MASTER

Forecasting orders for a specialized logistic service provider with a complex network

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with a complex network

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Abstract

In this thesis the possibility of forecasting orders in a logistic network is researched. The first step is the data preparation step. The raw data cannot be used directly. An order can be completed with a selection of the available tank containers (TC). Based on various criteria order types are created. A unique set of tank containers (types) is allowed for each order type. It is not possible to forecast orders for every location in the network, regions are therefore used. In most cases a tank container requires cleaning before loading the next order, this step is completed at a cleaning station. Next to the cleaning station is often a depot located where the TC can be stored if not yet used for a new order. These regions and order types are used to form combinations which are used as input for forecasting. A next step is viewing the numerous combinations, and search for trends and special patterns. The performance of different forecasting methods is researched. Finally, the overall achievable accuracy is calculated.

Management summary

This thesis is a study to gain insight in the possibility of forecasting demand at DH. The first step is the data preparation. DH is a specialized logistic service provider (LSP) for the chemical industry. This research is conducted for the business unit liquid logistics, they own almost 3000 tank containers. Products such as MDI, TDI, and hot rosin are excluded. In previous research (Jansen, 2014) categorized these tank containers into seventeen different types. This categorization is used in this research.

Research question: Can forecasting demand reduce costs for a specialized logistic service provider with a complex network?

If demand is known more days in advance, cost saving decisions can be made when taking the future into account. In reality demand is not known more days in advance, therefore it is interesting to research if it is possible to reduce costs at a logistic service company by using forecasted demand. The feasibility of reducing costs will depend on the achievable accuracy of the forecasts.
To answer the research question four sub questions are formed. These sub questions are presented and discussed below.

1) How should the data be prepared?
2) Are there long term trends in the network?
3) Is the performance of simple forecasting methods (exponential smoothing and moving averages) equal or better than more advanced methods (ARIMA and ANN)?
4) How accurate can demand be forecasted at the company and what steps can be taken to improve forecast accuracy?

How should the data be prepared? The raw data at DH cannot be used to generate useful forecasts. Based on time, DH requires forecasts per week for the next two weeks. Another important characteristic of an order is the location where the loading (delivery) occurs. There are more than a thousand different loading locations, for the deliveries this number is multiplied by three. This would result in too many different time series. Therefore, the choice is made to categorize the locations into regions. For most orders this will result into a realistic categorization. Because a tank container (TC) requires cleaning in most cases, and there are only a limited number of cleaning stations. Often a depot is located near a cleaning station. Another very important characteristic is which containers (types) are allowed to complete an order. In the current situation only the used TC/type is stored. Order types (OT) are created to include the flexibility of the process of assigning a TC to an order in reality. These are made with the characteristics of the TC types and the available data in mind. An OT is taken into account when at least 0.5 percent of total demand can be categorized as that specific OT. The eventual combinations used as input for forecasting are the region/order type combinations.
At first 95 percent of the orders is categorized in one of 23 order types. The decision is made to make some simplifications for the remaining orders. These simplifications limit the number of allowed TC types, but take into account the distribution of tank containers over the different TC types. After this step 99 percent of the orders is categorized in one of the 24 order types created. On average an order can be completed with 7.24 different container types.

This level of data aggregation resulted in 373 different loading combinations and 442 delivery combinations. These combinations form the input for the next steps.

Sub question 2): Are there long term trends in the network?
At a couple combinations long term trends are present. These trends are increasing as well as decreasing. There are also a number of cases where short term trends occurred. The increases and decreases in demand (level) per combination are often shown by shifts in demand. Acquiring new orders via a tender (long term) can result in increased demand. If a tender ended/an important customer is lost, then demand drops suddenly. Based on the combinations there are hardly any long term trends and it is dangerous to assume they will continue as shown in paragraph 6.2.

Sub question 3): Is the performance of simple forecasting methods (exponential smoothing and moving averages) equal or better than more advanced methods (ARIMA and ANN)?
To forecast demand various methods are used. The differences between the presented methods are small. Table 1 shows the performance of various methods for group E containing the large combinations. The simple exponential smoothing method performs on average most constant, there are no large differences between the training and validation set. The ARIMA method performs in the training set slightly better and in the validation set comparable. The ANN method has slightly over fitted the data, the performance in the validation set is significantly worse than for the training set.
As can be seen there are only small differences in accuracy between the simple and advanced methods. Based on these accuracy measures can be concluded that the simple forecasting methods perform equally compared to more advanced methods like ARIMA and ANN (for these combinations).

	Training			**Validation**		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
Ses	100.00	27.14	25.18	113.98	27.19	26.11
ARIMA	96.76	26.81	24.63	113.93	27.15	26.08
ANN	89.77	25.53	23.65	156.86	30.00	28.88
Hybrid	87.58	24.75	23.27	117.25	28.22	27.13
Combined	88.52	25.45	23.56	114.22	26.78	25.71

Table 1: Overall accuracy of different forecasting methods (group: E) (note: the MSE is scaled)

From table 1 can also be concluded that the forecasting accuracy (MAPE) can be slightly improved when a couple of forecasting methods are combined into a new forecast. However, the disadvantage of this method is the additional forecasts that have to be made.

The forecasting accuracy can also be improved by taking known pre-order information into account. In general, orders are planned two work days ahead. So the orders that are already known Wednesday week t, for the next weeks, can be used to update the forecasts (paragraph 6.5). This is mainly possible for week t + 1. Only in special cases updates for week t + 2 are possible.

Sub question 4: How accurate can demand be forecasted at the company and what steps can be taken to improve forecast accuracy? To answer this question, the demand is categorized in order types/regions. For these combinations weekly forecasts are made. The average error achieved (t+1) with the available information and methods used is around 36 percent based on the (g)MAPE. This is a relatively high error, therefore a relatively low accuracy can be achieved. As shown before DH has numerous different combinations, therefore the total demand is divided over a large number of combinations. As a result there are many small combinations which are hard to forecast. The variance of the demand at DH on combination level is high. The overall pattern for the larger combinations can be followed/predicted by statistical methods, but the fluctuations around this level are in most cases difficult to predict. For the smallest groups the forecasts made have a very low accuracy.

The accuracy of the forecasts is not as good as hoped for. The accuracy however does not tell the whole story, because of the flexibility in the process of assigning TC's to an order. If some order types are forecasted too high, these anticipated TC's can to a certain degree be used to complete other orders which were forecasted too low. More problematically is the case when hard orders are forecasted too high in one region and too low in another region. Which can result in required empty repositions.

The forecasts accuracy can be slightly improved if knowledge about if and when production stops where known is saved and could be used. Also information about the end or a start of a (large) new tender could be used to update the forecasts.

Research question: Can forecasting demand reduce costs for a specialized logistic service provider with a complex network?

In the current situation the algorithm makes suggestions based on the optimized costs over a time horizon of two days. When a larger time horizon is taken into account, the costs will be optimized over the longer horizon based on forecasted information. These forecasts can/will also change over the weeks. Based on information from the study of (Jansen, 2014), discussions with planners and my supervisor we concluded that adapting the algorithm to take the forecasts into account will not result in reduced costs.

Recommendations and insights

When the number of orders for a combination increases, on average the forecast accuracy increases. At the end of this project DH bought the company InterBulk, by this purchase DH became a top 3 player (LSP) for the chemical industry. The integration of InterBulk has just started. By the end of 2016 the data is likely integrated. The number of orders per combination is likely to increase.
It is therefore expected that the accuracy of the forecasts will increase.
This research has shown that for the larger combinations the simple methods perform equally compared to advanced methods. For the smallest combinations pre-order information can be used to generate a minimum number of expected orders.

To forecast demand, it is important that the different departments communicate relevant information to the one keeping track of the forecasts. For example, if an account manager knows that an important customer has a production stop for the next six weeks. This information could be used to manually adjust the forecast. Important information should be saved, also the date and time this information became known is relevant. For example, if new orders are acquired via a new tender and a shift in demand can be expected. The other way around is also possible. In case a large customer is lost, for example because the tender has ended and no new quote is agreed on. In this case additional information is available and should be used. As posed before, relevant information should be saved for future use. The forecast should be monitored and adjusted if necessary. If this information can be used, the forecasting accuracy can be improved.

The order types/forecasts can also help (new) planners to gain useful information on which type of orders (and an indication of the number) occur in which region. This can help in deciding which TC can be best assigned to an order. Also the time it will take to get a new planner acquainted with the order process is likely to be reduced.

Preface

This thesis is the final step of my graduation project and also the end of my time as a student at the TU/e. I conducted this project at Den Hartogh logistics, which is a logistic service provider for the chemical industry. I would like to thank some people for their support during this project and also during my time as a student at the TU/e.

First I would like to thank Arun Chockalingam, who became my mentor after Matthew Reindorp left the TU/e. During this project we had several meetings, and good discussions where I got useful feedback. You were always able to find some time at a short notice. I would also like to thank my second supervisor, Karel van Donselaar for his useful input during this project.

I would like to thank my colleagues at DH for the nice time I had. Gerrit Vis, my supervisor for this opportunity, his time and useful insights. Also I would like to thank two planners, Richard and Thijs for the discussions we had.

As well I would like to thank my family for their support during my study. My friends for the nice time we had. Finally, I would like to thank my girlfriend for her support.

Niek van den Bogaart

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1 Introduction

In the literature, much research is conducted on forecasting time series in the financial sector. These studies are based on data like exchange rates and indices. For the more difficult cases such as spare parts and product demand, some research is conducted, but not extensively. Hardly any research is available in the literature about forecasting demand in the logistic (transport) sector on company level. There is some research about general logistic flows, but this focuses on total volumes of the sector.

Research based on the demand of a logistics (transport) company can be valuable for the literature and the company. Accurate forecasts can help the planners in making decisions and thereby making the network more effective. Therefore, research into forecasting demand of a logistic network can be useful for logistic companies.

In the logistics sector, a large number of starting and end locations can be visited. This complicates forecasting the demand. Another complicating factor is the number of different containers the product can be stored in. The focus in the literature is on monthly time series, whereas the time series for a logistic company will most likely have a shorter time interval. This complicates forecasting, because the shorter the time interval, the more variable the data.

1.1 Den Hartogh

This study is conducted at Den Hartogh (DH) logistics. DH was founded in 1920. They provide logistic services to the chemical industry. In 2012 they started at their new head office in Rotterdam where the equipment planners ((MMP) multiple day's material planning) work. DH owns a number of storage depots where the fleet of tank containers can be stored. In regions where they do operate but not own a depot they rent spaces if needed. This Master Thesis project is connected to the business unit, Liquid logistics, which owns almost 3000 container units. In 2011, DH expanded their business outside Europe, so their market has become even bigger. The region outside Europe is handled by the business unit Global. Another specialization of DH is gas logistics, this is a separate business unit.

The order process at DH starts when a request for transporting a product comes in. The first step by DH is to make a quote. In a quote, information about the loading and delivery location is stored. Which type of product and the requested quantity that needs to be transported are also stored. (Keep in mind that only a small fraction of the quotes made will become an order). The next step in the order process is the creation of the standard pre-order (SPO). Every time a new order for the same product and location comes in this SPO is used to generate a pre-order. In the pre-order date and time are added. The next step in the process is assigning an appropriate tank container (TC) to the order. This step is conducted by the multiple day's material planning (MMP) department. After a TC is assigned to the order the truck chassis planning assigns a truck and driver to the order. After this step the administration and financial department complete the process.

