range(R):
                        if scenario == 1:
                            if jj == disregion:
                                change = round(demand[disperiod][ii,jj] * dispercentage) - demand[disperiod][ii,jj]
                                demand[disperiod][ii,jj] += change
                                executed[disperiod][ii,jj] += change
                                aggdemand[disperiod][ii] += change
                                iaggdemand[disperiod][jj] += change
                                exaggdemand[disperiod][ii] += change
                        elif scenario == 2:
                            if ii == disregion:
                                change = round(demand[disperiod][ii,jj] * dispercentage) - demand[disperiod][ii,jj]
                                demand[disperiod][ii,jj] += change
                                executed[disperiod][ii,jj] += change
                                aggdemand[disperiod][ii] += change
                                iaggdemand[disperiod][jj] += change
                                exaggdemand[disperiod][ii] += change
                        elif scenario == 3:
                            if ii == dislane[0] and jj == dislane[-1]:
                                change = round(demand.loc[ii,jj] * dispercentage) - demand.loc[ii,jj]
```

```
                            demand.loc[ii, jj] += change
                            executed.loc[ii, jj] += change
                            aggdemand.loc[ii] += change
                            iaggdemand.loc[jj] += change
                            exaggdemand.loc[ii] += change

        dellist=[]
        #delete arrivals from order and demurrage wip
        for d in reversed(range(len(DWIPlist))):
            if DWIPlist[d]['arrival'] == cPeriod:
                del DWIPlist[d]
        #update arrivals
        for i in range(R):
            SFA[cPeriod][i] = AvailableInventoryMatrix.loc[i][cPeriod-1] + SFA.loc[i][cPeriod] + SEA.loc[i][cPeriod]

        #order acceptance
        for i in range(R):
            if AvailableInventoryMatrix[cPeriod][i] - aggdemand[cPeriod][i] < MinInv[i]:
                #lost sales
                executed[cPeriod] = demand[cPeriod].copy()
                #calculate how many orders must be declined
                if MinInv[i] >= AvailableInventoryMatrix[cPeriod][i]:
                    lostnumber = aggdemand[cPeriod][i]
                else:
                    lostnumber = aggdemand[cPeriod][i] - (AvailableInventoryMatrix[cPeriod][i] - MinInv[i])

                LostSales = {}
                for l in range(R):
                    LostSales[l] = math.ceil((demand[cPeriod][i,l] / aggdemand[cPeriod][i]) * lostnumber)
                    executed[cPeriod][i,l] -= LostSales[l]
                exaggdemand[cPeriod][i] -= sum(LostSales.values())
                LSdf.append(['Lost sales ' + str(lostnumber), 'Region ' + str(i), 'Period ' +  str(cPeriod)])
                op += LSI[i] * lostnumber
                lsn[cPeriod][i] = lostnumber
                lsc[cPeriod][i] = LSI[i] * lostnumber

            #executed orders are put in arrival schedule
            AvailableInventoryMatrix[cPeriod][i] -= exaggdemand[cPeriod][i]
            for j in range(R):
                dem = random.choices(OLT.both[i,j], k = int(executed[cPeriod][i,j]))
                for x in range(len(dem)):
                    leadtime = dem[x]
                    DWIPlist.append({'lane': (i,j), 'startperiod': cPeriod, 'arrival': cPeriod + leadtime})
                    try:
                        SFA[cPeriod + leadtime][j] += 1
                    except KeyError:
                        pass

        #Start repo process
        exarrays = []
        exlist = []
        wipdf = pd.DataFrame.from_dict(DWIPlist)
        wipdf = wipdf.groupby(['lane', 'startperiod']).count()['arrival']
```