1.2 Thesis outline

In chapter 2 the order process at Den Hartogh is discussed. Also the interest of DH in forecasting orders is presented. In chapter 3, the research assignment is presented. As a first step the scope of the project is defined. After which the research and sub question are discussed. Forecasting methods and the associated error are discussed in chapter 4. The data preparation steps are shown in chapter 5. Order types are presented in detail in paragraph 5.2. The data used as input for forecasting is presented in paragraph 5.3. Chapter 6 reveals the results of forecasting, and the steps taken. In chapter 7 the discussion, insights and limitations are presented. Finally, conclusions and recommendations can be found in chapter 8.

2 Current situation at DH

If an order comes in and the requested services can be provided by DH, an appropriate tank container and truck are sent to location X where the product is loaded. DH works with full truck loads, therefore only one loading and one delivery location is visited per trip. So after loading the product, the truck transports the product to location Y, where it is delivered. Typically, when the order is completed, the container needs to be cleaned before it can be used for another order. If the same product will be loaded for the next order, then the tank container often does not require cleaning. There are also products which are not allowed to follow each other, even after cleaning, these are on the blacklist. Customers can also have their own blacklist.

The order process at DH starts when a (new) request for transporting a product comes in. At this point, a quote will be made. A quote contains information about the loading and delivery location. Information about the product and the requested volume is also stored in the quote. In the quote process, the price for the requested services is calculated and presented to the customer. Only a small fraction of the quotes will become an actual order.

After a quote is made, a standard pre-order (SPO) is created. The SPO contains information about the customer, product, loading- and delivery location which is based on the quote made before. After the SPO is completed, a pre-order is made. This step adds the loading and delivery date and time slot. The pre-order also updates the requirements (of the 'order') as can be seen in figure 1.

The multiple day's material planning department (MMP) completes the next step. At this step a tank container is assigned to a pre-order. Their choice is based on various information, for example the available containers in a certain region, the requirements of the pre-order, experience, and the suggestion made by the MMP algorithm. After this step the order is created, an order contains all information of the previous steps. The next step is completed by the truck chassis planning (TCP) at this step a truck and a driver are assigned to the order. In parallel, the modality planning is made. This planning is responsible for which route to take, via road, ferry and or rail.

The final steps of the order process are, providing the requested services, administrational handling, invoicing and payment.

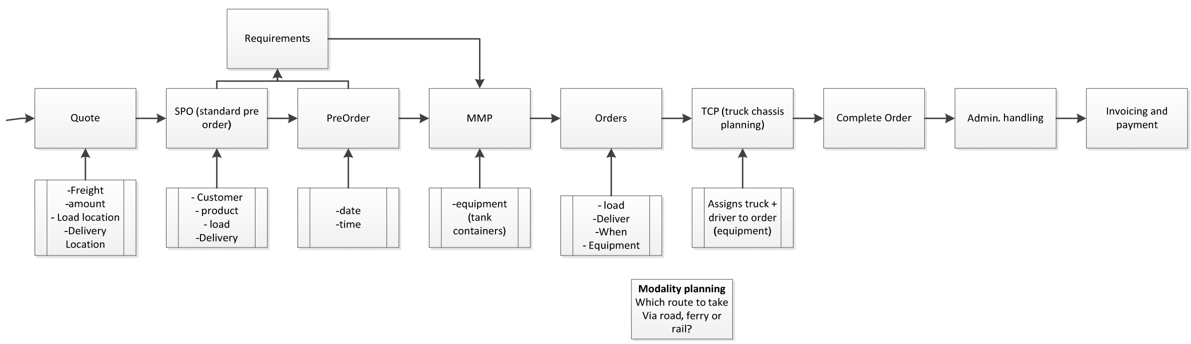

Figure 1: Order process at den Hartogh logistics

Besides the regular quotes there are also quotes made for tenders. If a tender is won, DH has an indication of the number of orders a customer is expected to place over a year. This number is only an indication and can/will be higher or lower in reality. Thereby are the expected number of orders provided per year, on weekly basis large deviations are possible. These tender quotes are often valid for one or two years.

DH is interested in how accurate orders (demand) can be forecasted. From (Jansen, 2014) and CQM they know that when demand for order types could be forecasted one hundred percent accurate, four weeks ahead, seven percent of the costs can be saved. This level of accuracy is, of course, not possible, but they are interested in how accurate their demand can be forecasted. Currently DH does not make forecasts (on region/type level).

Demand at DH is not clearly specified. It is not relevant or useful just to forecast the number of orders in a certain time frame. The location of the loading (and delivery) is of importance. Another difficulty is the fact that an order requires certain characteristics of a tank container. There are orders where only a very small number of tank containers can be used, whereas for some orders (almost) all available tank containers can be used. At DH the used TC and which TC type was used is stored. However, they do not have an overview of which type(s) of tank containers could be used to complete an order.

Based on forecasts planners can make repositioning decisions as well as deciding which container can be best assigned to an order. Another benefit of forecasting demand, is the overview the different planners and departments get in where what type of demand is expected to occur. If demand can be forecasted with a high accuracy, the MMP algorithm could be updated to take a longer planning horizon into account based on the forecasts. In the current situation the algorithm optimizes the costs over a two-day horizon.

3 Research assignment

3.1 Scope

DH is a large logistic service provider (LSP) for the chemical industry. This project is not conducted for the company in its complete form, but focuses on the liquid logistics business unit. This business unit is the largest business unit of DH. In this study only orders for transport of liquids are taken into account. These orders have to be geographically located in Europe. Not all orders which are connected to the business unit liquid logistics are taken into account. Contract work (dedicated-calculated) where a TC (in general) is fixed on a specific route is excluded from this project. The TC assigned to this type of work cannot be used for other orders. Work on location for a large customer is also excluded from this research. Again these TCs can only be used by orders from this customer and cannot be used to complete other orders.

DH liquid logistics also transports chemicals such as MDI, TDI, and hot rosin. Specialized TCs are used to complete these orders. The cleaning costs are high for these type of products due to the difficulty of cleaning. These products and specific TCs are out of scope. Finally, DH has TCs as well as road barrels. For this study only TCs are taken into account. These filters result in only including flexible orders, where the TCs can be used flexible.

This thesis is a study to gain insight in how accurate demand can be forecasted at DH. They know that if demand is known four weeks upfront instead of two days, seven percent cost savings can be achieved. The liquid logistics business unit has almost 3000 TCs excluding the MDI, TDI, and hot rosin TCs. With the purpose of this study in mind it is not possible to look at these 3000 TCs separately. Therefore the categorization made by (Jansen, 2014) is used. The available TCs are categorized into seventeen different types. These seventeen different types are used in this research.

This project has as main goal to research how accurate demand can be forecasted at DH. To achieve this the first step is the data preparation. This is an important and time consuming step, as this project is not a straight forward forecasting project. After this step the forecasts can be made. When the forecasts are finished the overall accuracy can be determined. Based on the achieved accuracy further steps could be taken. This study is used as a pilot study into the possibilities of forecasting demand at DH. To guide the research, the research question presented in paragraph 3.2 is formed.

3.2 Research question and sub questions

Research question: *Can forecasting demand reduce costs for a specialized logistic service provider with a complex network?*

It is known that if demand is known more days in advance, cost saving decisions can be made when the future is taken into account. In reality demand is not known more days in advance, therefore it is interesting to research if it is possible to reduce costs at a specialized logistic service company by using forecasted demand. The feasibility of reducing costs will depend on the accuracy of the forecasts, and the cost/benefit tradeoff of a certain accuracy level (depends also on the type of demand).

To answer the research question four sub questions are formed. These sub questions are presented and discussed below.

1) How should the data be prepared?
The data preparation step is a very important and time consuming step. First the ins and outs on how the company works should be investigated, based on this knowledge a decision should be made on how to aggregate the data. What is included and what is excluded? These are all important decisions and should be carefully researched. The prepared data will be used as input for forecasting. The goal is to automate the data preparation process, so it can be directly used for forecasting.

2) Are there long term trends in the network?
For a logistic network company, it is of interest to know whether there are long term trends in the network and if it is possible to flag a trend break. The forecasts should be adjusted if long term changes occur.

3) Is the performance of simple forecasting methods (exponential smoothing and moving averages) equal or better than more advanced methods (ARIMA and ANN)?
Forecasting demand is the main goal of this project. In the literature various methods are proposed to forecast demand. The first step is to generate forecasts via various techniques presented in paragraph 4.2. It is also of interest to research whether simple methods or more advanced methods result in more accurate demand forecasts at a logistic service provider.

4) How accurate can demand be forecasted at the company and what steps could be taken to improve forecast accuracy?
The eventual goal of the forecasts is to use them, and improve the process of assigning a tank container to an order. Therefore, it is of interest to know how accurate demand can be forecasted. It is also interesting to research possible steps to increase forecast accuracy in the future.

4 Discussion on forecasting methods and associated error

In this chapter some required insights on forecasting are discussed. The first paragraph presents insights on error measures and the accuracy evaluation. In paragraph 4.2 various forecasting methods are discussed. Demand categorization is discussed in paragraph 4.3. Finally, special methods for lumpy and intermittent demand patterns are presented and discussed.

4.1 Error measures and accuracy evaluation

It is important to use the right error measure(s). The error measures presented in this section are often used in the literature (Dekker, van Donselaar, & Ouwehand, 2004), (Nahmias, 2009). These are the mean absolute deviation (MAD), mean squared error (MSE), mean absolute percentage error (MAPE) and the symmetric mean absolute percentage error (sMAPE). The use of the MSE error measure will result in favoring a number of small errors above one big error (Chiulli, 1999). When the MAD error measure is used, the total absolute error will be minimized. The MAPE is a scale free error measure (Mukhopadhyay, Solis, & Guttierrez, 2012). A special version of the MAPE is the symmetric MAPE which was used instead of the MAPE in (Makridakis & Hibon, 2000). The next presented formulas were found in (Dekker, van Donselaar, & Ouwehand, 2004). These error measures will be used to evaluate the forecasts.

MAD (mean absolute deviation) $\frac{1}{n}\sum_{t=1}^{n}|x_t - \hat{x}_{t-1,t}|$

MSE (mean squared error) $\frac{1}{n}\sum_{t=1}^{n}(x_t - \hat{x}_{t-1,t})^2$

sMAPE (symmetric mean absolute percentage error) $\frac{1}{n}\sum_{t=1}^{n}\frac{|x_t-\hat{x}_{t-1,t}|}{(x_t+\hat{x}_{t-1,t})/2} * 100\%$

To evaluate the accuracy, the data should be split into two parts. The first part is used as a training set, whereas the second part is used to evaluate the accuracy of the forecast (validation set). In the M3-competition (Makridakis & Hibon, 2000) the 6/8/18 last observations are used to evaluate the accuracy of the forecast. The hold-out sample (validation set) which will be used will be approximately 15.3% of the total sample (average used in monthly time series M3 competition (Makridakis & Hibon, 2000)).

4.2 Univariate methods

In most literature on forecasting only one variable is used as input for forecasting. The historical demand/orders are used to fit a model, evaluate performance and make future forecasts. (Makridakis & Hibon, 2000) show that simple forecasting methods perform on average equal or even better than the more advanced methods. Therefore, simple methods are used to generate a baseline forecast. With these baseline forecasts comparisons can be made with more advanced methods.