```
wipdf = wipdf.reset_index(level=[0,1])
for _ in range(np):
    Expected = AvailableInventoryMatrix[cPeriod].copy()

    for pred in range(1, RPH+1):
        predper = cPeriod + pred
        #determine expected incoming orders and
        for regfrom in range(R):
            for regto in range(R):
                if pred != RPH:
                    lane = demand[predper][regfrom,regto]
                    draw = random.choices(OLT.both[regfrom,regto], k = int(lane))
                    for x in range(len(draw)):
                        if draw[x] <= RPH - pred:
                            Expected[regto] += 1

            #demand out and repo in
            Expected[regfrom] -= aggdemand[predper][regfrom]
            Expected[regfrom] += SEA[predper][regfrom]

    for x in range(len(wipdf)):
        regfrom = wipdf['lane'][x][0]
        regto = wipdf['lane'][x][1]
        clane = np.array(OLT.both[wipdf['lane'][x]])
        elapsed = cPeriod - wipdf['startperiod'][x]
        clane = clane[(clane > elapsed)]
        draw = np.array(random.choices(clane, k = wipdf['arrival'][x])) + wipdf['startperiod'][x]
        for xx in draw:
            if xx > cPeriod and xx <= cPeriod + RPH:
                Expected[regto] += 1


    exarrays.append(Expected)

#Determine the amount of runs for desired accuracy
nrruns = 0
SS = [[] for _ in range(R)]
DD = [[] for _ in range(R)]
for b in range(R):
    test = [item[b] for item in exarrays]
    for v in test:
        if v > MinInv[b]:
            SS[b].append(round((v - MinInv[b]))*RA[b])
            DD[b].append(0)
        else:
            SS[b].append(0)
            DD[b].append(MinInv[b] - v)

for b in range(R):
    inruns = math.ceil(((1.96*np.std(SS[b]))/predictacc)**2)

    if inruns > nrruns:
        nrruns = inruns
    inruns = math.ceil(((1.96*np.std(DD[b]))/predictacc)**2)

    if inruns > nrruns:
        nrruns = inruns

```

```
runsleft = max(nrruns - np, 0)
#Run prediction for runs determined
for _ in range(runsleft):
    Expected = AvailableInventoryMatrix[cPeriod].copy()

    for pred in range(1, RPH+1):
        predper = cPeriod + pred
        #determine expected incoming orders and
        for regfrom in range(R):
            for regto in range(R):
                if pred != RPH:
                    lane = demand[predper][regfrom,regto]
                    draw = random.choices(OLT.both[regfrom,regto], k = int(lane))
                    for x in range(len(draw)):
                        if draw[x] <= RPH - pred:
                            Expected[regto] += 1

            #demand out and repo in
            Expected[regfrom] -= aggdemand[predper][regfrom]
            Expected[regfrom] += SEA[predper][regfrom]

    #order arrival from wip
    for x in range(len(wipdf)):
        regfrom = wipdf['lane'][x][0]
        regto = wipdf['lane'][x][1]
        clane = np.array(OLT.both[wipdf['lane'][x]])
        elapsed = cPeriod - wipdf['startperiod'][x]
        clane = clane[(clane > elapsed)]
        draw = np.array(random.choices(clane, k = wipdf['arrival'][x])) + wipdf['startperiod'][x]
        for xx in draw:
            if xx > cPeriod and xx <= cPeriod + RPH:
                Expected[regto] += 1
    exarrays.append(Expected)

#Determine expected surplus and deficit
Expec = np.mean(exarrays,axis=0)
Deficit = [0 for i in range(R)]
Surplus = [0 for i in range(R)]
for E in range(len(Expec)):
    if Expec[E] - MinInv[E] > 0:
        Surplus[E] = round((Expec[E] - MinInv[E])*RA[E])

    else:
        Deficit[E] = round(MinInv[E] - Expec[E])
print('surplus:' + str(Surplus))
print('deficit: ' + str(Deficit))

#solve the repo model
model = grb.Model(name="Repo")
model.modelSense = grb.GRB.MINIMIZE

# ##########################################################################

#Defining the variables
#Decision variable, number of repo's from region to region