It can be the case that more advanced methods provide a better fit to the data. A start will be made with the use of the ARIMA method (sub paragraph 4.3.4). Secondly the artificial neural network method will be used. After forecasting with both these methods, a hybrid method is used. With this hybrid method first the ARIMA method is used and secondly the ANN method on the residuals of the forecasts made with the ARIMA model. Finally, the forecasts made are combined which was recommended by (Armstrong, 1984).

4.2.1 Exponential smoothing

If no clear trend is visible in the data, the exponential smoothing method can be used to forecast and achieve a benchmark level of performance. Various values for the smoothing parameter can be tested on the different time series. Forecast $=\alpha(last\ value\ of\ demand) + (1-\alpha)(last\ forecast)$ (Nahmias, 2009). A small alpha will result in a stable forecast, whereas an alpha close to 1 will result in a very unstable forecast which is almost the last value of demand. In case alpha is one, the exponential smoothing model behaves like a random walk (forecast = last value of demand).

4.2.2 Moving averages

Another simple method is the moving averages method. In this method the last X observations form an average, which is the forecast for period t + n. So the forecast for week t + 1 is the same as for t + 2. As the time continues to the next time period, a new forecast should be calculated, based on the previous X observations. The required number for X should be determined per combination. This method is not very convenient when a trend is present in the data, because it will lag behind the trend.

4.2.3 Holt's method

In case a trend is present in the data the exponential smoothing and moving averages methods are probably not the best methods to use. In this case Holt's method will be used to set a benchmark forecast. Holt's method is also a kind of exponential smoothing method. But his method uses two smoothing equations. One is for the intercept and one for the trend. The below presented formulas were found in (Nahmias, 2009).

Intercept $S_t = \alpha D_t + (1-\alpha)(S_{t-1} + G_{t-1}),$

Trend $G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1}.$

4.2.4 ARIMA

After setting benchmark forecasts for the core combinations, more advanced methods will be used and evaluated to see if they generate improved forecasts. The most popular method in the literature is the ARIMA method. This method will therefore be used first. ARIMA stands for autoregressive integrated moving averages. In this method the Auto regressive model is combined with a moving averages model. The integration factor depends on the underlying structure of the time series. If the time series is stationary, then the integration factor is zero and the ARIMA model is reduced to an ARMA model (Brockwell & Davis, 2002). In case the underlying data is non-stationary, the aim of introducing an integration factor is to get the time series stationary. The first step is the model identification (Box & Jenkins, 1970). In this step the order of the three parameters (p,d,q) has to be determined. The AIC statistic will be used to determine the order for p and q.

4.2.5 ANN

Another advanced method which will be used is the artificial neural networks (ANN) method. These ANNs are divided into three layers. The input layer, hidden layer and output layer. The optimal number of input neurons has to be determined by trial and error (Hamzacebi, Akay, & Kutay, 2009). Whereas the number of hidden layers is commonly one (Turban, Sharda, & Delen, 2010), the number of output neurons depends on the output horizon and the forecasting method used. As horizon is chosen two periods. As forecasting method, the direct method is chosen because this method delivers better performance than the iterative method (Hamzacebi, Akay, & Kutay, 2009). The number of output neurons will be two. ANN type multi-layer perceptron (MLP) will be used for forecasting, this is the most used type (Hamzacebi, Akay, & Kutay, 2009).

4.2.6 Hybrid approach

Another method that will be used to forecast is the hybrid approach proposed by (Zhang, 2003), where at the first step the linear part is modeled with the use of an ARIMA model. The artificial neural network method will be used in step two, to model the residuals from the ARIMA method. The artificial neural network model is then used to predict the error terms of the ARIMA method (Zhang, 2003). For his method the data is divided into two parts, a training set where the model is developed and the test sample. The test sample is used to test the accuracy of the model. This method will be used to make forecasts and evaluated against the benchmark forecast.

4.2.7 Combining forecasts

(Armstrong, 1984) suggested that combining forecasting methods will lead to improved accuracy. (Makridakis & Hibon, 2000) conclude that in case various forecasting methods are combined, the performance is on average increased. To combine the forecasts the simple average is used, which resulted in improved accuracy for almost all combinations (Makridakis & Hibon, 2000). (Armstrong, 1984) suggests to use three or four methods and calculate the average forecast. So when the forecasts are generated with the in paragraph 4.2 suggested methods, these will be used to form the combined forecasts. This type of combining (simple average) forecasts is a very often used method in the literature (de Menezes, Bunn, & Taylor, 2000).

(de Menezes, Bunn, & Taylor, 2000) recommends five different ways of combining forecasts based on various characteristics. Depending on the size of the time series, correlation and variances. Combining with the use of the outperformance method (in case of a small data sample (not relevant)), optimal method with independence assumption, optimal method, restricted regression model, or simple average model. The data should be well-behaved and stable forecasting conditions present (de Menezes, Bunn, & Taylor, 2000).

The simplest method is the simple average model. This method is recommended by (de Menezes, Bunn, & Taylor, 2000) in case the error variances between forecasts are similar and the positive correlation is less than 0.5 (weak or unstable). By using this method just the simple average is taken of the included forecasts.

For combining forecasts all these methods use a linear formula with a vector f, of n forecasts which are combined via a linear weighting vector (w) (de Menezes, Bunn, & Taylor, 2000) $f_c = w'f$.

Optimal method: the error variances of the combination is minimized using linear weights (de Menezes, Bunn, & Taylor, 2000) $w = \frac{S^{-1}e}{e'S^{-1}e}$ where S is the (n x n) covariance matrix and e is the unit vector (n x 1). When the sample size is large, the optimal method is recommended.

The adaptive optimal method with independence assumption: when using this method, the estimate of S can only be diagonal, so representing only the individual forecast error variances (de Menezes, Bunn, & Taylor, 2000). In case the sample has a medium length and low correlation this is the recommended method.

Restricted regression method, this method uses least squares regression with a constant and the weights have to sum to one. With this regression the weights on the individual forecasts are determined and used to combine the individual forecasts into a new forecast. This method was recommended by (de Menezes, Bunn, & Taylor, 2000) as alternative to the optimal method in case the sample size was large.

However, (Makridakis, et al., 1982) found that taking the simple average of the forecasts results on average in better accuracy than taking a weighted average based on the correlations. (Schnaars, 1986) Concluded that forecasting accuracy can be improved by combining forecasts and no evidence is found that weighted combinations lead to improved accuracy compared to the simple average. Also a more recent study by (Costantini, Gunter, & Kunst, 2010) showed that for a horizon of one or two steps ahead, the performance of other combining methods than the simple average do not result in clear improved results. Therefore, for this thesis the simple averaging method will be used.

4.3 Demand categorization

(Altay, Rudisill, & Litteral, 2008) based on (Syntetos, Boylan, & Croston, 2005) categorized demand in four different patterns. Therefore, they used two different kind of measures, the average demand interval (ADI) with a cut off value of 1.32 and the squared coefficient of variation cv^2 with a cut off value of 0.49. Demand with a low cv^2 and a low ADI is called smooth demand. If the demand pattern has a low ADI and a high cv^2 then it is called erratic demand. Intermittent demand is characterized by a high ADI and a low cv^2. Finally demand with both high cv^2 and ADI is called lumpy. An ADI of 1.32 corresponds with around 24 % of the time zero demand (Altay, Rudisill, & Litteral, 2008). Smooth demand is probably the easiest demand to forecast. The more complex demand patterns, intermittent and lumpy, require specialized forecasting methods. In the next subparagraph specialized forecasting methods for these complex demand patterns are discussed.

4.3.1 Methods for intermittent or lumpy demand patterns

Intermittent and lumpy demand patterns are patterns where at least 24 percent of the time zero demand occurs. Intermittent demand patterns are often observed for spare parts (Kourentzes, 2014). In the literature a couple of methods are proposed for intermittent demand. (Croston, 1972) was probably the first one who proposed a method specific for intermittent demand. Croston's method works as follows: the original time series is divided into two parts. The first part is derived from extracting only the times where demand occurs. The second time series consists of the time intervals between demand occurrences. After extraction, the data is smoothed and two independent forecasts are made with the use of exponential smoothing (Kourentzes, 2014). The smoothing parameter is chosen equally for both forecasts (Kourentzes, 2014). A smoothing parameter value ranging between 0.1 and 0.3 is suggested by (Croston, 1972). The final step to come up with a forecast is dividing the estimates. The future average demand per time period is now predicted (Kourentzes, 2014).

Over time, the method by Croston is updated a couple of times. (Syntetos & Boylan, 2005) presented an improved version of Croston's method. This method takes into account the bias approximation for Croston's method made by (Syntetos & Boylan, 2001). The estimator of new demand is updated as follows: $Y_t' = (1 - \frac{\alpha}{2})\frac{z_t'}{p_t'}$, Where α is defined as the smoothing constant.

(Syntetos & Boylan, 2005) tested their method against simple moving averages (13 periods), simple exponential smoothing, and Croston's original method on 3000 different time series. They concluded that their method is the most accurate for what they call faster intermittent demand (Syntetos & Boylan, 2005). Also on average their method performed the best.

(Teunter, Syntetos, & Babai, 2011) introduced a new method which updates the probability of demand continuously, whereas Croston's method only updates when nonzero demand has occurred (Kourentzes, 2014). This was also (Teunter, Syntetos, & Babai, 2011) main concern with Croston's method. Their second issue was already solved by (Syntetos & Boylan, 2005), their method can deal with obsolesce and is always up to date (Teunter, Syntetos, & Babai, 2011). In the method by (Teunter, Syntetos, & Babai, 2011) the demand probability is updated (every period), instead of updating the demand interval only when demand occurs as with Croston's method. (Teunter, Syntetos, & Babai, 2011) Posed that using demand probability instead of demand interval removes the forecasting bias when an arbitrary point in time is chosen. The TSB method as they call it, updates the estimate of the demand size after demand has occurred.

In case the variability of the data is high (and at least 24% zero demand) the demand can be categorized as lumpy. Another approach to lumpy demand forecasting was used by (Gutierrez, Solis, & Mukhopadhyay, 2008) they applied a neural network to forecast lumpy demand. They compared the results of their neural network with three traditional methods used for lumpy demand which are, single exponential smoothing, Croston's method and the Syntetos-Boylan approximation (SBA). Syntetos-Boylan approximation performs better than Croston's method and exponential smoothing in case of lumpy demand forecasting (Gutierrez, Solis, & Mukhopadhyay, 2008). The second objective of their study was to get information in which cases neural network models perform better or worse than traditional methods.

To compare the various forecasting methods, (Gutierrez, Solis, & Mukhopadhyay, 2008) used an alternative version of the MAPE developed by (Gilliland, 2002): (g)$MAPE = \frac{\sum_{t=1}^{n}|E_t|}{\sum_{t=1}^{n} D_t} * 100\%$.

This alternative version of the MAPE is used because of the zero demand periods in lumpy demand, which causes the original MAPE error measure to fail (Gutierrez, Solis, & Mukhopadhyay, 2008). Of the 24 time series tested, the neural network performed better in 21 cases (Gutierrez, Solis, & Mukhopadhyay, 2008). The average MAPE over 24 time series found by (Gutierrez, Solis, & Mukhopadhyay, 2008) was 111.42% for the neural network method and 126.95% for the SBA method which is the best traditional method used in their study. They mention that all the MAPEs are higher than 100% because they used all periods including the ones with zero demand.

(Gutierrez, Solis, & Mukhopadhyay, 2008) also calculated the percentage best (PB) statistic. In this statistic, one method is compared against another, where the percentage is measured of how much time the first method performs better than the second. Their results show that neural networks had the highest performance for the first 22 series. For series 23 and 24 exponential smoothing performed slightly better. The overall conclusion based on the PB statistic by (Gutierrez, Solis, & Mukhopadhyay, 2008) is that the neural network method performed by far the best, 62.37%. Single exponential smoothing became second with a PB of 23.14% and SBA third with a PB of 14.52%.

(Gutierrez, Solis, & Mukhopadhyay, 2008) also calculated the variances of the forecast errors. They used two tests, equality of variances and the Cochran and Cox test. Based on the variances the neural network method performed significantly better on most of the time series (Gutierrez, Solis, & Mukhopadhyay, 2008). Only for two out of 24 the SBA method had performed significantly better.

When the average of nonzero demand sizes significantly decreases between the training and test sample the performance of the traditional methods improves more than the forecasts generated by neural networks (Gutierrez, Solis, & Mukhopadhyay, 2008).

An important note on the neural networks used by (Gutierrez, Solis, & Mukhopadhyay, 2008) is that they did not tweak the parameters for every time series individually. So possibly the ANN method could perform better if it was specially fit on each time series individually. One possible problem of using neural networks for forecasting is overfitting. When the neural network is over fitted to the data, its generalizability becomes less, to avoid overfitting (Gutierrez, Solis, & Mukhopadhyay, 2008) started with a small network.

Based on the results of the previously discussed methods the ANN method will be used to generate forecasts for the combinations where an intermittent or lumpy demand pattern is present.

5 Data

Den Hartogh has various information stored about their orders, such as locations, product type, quantity, dates, etc. The tank container used to complete the order is also stored. The forecasts could be based on this information, but this would not represent the flexibility of reality. Often various tank containers (types) could be used to complete an order. In the planning tool, the planners of DH can choose a possible container out of the available tank containers based on various characteristics such as volume, heating, available time, etc. The planning system takes every individual tank container into account. For this thesis it is not possible to use individual tank containers, therefore the categorization made by (Jansen, 2014) is used. In this study not all tank containers are categorized, out of scope are the special tank containers for products as MDI, TDI, and hot rosin. Some old containers are categorized as other, and are also out of scope.

For this project the data (orders) cannot be used directly. There is a large number of starting and ending locations involved. For the purpose of forecasting orders are aggregated based on locations and available depots. For DH liquid logistics (DHLL) Europe is divided into regions. These regions are chosen in consultation with DH. Only the countries where DHLL operates are included. Some countries consist of multiple regions. A loading/delivery location is assigned to the nearest region/depot. For a logistic company like DH the number of incoming and outgoing orders in a region is of great importance. Margins are small in the transport sector and empty repositioning is costly.

Balancing of orders is more complicated as it seems, for example the number of containers is limited. Another important factor is the fact that there is a diverse fleet of tank containers, on average an order (included orders) can be executed by 7.24 different container types. Time is another important characteristic of balances in regions. For example, a region could have 10 incoming and 10 outgoing orders, but if the outgoing orders are in the first half of the year and the incoming orders are in the second half of the year, the inflow and outflow of tank containers is not balanced over time.

The tank containers are categorized by (Jansen, 2014) into seventeen different types. In figure 4 (p.14) the seventeen different container types are presented. These container types will be used in this thesis. As can be seen in figure 4, the categorization is based on a number of different characteristics. For example, the number of compartments, heating system and size (length).

An option is to use the actual used containers as input for forecasting, but by using actual used tank containers flexibility is lost. On average an order can be completed by 7.24 TC types. A part of the orders can only be completed by one specific tank container. In paragraph 5.2 an alternative for using the actual used tank containers is presented. So the flexibility involved in assigning a container to an order is maintained.

After the data is aggregated based on location, time and type, this data can be used as input for forecasting. The forecasts can thus be for the expected number of loadings in region X for week T and container type Y. The other option is to forecast the expected number of loadings in region X for week T and order type Y.

The dataset provided by DH consists of numerous characteristics for every order. Two years of data is provided by DH. This data is used to create the order types and make forecasts. This two-year data set (104 weeks) results in a training set of length 88, and validation set of length 16. In paragraph 5.1 the data preparation steps are discussed in more detail.

5.1 Data preparation

DH has a lot of information but not all information is easily accessible. As presented before DH is a logistic service provider for the chemical industry. This means they do not have one product. The raw order data can therefore, not be used directly for the purpose of forecasting. The data has for example loading and delivery dates per day. Also every exact loading and delivery location is included. With forecasting as goal, the raw data requires aggregation. In the following subparagraphs important data aggregation steps are presented. A start will be made with the included locations.

5.1.1 Regions

The included orders have numerous loading and delivery locations. They occur at locations where chemical plants/customers are located. The data set contains around a 1000 different loading places. There could be even more loading locations, because some places have more than one customer. For the deliveries there are more than 3000 places in the data set. With the purpose of forecasting the loadings and deliveries in mind this representation of data will not be usable. Therefore, in consultation with DH the locations are categorized in regions, based on the locations where DH operates and density of demand (an order is assigned to the nearest depot from loading/delivery location). This resulted in 25 regions. In figure 2, 24 regions are shown (the 25th region is region other). These regions are also based on the fact that in most cases a TC requires cleaning before being able to complete another order (only in case of the same product the TC does not (in most cases) require cleaning). Often a depot is located near a cleaning station. A driver drops the TC at a cleaning station for cleaning and after cleaning the TC is often stored at the depot waiting for a driver to pick it up.

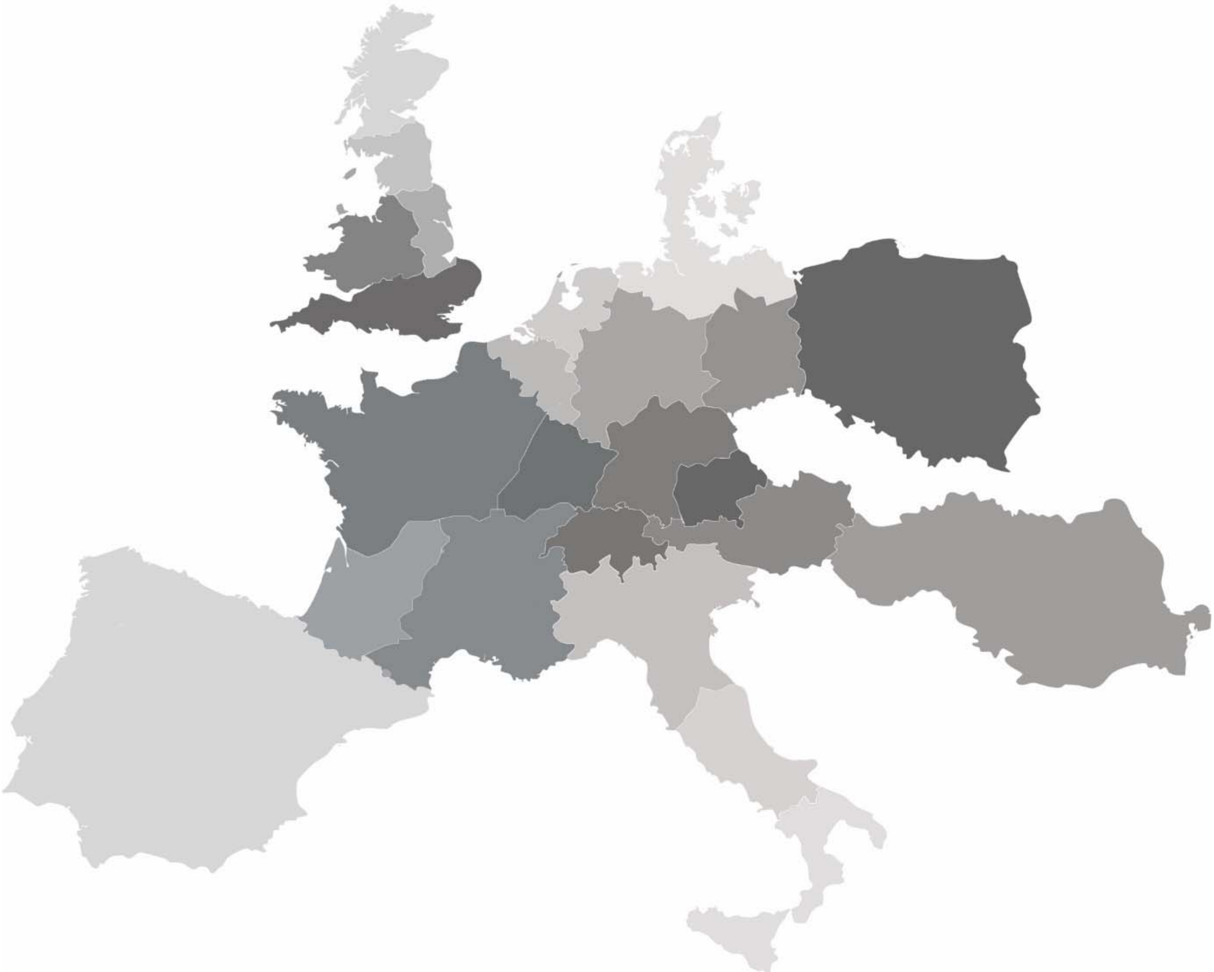

Figure 2: Regions

Based on these regions the order data will be aggregated. This is one possible categorization of regions used by DH. This categorization of locations was chosen to be used as input for forecasting, as this represents a good tradeoff between accuracy and usefulness for DH.

5.1.2 Time

Another important characteristic for forecasting is the time unit included to calculate the demand/supply. In (Makridakis & Hibon, 2000), 3003 time series are used. In almost half the cases demand is aggregated monthly. Quarterly and yearly are also an often used form of aggregation. For DH this type of aggregation based on time is not useful, TC's are used multiple times over these time periods. After discussions at DH the choice is made to aggregate the data based on time in weeks. This type of aggregation was also recommended by (Jansen, 2014) and CQM for the data of DH. So the data will be aggregated weekly, in total two years of data is provided by DH.

A problem with the week interval is the chosen notation. DH uses a week notation where 1-1-yyyy is always the beginning of week 1. Also they do not use a week 53. These days are added to week 52. Therefore, it is possible, for example, to have a week 52 with 10 days and a week 1 with only 4 days. This results in more variable demand patterns for weeks 1 and 52. Demand in week 52 and 1 also suffers from the Christmas holiday. So there are a couple of problems with forecasting demand for weeks 52 and 1. A possibility is to change the week structure to standardized weeks (ISO weeks), but then there is once in 7 years a week 53. It should be remembered that demand in these weeks is dependent on in which weeks the holiday is, and then especially the 1st and 2nd Christmas day and New Year. For 2015/2016 and using ISO weeks, Christmas will be in week 52 and New Year in week 53. Therefore, it is expected that in these weeks the demand will be lower.