Rij = pd.DataFrame()
```

```
for i in range(R):
    list = []
    for j in range(R):
        list.append(model.addVar(vtype=grb.GRB.INTEGER, name='R' + str(i) + '_' + str(j), lb=0))
    Rij[i] = list


Dj = []
for i in range(R):
    Dj.append(model.addVar(vtype=grb.GRB.INTEGER, name='D' + str(i), lb=0))

model.update()

# ########################################################################
#Define objective
objective = grb.quicksum(Rij[i][j] * RI[i][j] for i in range(R) for j in range(R)) + grb.quicksum(Dj[i] * 100000000000 for i in range(R))
model.setObjective(objective)
model.update()

# ########################################################################
#Defining the constraints of the model

#The deficits must be filled
for j in range(R):
    model.addConstr(grb.quicksum(Rij[i][j] for i in range(R)) + Dj[j] == Deficit[j])

#a region cannot supply more than its surplus
for i in range(R):
    model.addConstr(grb.quicksum(Rij[i][j] for j in range(R)) <= Surplus[i])

#Repo can only take place on a allowed lane
for i in range(R):
    for j in range(R):
        model.addConstr(Rij[i][j] <= 500000000 * RB[i][j])

#Repo amount cannot go lower than inventory on hand
for i in range(R):
    model.addConstr(grb.quicksum(Rij[i][j] for j in range(R)) <= AvailableInventoryMatrix[cPeriod][i] - MinInv[i])

model.setParam( 'OutputFlag', False)
model.update()
model.optimize()

#update arrival of empty repo and inventory
for i in range(R):
    for j in range(R):
        if Rij[i][j].X > 0:
            try:
                SEA[cPeriod+RLT[i][j]][j] += Rij[i][j].X
```

```
                        except KeyError:
                            pass
                        AvailableInventoryMatrix[cPeriod][i] -= Rij[i][j].X

                for i in range(len(Rij)):
                    for j in range(len(Rij)):
                        Rij[i][j] = Rij[i][j].X
                repodf.append(Rij)
                totalrepo += Rij
            del AvailableInventoryMatrix[0]

            #Calculate costs of run
            repocost = (totalrepo * RI).sum().sum()
            reporesults.append(totalrepo)
            lostsalesnr.append(lsn)
            lostsalescost.append(lsc)
            inventorycost = (AvailableInventoryMatrix.sum().sum() * IC)
            totalcostindicatorlist.append(repocost + op + inventorycost)
            inventory.append(AvailableInventoryMatrix.copy())
            print('Total repo costs = ' + '${:,.2f}'.format(repocost))
            print('Total lost sales cost = ' + '${:,.2f}'.format(op))
            print('Total inventory cost = ' + '${:,.2f}'.format(inventorycost))


    #Save results in csv files
    reporesults = sum(reporesults) / len(reporesults)
    cost = round((reporesults * RI).sum().sum())
    pd.Series(cost).to_csv('reposcostnumber p=' + str(p) + '.csv')
    repograph.append(cost)
    reporesults.to_csv('repo outf p=' + str(p) + '.csv')

    lostsalesnr = sum(lostsalesnr) / len(lostsalesnr)
    lostsalesnr.to_csv('lsn p=' + str(p) + '.csv')
    lostsalescost = sum(lostsalescost) / len(lostsalescost)
    lsgraph.append(lostsalescost.sum().sum())
    lostsalescost.to_csv('lsc p=' + str(p) + '.csv')
    inventory = sum(inventory) / len(inventory)
    inventory.to_csv('inventory p=' + str(p) + '.csv')
    invcost = (inventory.sum().sum() * IC)
    inventorygraph.append(invcost)
    totalgraph.append(cost+lostsalescost.sum().sum()+invcost)

#Save total cost for all p
pd.Series(repograph).to_csv('repograph.csv')
pd.Series(lsgraph).to_csv('lsgraph.csv')
pd.Series(inventorygraph).to_csv('invgraph.csv')
pd.Series(totalgraph).to_csv('totalgraph.csv')
```