A problem with the ISO week notation is, when using a pivot table in Excel (data preparation), a part of week 1 which falls in the previous year is seen as week 1 2013 instead of week 1 2014. Because every notation has his own problems, the notation of DH is used for their convenience. The dataset will therefore consist of 104 weeks of data.

5.1.3 Type

After these two types of data aggregation it is not yet possible to use this data as input for forecasting. In (Jansen, 2014) the tank containers available at DH are categorized in seventeen different types, based on various characteristics. Figure 4 (p.14) shows the container types by (Jansen, 2014). In reality DHLL has almost 3000 TCs. An order can be completed by numerous different TCs. There are two options to aggregate the data based on type. The first is to aggregate the data based on chosen TC type. Appendix I shows the available TCs per type at DHLL.

Aggregating the data based on used TC type will limit the flexibility of assigning a TC to an order. The assumption is then made that in the future the 'same' decisions are made when assigning a TC to an order. This data is available at DH. So the first step was to examine the possibility of using this type of data for the purpose of forecasting.

Another option is to create order types. An order type can be completed with a unique set of tank container types. The data will then be aggregated based on order types. This type of aggregation is discussed in paragraph 5.2.

5.1.4 Loading and delivery

An order has a loading and delivery location. (Jansen, 2014) posed that it is not possible to forecast orders from one region to the other (for DH). DH is interested in separated forecasts for the loadings in a region and the deliveries in a region. An order is therefore split into two parts, a loading and a delivery part. There are 25 regions, if the flow from region A to region B would be taken into account, 25 * 25 flows are possible which results in 625 possible loading – delivery combinations.

5.1.5 Actual used TC

As posed before, the data could also be prepared based on the actual used TC, but then a lot of flexibility is lost. The forecasts show the number of required TCs per tank type in a region. But this limits the usefulness of the research, therefore the order types are created.

In case the TC types would be used, seventeen different types are present. A small number of container types represents a relatively large number of the total available tank containers. There are also a couple of tank containers which represents only a small number of the total available TCs. In figure 3 two examples of region/container types are presented.

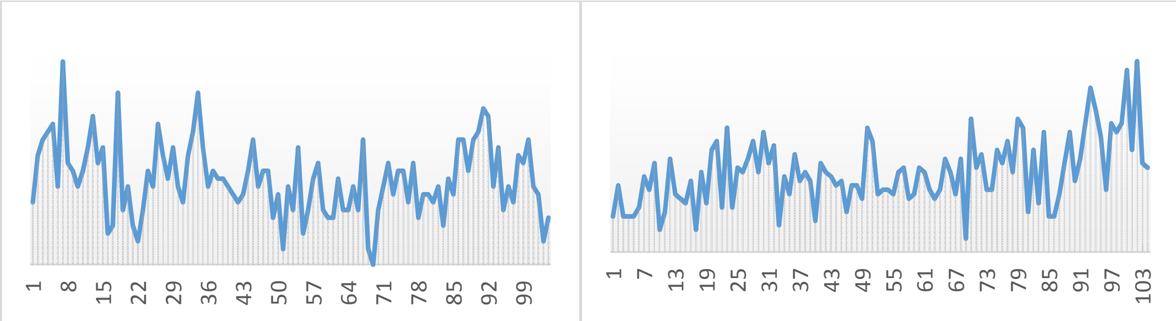

Figure 3: Example combinations, of container type X in region A and B.

5.2 Order types

In the current situation DH only has data available of which tank container (TC) was used to complete an order. In reality various types of TCs could be used for most orders. Each order can be completed by a set of TCs. Some orders can be completed by every TC type whereas others can only be completed by one or two TC types. By using order types instead of actual used TCs the flexibility of assigning a TC to an order is maintained. For the creation of order types (OT) the characteristics of the different TC types and various order characteristics are used. Based on these characteristics unique sets of possible TC types are formed, the order types.

The first order characteristic discussed is the number of compartments allowed (to load the product). These are categorized into six different sets, the first set are the orders where only one compartment (tank) is allowed. There are also orders where the product can be transported in one or two compartments. The orders where the minimum number of compartments is one and the maximum is 3, 4 or 8 (>=3) is categorized as 1-4. This is done because the containers are categorized in types with 1, 2 or 3/4 compartments. A small number of orders have to be transported in two compartments, these orders result in another category. For the sake of completeness the category 2-4 compartments is added. This category occurs sporadically and is therefore not considered further. The last group included are orders where the product has to be loaded in three or four compartments. This order requirement is almost nonexistent and is therefore not considered in the remainder of this thesis.

Another important characteristic is whether the transport requires ADR (Accord Européen relatif au transport international des marchandises dangereuses par route) filling levels. ADR is only used for hazardous materials or if the customer requires it. ADR allows filling levels between 0-20%, and 80-95%. If the product is transported in a baffle tank, a fill level between 0 and 95% is allowed. Products can still have their own minimum and maximum fill level, these cannot be less restrictive than the ADR requirements.

The volume of an order is another important characteristic. A customer orders a certain quantity of a product. The volume of the order is calculated with the corresponding density of the product. The container types (figure 4, p.14) are grouped in small, medium and large (based on length) (Jansen, 2014). Cut-off values for the different sizes have to be made. Six groups have been formed (for non ADR). Only small, only medium, only large, small + medium, medium + large and all sizes allowed. A complicating factor is the fact that not all containers of the same size (length) have equal capacity (volume). For example, medium containers have a volume around 31 M3. High insulated containers are categorized as large but only have a volume of 30 M3. These containers will be seen as medium sized (volume). Each TC type consists of a number of tank containers. Within a type TCs can have different capacity (volume), this complicates the process of creating OTs. If for example all small TCs have volume X, all medium Y, and all large Z, the cutoff values are clear. In reality this is not the case.

There are differences in volume for example between various small TC types and as posed before also within container types.

In approximately seven percent of the orders less loading is allowed. Another important fact is the density of the product, in the system a factor corresponding to a specific temperature is used. In reality the temperature and thereby the volume can differ from calculated volume. The assumption is made that the calculated volume is correct.

With the purpose of forecasting in mind it is better to have fewer order types, resulting in more aggregated data (more orders per OT). Three groups of different container sizes (volumes) are made. The first are the small containers which have a maximum volume of 26.1 M3 and an average volume of 25.2 M3, the medium containers have a maximum volume of 31.1 M3 and an average volume of 30.6 M3, and finally the large containers have a volume ranging from 33 till 36.5 M3 with an average volume of 35 M3. Each order has a minimum and maximum fill percentage included. In most cases the maximum fill percentage is set at 95%. Order volumes can be based on the SPO (standard pre-order), PO (pre-order) or on actual loaded volume. The different kind of orders can have other values compared to each other. Also the actual loaded volume is not always noted correctly. For this project the PO data is taken as input, this is the actual input from the customer, and thereby best represent the demand.

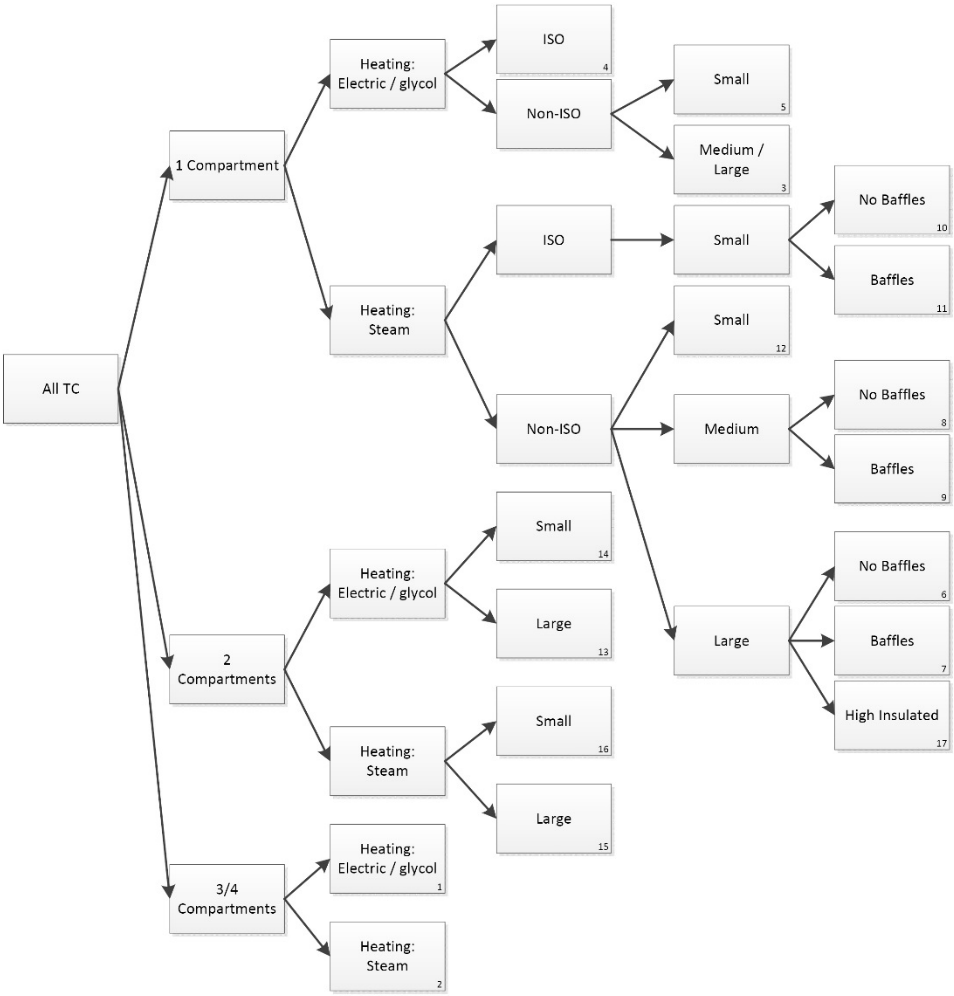

Figure 4: Container types created by (Jansen, 2014)

As posed before the ordered volume is an important characteristic of an order and determines (partly) which tank container types are allowed. The process is not straight forward. The volume depends on the loading temperature. In some cases, more/less loading is allowed. Other complicating factors are the different volumes of the container types used by DH. For example, most tank containers of type small have a volume ranging from 25 till 26 M3. If the cutoff value for small was set at 25 M3 then almost all the orders included (non-ADR) can be executed with a tank container of this type. A disadvantage of this is the fact that numerous orders cannot be completed by a small tank container based on the categorization but in reality they could. After discussions and checks with historical used TC for orders the choice is made to set the cut-off value for small tank containers at 26 M3. One of the reasons for this choice is the fact that new small tank containers have a volume of 26 M3. (For additional information see sub paragraph 5.2.1: additional information cut-off values)

As posed before the volumes of tank containers in a specific type often have multiple values. For ‘medium’ TC the volumes ranges from 30 till 31 M3. Cutoff values were first tested over a range from 30 to 31 M3, but after consultation with the planners and checks with reality this limit was increased till 31.5 M3. In reality often less loading is requested/allowed for these ordered volumes. A large percentage of the orders which had an ordered volume ranging from 29.45 (31*.95) till 29.925 (31.5*.95) are completed with a medium sized tank container. So less loading was allowed/requested or a higher fill percentage was used (max volume medium is 31 M3). This is probably caused by the availability of large (volume) containers.

In case of ADR requirements the allowed fill levels for a non-baffle tank container range from 0 till 20 and from 80 till 95 percent. After discussion with a planner and checks with reality it is chosen to calculate the allowed volumes per group by multiplying the lower bound (25 for small) volume by 80 percent and the upper bound (26 for small) volume by 95%. This is slightly less strict but in this case more realistic (otherwise a lot of baffle tanks are required). Only a limited percentage of orders have volumes in the ‘critical’ ranges. This slight adjustment of allowed volumes is made so the order types are more useful for DH. The assumption is made that orders which require ADR and fall into the suggested range can be completed with a tank container of the category (a slight change of the loaded volume is sometimes required). In case of overlap of allowed order volumes these are added to the corresponding allowed container sizes (for example small + medium). As posed before, if a baffle tank is used for ADR, the allowed fill percentage ranges from zero till 95 percent.

As can be seen in figure 5 the volumes loaded can differ from the volumes ordered (95 percent of the orders is included). On average less is loaded than ordered. In six percent of the cases the actual loaded volume is not noted correctly. Another important characteristic is the maximum fill level allowed. In general, the maximum fill percentage is 95%, but for some orders this can differ. The volume at the temperature of loading can also differ from the volume stated in the system. Appendix II presents an overview of the ordered volumes.

In reality sometimes less loading or more loading is allowed. This is not taken into account on an individual level. It was not possible to make this available in the dataset in reasonable time. The assumption is made that a little bit more/less can be loaded so every order categorized as small can be completed with a tank container of size small, which have volumes ranging from 25 till 26 M3. The same assumption is made for medium and large where the volumes range respectively from 30 to 31 and 33 to 36.5 M3.

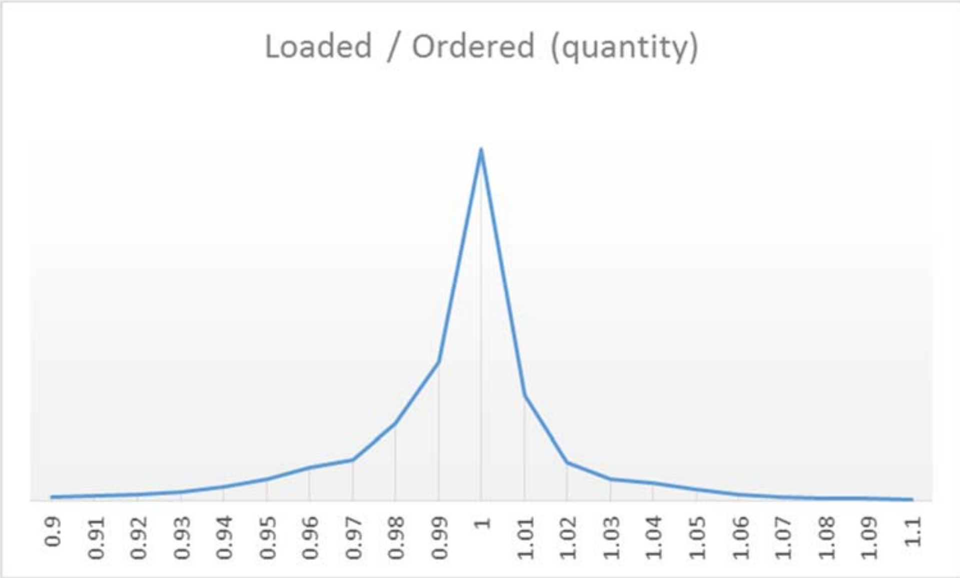

Figure 5: Loaded vs. ordered volume (quantity)

Another characteristic taken into account is whether the use of a baffle tank is required, forbidden, or not important. A baffle tank can be required based on ADR requirements in combination with the required volume. Baffles forbidden are not taken into account because they are actually not really forbidden but additional costs are involved for cleaning. The assumption is made that the additional flexibility delivers more costs savings than the possible extra cleaning costs. The planners suggest to take baffles forbidden not into account. Baffles required are a hard request and are therefore taken into account.

Often products DH transports require heating during transportation. Therefore, the different heating methods are also important to take into account. The different heating methods are: steam, electrical, and glycol. These result in another characteristic that limits the possible container types for an order. Every tank container DH owns has a (specific) heating system onboard. A significant part of the orders requires one specific type of heating. The tank container categorization used by DH divides heating systems in steam and electrical/glycol. Therefore, the (order types) dataset is prepared with a maximum function on electrical/glycol. The following categories are formed: all heating types allowed + no heating required, heating required: only steam allowed, heating required: only EG allowed.

An equally important characteristic is whether a TC with a standardized (ISO) size is required. In case of intermodal transport an ISO container is often required. This ensures that the cost of intermodal transportation is minimized. Another characteristic is whether high insulation is required or not. High insulation is used in case the product is not allowed to cool/heat much in the period of transport.

All these characteristics limit the possible tank container types for an order. Based on these characteristics, the different order types are created. These order types are evaluated against reality and discussed with the planners. A couple of adjustments were made, orders just over the limit of a medium volume container are often adapted so they fit in a medium sized container.

Below the characteristics used to create the order types are presented. (Some combinations use the same set of container types and will therefore be combined).

- Number of compartments allowed.
    - 1
    - 1-2
    - 1-4
    - 2
    - 2-4
    - 3-4
- Order volume
- Min and Max fill level of the container
- Capacity (volume) of a container of type X.
    - Small
    - Medium
    - Large
- The volume of the container in combination with the min and max fill level and volume of the order results in the following possibilities(non-ADR):
    - Small
    - Medium
    - Large
    - Small or Medium
    - Small, Medium or Large
    - Medium or Large
- Baffles
    - Required
    - Not important
- Heating
    - Heating not required/specified
    - Heating required
        - EG allowed
        - Steam allowed
- Iso
    - Iso required
    - Iso not required
- High insulated
    - High insulated required
    - High insulated not required
- ADR Filling required: No or Yes, if Yes:
    - 0-20%
    - 80-max fill (95%)
    - Or baffle tank (0-95%)

With these characteristics in mind and every order type corresponding to a unique set of allowed containers, the order types presented in table 2 and 3 are created. Note that only the OTs which represent at least 0.5% of the total orders are included. It is possible to generate each and every possible order type, but with the purpose of forecasting in mind this will not be useful.

Type	**ADR**	**ISO**	**High**	**Heating**	**Min-Max**	**Baffles**	**Allowed TC types**
1	X	1	0	All + no	X	X	4,10,11
2	X	1	0	Steam	X	X	10,11
3	X	0	1	X	X	X	17

Table 2: ISO & High insulated order types

Type	ADR	Heating	Min-Max	Baffles	Size	Allowed TC types
4	0,1	All + no	1—1	NR	L	6,7
5	0,1	All + no	1—1	NR	ML	3,6,7,8,9,17
6	0,1	Steam	1—1	NR	ML	6,7,8,9,17
7	0	All + no	1—1	NR	SML	3,4,5,6,7,8,9,10,11,12,17
8	0	Steam	1—1	NR	SML	6,7,8,9,10,11,12,17
9	0	All + no	1—4	NR	ML	1,2,3,6,7,8,9,13,15,17
10	0	All + no	1—4	NR	SML	All types
11	1	All + No & Steam only		Required	SML	7,9,11
12	1	All + No	1—1	NR	S + ML baffles	4,5,7,9,10,11,12,15
13	1	All + no	1—4	NR	S + ML baffles	1,2,4,5,7,9,10,11,12,13,14,15,16
14	1	Steam	1—1	NR	S + ML baffles	7,9,10,11,12
15	1	All + no	1—1	NR	M + L baffles	3,7,8,9,17
16	1	All + no	1—1	NR	S+M & L baffles	7,8,9,10,11,12,17
17	1	All + no	1—4	NR	M + L baffles	1,2,3,7,8,9,13,15,17
18	0,1	All + no	1—4	NR	L	6,7,15
19	1	Steam	1—1	NR	M + L baffles	7,8,9,17
20	0	EG	1—1	NR	SML	3,4,5
21	0	All + no	1—2	NR	ML	3,6,7,8,9,13,15,17
22	0,1	EG	1—1	NR	M/ML	3
23	0	All + no	1—2	NR	SML	3 till 17

Table 3: Order types

In total these order types represent 95.4 percent of the orders included in this study.

5.2.1 Additional information cut-off values

These order types are made with the available information. Some simplifying assumptions had to be made to be able to create a limited set of order types. For the volumes (sizes) a couple of decisions could be made. It could be chosen to limit the size of a small TC at the volume of the smallest available TC so the included orders will always fit in a small tank container (non-ADR). But the new bought tank-containers have a volume of 26 M3. Orders with a volume till 24.7 M3 should be able to be transported with these containers. This was one of the reasons why the choice was made to set the cut-off value at 26 M3 for small sized tank containers. The assumption is made that it is possible to load slightly more/less so it is possible to use every small sized tank container for these orders. (On average the volume of the small TCs is 25.2 M3). In reality planners will use (assign) the available TCs in a region wisely.

For medium the 'same' choice is made as there are tank containers with volumes ranging from 30 till 31 M3. The new bought tank medium sized TCs have a volume of 31 M3. For medium containers this limit is increased till 31.5 M3. This is done because the checks with reality showed that a large percentage of the orders between (31-31.5) *.95 M3 are completed by a medium sized TC. The assumption is therefore made that orders categorized as being allowed to be completed by a medium sized TC can be completed with every medium sized TC. If the limit was set on the average of 30.6 M3 then numerous orders require a large tank, where some of them could be completed with a medium sized TC. So this will limit the use of numerous medium TCs. Also this would not replicate reality and is therefore less useful.

It should be kept in mind that the 'critical' volumes represent only a limited number of orders in an order type. Also the tank containers with an insufficient capacity included at an order type are very small. As posed before sometimes more/less loading is allowed.

It should be noted that the chance of being able to complete a random order of an OT with a random specified TC, is for OTs where all sizes are allowed, more than 95 percent. In reality less loading or a higher fill percentage is sometimes allowed. This percentage will therefore be higher in reality. A planner can also take this into account when assigning a TC to an order. For ML OTs the percentage based on the included variables is lower, but in reality almost always a medium TC is used, therefore this assumption can be made.

The changes in cut-off values are based on numerous checks with reality and advice of a planner. With these adaptions the order types will be more realistic and therefore of better use for the planners.

The categorization based on these cut-off values is also more future proof with the knowledge of the volumes of the new bought TC's in mind.

What should be kept in mind is that this study is a pilot study, to research whether it is possible to generate forecasts accurate enough to be used in practice. If they are found accurate enough the first step at DH will be to use these forecasts as additional information for the planners to base the decision of assigning a TC to an order on. Of importance is the 'balance' of TCs (types) in a region. The expected loadings (of various OTs) and deliveries. The planner creates flexibility in this process.

5.2.2 Extension order types

In the previous section 23 order types were created. These represent around 95 percent of the included orders. The remaining five percent of the orders are distributed over numerous different order types. Each order type is divided further over the regions where demand occurred. These result all in very small order type region combinations and thereby limit the forecasting possibilities. It can be chosen to not include these orders. Another option is to include these orders but make these additional order types less strict. The focus will be on the most important factors (based on the available TC types).

For the remaining order types the assumption is made that they can only be transported in a one compartment tank container (instead of 1, 1-2, 1-4). This results in less flexibility compared to reality but most of the new (simplified) order types can now be added to some of the earlier created order types. These newly created (simplified) order types can at least be transported by one of the suggested tank containers. The other option is to not include the orders.

For these new created (simplified) order types the heating requirements all + no and steam are combined, the assumption is made that this order type can only be completed by a steam heated tank container. The fleet of tank containers of DH Rotterdam consists out of more than 85 percent steam heated tank containers. The other simplification made is the number of allowed compartments (filling). Most tank containers have only one compartment. Therefore, another simplification is made for the remaining orders, every order which can be executed in a one compartment tank is added. Based on these two simplified characteristics more than 82 percent of the fleet can be used.

Other characteristics such as ADR and volume are kept in their original form. The remaining orders do not require an ISO tank or high insulated tank. So these characteristics are out of scope.

The following simplified order types can be formed from the remaining five percent of the orders (table 4).

ADR	Volume	Heating	Compartments	Baffles	Allowed TC types	Add to:
0,1	S + M	Steam	1	NR	8,9,10,11,12,17	O24
0,1	M + L	Steam	1	NR	6,7,8,9,17	O5
0,1	SML	Steam	1	NR	6,7,8,9,10,11,12,17	O8
0,1	L	Steam	1	NR	6,7	O4
1	S + ML baffles	Steam	1	NR	7,9,10,11,12	O14
1	M + L baffles	Steam	1	NR	7,8,9,17	O19
0	ML	EG	1	NR	3	O22
0	SML	EG	1	NR	3,4,5	O20
1	SML	Steam	1	Only Baffles	7,9,11	O11

Table 4: 'Simplified' additional order types

Almost 99 percent of the included orders are now categorized by order type. Nine new "simplified order types" are constructed which represent at least 0.1% of the included orders. Eight out of nine simplified order types can be added to the existing order types. After a discussion at DH the choice is made to add these 'simplified' OTs to the already created OTs. This is found more useful than leaving these orders out of scope.

Now the simplified order types are added this results in the following OTs, as can be found in table 5 and 6.

Type	ADR	ISO	High	Heating	Min-Max	Baffles	Allowed TC types
1	X	1	0	All + no	X	X	4,10,11
2	X	1	0	Steam	X	X	10,11
3	x	0	1	X	X	X	17

Table 5: ISO & High insulated order types

Type	ADR	Heating	Min-Max	Baffles	Size	Allowed TC types
4	0,1	All + no	1—1	NR	L	6,7
5	0,1	All + no	1—1	NR	ML	3,6,7,8,9,17
6	0,1	Steam	1—1	NR	ML	6,7,8,9,17
7	0	All + no	1—1	NR	SML	3,4,5,6,7,8,9,10,11,12,17
8	0	Steam	1—1	NR	SML	6,7,8,9,10,11,12,17
9	0	All + no	1—4	NR	ML	1,2,3,6,7,8,9,13,15,17
10	0	All + no	1—4	NR	SML	All types
11	1	All + No & Steam only		Required	SML	7,9,11
12	1	All + No	1—1	NR	S + ML baffles	4,5,7,9,10,11,12,15
13	1	All + no	1—4	NR	S + ML baffles	1,2,4,5,7,9,10,11,12,13,14,15,16
14	1	Steam	1—1	NR	S + ML baffles	7,9,10,11,12
15	1	All + no	1—1	NR	M + L baffles	3,7,8,9,17
16	1	All + no	1—1	NR	S+M & L baffles	7,8,9,10,11,12,17
17	1	All + no	1—4	NR	M + L baffles	1,2,3,7,8,9,13,15,17
18	0,1	All + no	1—4	NR	L	6,7,15
19	1	Steam	1—1	NR	M + L baffles	7,8,9,17
20	0	EG	1—1	NR	SML	3,4,5
21	0	All + no	1—2	NR	ML	3,6,7,8,9,13,15,17
22	0,1	EG	1—1	NR	M/ML	3
23	0	All + no	1—2	NR	SML	3 till 17
24	0,1	Steam	1—1	NR	S+M	8,9,10,11,12,17

Table 6: Final order types

Based on the earlier created OTs and simplified order types, 24 unique usable sets of TCs are formed. Which are used by almost 99 percent of the total included orders. So one percent of the orders is not represented in the OTs. On average an order (included) can be completed by one of 7.24 different TC types. From the TC type perspective there are two TC types which can only be used for three OTs, however these two TC types account for around one percent of the total included TCs. The "hard" order types are the ones where only a few container types are allowed. There are eight order types which can be completed by three or less container types. As can be seen there are two OTs which can only be completed by one specific TC type. These are the most "demanding" order types included.

A quick check for demand over time for each order type resulted in the exclusion of one order type which received almost no demand during 2015. For this order type no forecasts will be made.

The OTs presented in table 5 and 6 will be used for forecasting. In the next chapter the data is divided over the regions. Demand and deliveries of these OT/region combinations will be forecasted.

5.2.3 Available data/limitations

All characteristics used (except volume/quantity) in the creation of order types are based on the SPO data. For a very small number of orders (based on a random sample) there is a difference between the PO and the SPO, but for DH the increased accuracy did not outweigh the effort required to adapt their information system to be able to include this data. It was also not possible to receive data about less/more loading allowed.

There was no data/tool available to validate which tank containers (types) are allowed for each order. The container types DH uses are also a simplification from reality. This thesis has as main purpose to be a case study whether it is possible to use forecasts to improve decision making, and thereby save costs. The order types are therefore made with the characteristics in mind of the container types and validated with the knowledge of planners.

5.3 Prepared data: combinations

After the data preparation/aggregation steps are finished, the combinations order type/region can be viewed. These combinations will be used as input for forecasting. As posed before DH has not one product on one location which has to be forecasted, but different order types which can be completed by unique sets of container types in different regions. Based on the number of orders per combination groups are created. Table 7 shows the five different groups. Group A contains the combinations with the lowest number of orders and E with the highest number of orders. The best forecasting accuracy is expected for group E. In total there are 373 loading and 442 delivery combinations included.

Groups (based on the # orders)	*A*	*B*	*C*	*D*	*E*

Table 7: Groups based on the number of orders per combination

Based on the number of orders at a combination a first selection is made. The data is viewed again to gain insight in whether the demand is stable, contains as trend, shifted, stopped, or started in the period of investigation. This resulted in a number of combinations which are excluded from the study.

5.4 Answer sub question 1

After the data preparation step, sub question one can be answered. How should the data be prepared? To be able to capture the flexibility in assigning a TC to an order, order types are created. Based on previous research by (Jansen, 2014), the data is aggregated based on time in weeks. The third factor to prepare the data is the location where the order originates/ends. This should be into regions, tank containers are often stored at a depot in a region or require cleaning at a cleaning station before being able to complete the next order. The regions used for aggregating are regions used by the company. To conclude, the data is prepared based on time in weeks, based on location in regions and based on demand in order types. These combinations will be used as input for forecasting

6 Results of forecasting

After the data preparation step is completed, the forecasting process can begin. First the prepared data has to be evaluated for correctness and special characteristics. (Cowpertwait & Metcalfe, 2009) Suggested to view plots to be able to comment on the data. The first plot that is viewed is shown in figure 6. This figure represents the total orders over the selected period. What can be seen is that the demand is very low at week 1 (as expected, only 2 and 1 workday) and a reduced demand during the Christmas period. This week 1 effect has to be resolved so the forecasts are not affected by this fact. An adjustment could be made to the forecasts when the Christmas period occurs, but this will also depend on the region and order type. A small drop in demand also occurs in the summer holiday, but this is far less severe than for the Christmas period.

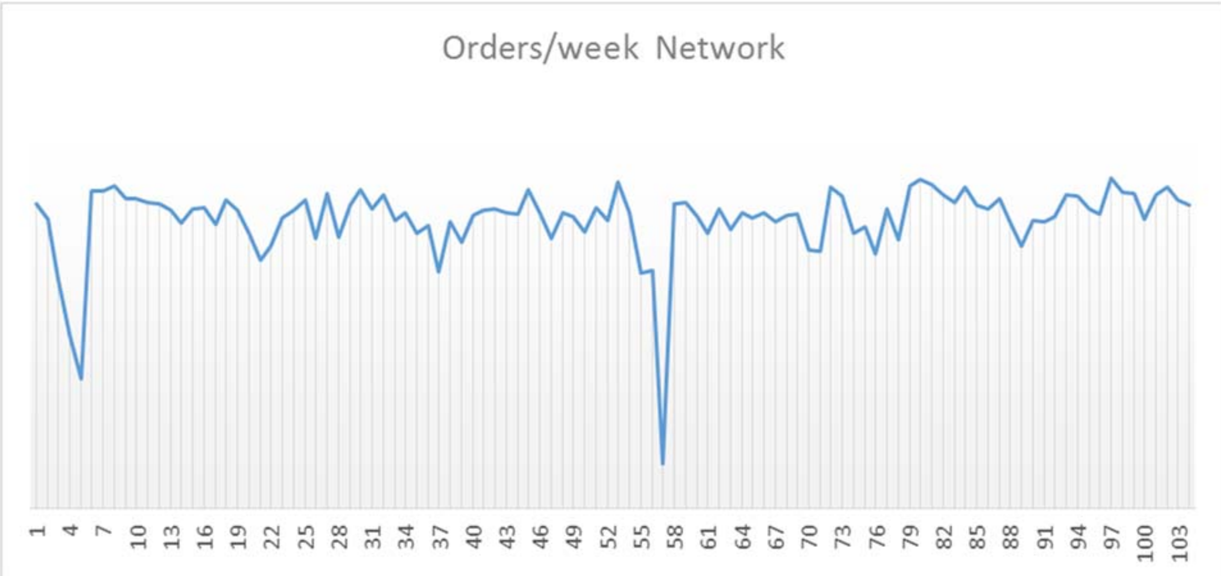

Figure 6: Number of orders over time (total network, not adjusted for week 1)

Figure 6 shows the weekly orders for the total network, so no filters are included. It could be the case that some regions have more or less effect from holidays or have special days which cause less demand in certain weeks. There are some regions where demand increases but also some regions where demand has collapsed, after for example losing an important customer. If this occurs, the forecasts should be updated with this information. Communication between the various departments is therefore of crucial importance.

When a new tender is won, for which orders can be expected often, the forecasts could be updated based on this information. For example, in region X the number of deliveries raise enormously at the end of 2015. Demand in this type of business is not very stable, and new information which has impact on the demand should be included to update the forecasts.

All the forecasts should be rounded to the nearest integer for actual use. Because demand is in whole tank containers. This could result in higher or lower errors as shown. This is also a problem for the combinations with low demand.

It is not possible (even more combinations (Jansen, 2014), CQM) to forecast the movement of orders from one region to another. In this thesis the loadings and deliveries in a region are going to be forecasted. So each order is separated in a loading and delivery part. DH has three sorts of possible uses for the forecasts.

DH could develop a tool to guide the planners in the process of assigning a tank container to an order, which takes the required containers in a certain region and the required containers in their own region based on forecasted order types into account. Planners could use this tool to see the effect (on the "balances" in the sending and receiving region based on forecasted supply and demand and currently available containers in the regions) of sending a specific container to a region.

Another way the forecasts can help DH, is to use them to get new planners acquainted to the demand for order types (and thereby containers) in other regions than their own. A planner works often only on his/her own region and does not have a detailed understanding of the demand in other regions. If he/she just picks the nearest possible tank container, this could result in high repositioning costs in other regions. By using the knowledge of forecasted demand the planner can form an improved understanding of what order types (containers) are required in other regions.

If the effect of using forecasts has proven to be beneficial in reality, then the most complex step could be to add forecasts to the MMP algorithm. In the current situation the planning algorithm takes the orders that have to be planned today and tomorrow into account. The process of assigning tank containers could be improved, when orders can be forecasted very accurate. It is not yet known how accurate the forecasts should be to be able to reduce costs. The most important costs are the empty repositioning costs. The greater the distance the tank container has to travel empty the more expensive. When future demand can be taken into account the planning process can be more optimal in the long run. In the current situation the short term (two days) costs are optimized. In the situation with forecasts the costs over the selected horizon will be optimized.

Note: For confidentiality reasons the MSE presented in this chapter are scaled. The MSE can therefore only be used for comparison of the presented methods.

6.1 Short weeks

The data is prepared based on time in weeks. Earlier in this report the Christmas period is discussed, the length of week 52 and week 1 differs over the years. There are also other weeks which have less than five working days. For example, eastern or ascension is in most regions a holiday. For every region the holidays and thereby the week length has to be determined. For example, in the Netherlands we do not have a holiday at Labor Day, whereas most other European countries have this official holiday. (Armstrong, 1984) recommended to adjust for holidays. For combinations with sporadic/intermittent demand patterns, the difference in week length (four or five days) will not be important.

The first step was to research the effect of the week length for the core combinations (group E). On average the weeks with four workdays had less demand than five day workweeks. But for Belgium on the two years' dataset there are thirteen weeks with four workdays (excluding week 52). For the region Netherlands only eight weeks had a four-day workweek (excluding week 52). At an example combination OTx/Belgium, the average demand at a four-day workweek was, 84 percent. With a low of 52 percent and a high of 150 percent.

The demand will be adjusted for the week length as follows, $D_t * (\frac{average\ number\ of\ work\ days\ per\ week}{Number\ of\ workdays\ week\ t})$. This value is then used to fit the model. Afterwards, the forecast will be adjusted back for use. $Fadj = F * (\frac{number\ of\ workdays\ week\ t}{average\ number\ of\ work\ days\ per\ week})$. This type of calendar adjustments was based on the month length adjustment (trading days) presented in (Hyndman, 2013).

The adjustment for week 1 should be seen separate from the adjustment of 'normal' (4days) short weeks. Table 8 shows the differences in accuracy, for a sub set (for the most important regions) of time series (group: E) with adjustments for only week 1, compared to short week adjustments (based on SES).

	Training			**Validation**		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
W1	100.00	27.65	25.59	87.83	26.76	25.63
Week length	101.27	27.33	25.66	89.67	27.12	25.97

Table 8: Effect week length adjustment for subset of group E

From table 8 can be concluded that on average (for group: E) no significant improvements are possible. So differences are small. Therefore, only demand for week 1 will be adjusted. The extra data preparations required for taking short weeks (week length) into account do not result in significant accuracy improvements. It can be the case that for some regions and some short weeks adjusting the number of orders can result in improved accuracy. With the limited amount of data, and thereby the length of the validation set no further adjustments will be made.

	Training			**Validation**		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
W1	100.00	46.80	41.81	178.38	48.77	48.85
Week length	100.09	47.24	43.23	180.36	48.93	49.75

Table 9: Effect week length adjustment for subset of group D

In table 9 the average effect of the week length adjustment for most of the combinations of group: D is presented. As can be seen there is no real difference. Again adjusting for short weeks will not result in a significant improvement, therefore this process is not continued. For combinations with a low number of orders adjusting for the length of the week is also not helpful.

A general rule where the demand is adjusted with the length of the week will not result in an average accuracy improvement for the group. As seen in table 8 and 9 on average no significant improvement is possible, it seems that adjusting for short weeks has a negative effect on forecast accuracy. Therefore, the demand will not be adjusted for the number of working days per week (except week 1).

6.2 Trends

For the purpose of forecasting it is important to know whether there are long term trends in the network. There are 373 loading combinations. For the smallest combinations no trend can be fitted. For some other combinations trends can be found, these are only a small percentage of the total. There are decreasing as well as increasing trends found in the network. There are also examples where at first an increasing trend could be fitted, but after a sudden point the trend changed into a decreasing one or demand stabilized.

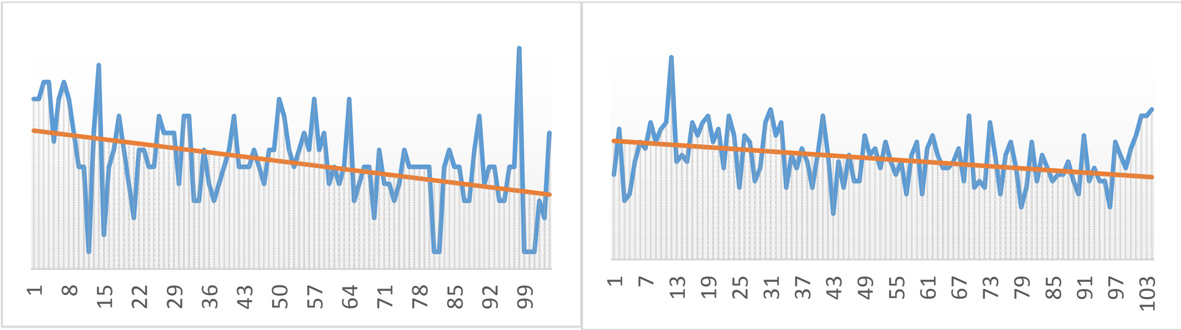

Figure 7: Examples of a decreasing trend

As can be seen in figure 7 a decreasing trend can be fitted to the presented combinations (based on t 1-88). We cannot assume that this (linear) trend will continue. As can be seen in the right graph of figure 7, it looks like the trend (fitted on the training set) is broken in the last few periods. This trend change can be the cause of newly acquired orders via a tender.

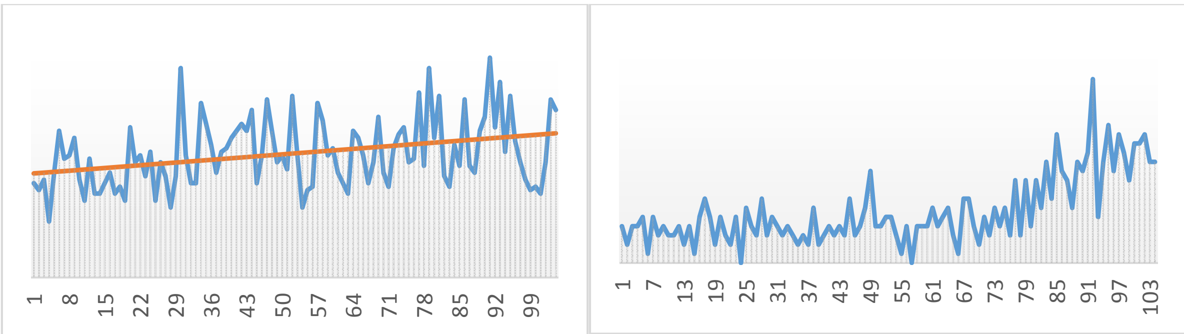

Figure 8: Examples of an increasing trend/demand

The left graph of figure 8 shows an increasing trend found for a combination. But again in the validation period it looks like there is a deviation from the trend. This decrease in demand is probably caused by a production stop at an important customer. For this kind of business, it is probably better to use a method like Holt's to take the trend into account instead of removing the trend by decomposing the time series. The graph on the right (figure 8) represents another combination. At first the demand is relatively stable, where around t = 70 a trend starts. This trend probably ends at t = 97 where the demand stabilizes at a new level.

6.2.1 Answer sub question 2

Are there long term trends in the network?

If the data is used as prepared for forecasting, then region/order type combinations are used as input. DH (and most likely other specialized LSPs) works with tenders which are valid over a duration of often one or two years. Tenders are a part of the demand, there are also numerous spot orders. The most obvious shifts in the number of orders are caused by the fact that an important customer is lost (end of a tender) or a new tender is won, and thereby a new important customer is acquired. This knowledge is available at the quote/account management department. If they know that a significant customer (tender) is lost/acquired the forecasts should be updated based on this information.

In the numerous data sets there are some significant trends, increasing as well as decreasing number of orders. As discussed in the previous paragraph it is dangerous to assume that the trend will continue in the future. It is therefore important that the forecasting methods use no 'fixed' trend. For the combinations where a trend is present, removing the trend is not the best solution. This can be seen when the validation period is considered. The plots show an increasing error because the model assumes the forecast will continue in the future. Therefore, it is better to use a more flexible trend estimation, such as Holt's method.

Another factor that has to be taken into account is the number of available tank containers (is fairly constant, only changes when old TC are discarded or new are bought), this will limit the number of orders that can be completed. In some special cases, orders have to be rejected/sold because it is not possible to complete them with the current number and distribution of TCs.

The increases and decreases in demand per combination are often shown by shifts in demand or short trends. In paragraph 6.3 special patterns such as shifts are discussed, also a method designed to react on shifts in demand is discussed.

To conclude: there are some long term trends in the network (order type/region level). But these trends are not likely to continue for a long time. Mostly demand fluctuating around a constant level, short trends, and shifts in demand.

6.3 Special patterns

Some of the combinations have curious patterns which the (traditional) statistical methods used cannot predict accurately. An example of such a pattern can be found in figure 9.

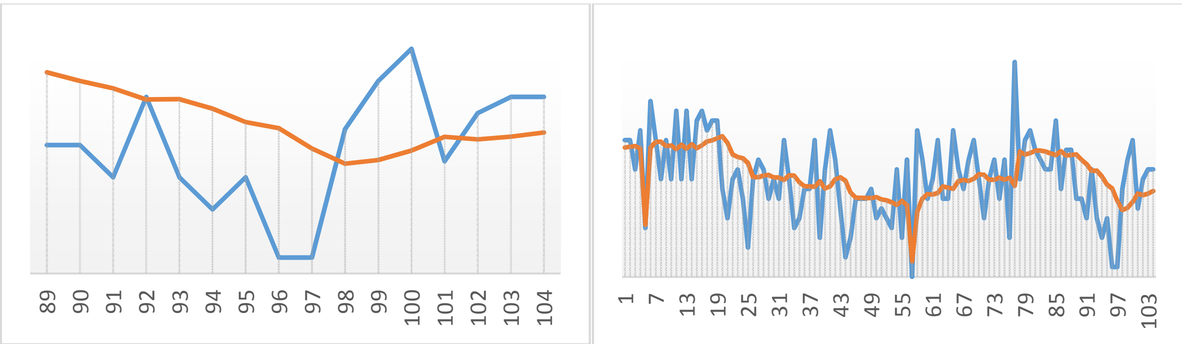

Figure 9: Example of demand vs. forecast for a combination with a special pattern

As can be seen from figure 9, the demand is non-stationary in original form, and therefore differenced for forecasting. In the validation period a steep decline in demand can be found. The forecast lags behind this decline in demand. If the reasons for a decline in demand are known in time, then this information could be used to update the forecasts. A first step to search for reasons why demand decreases is a lane analyses. At the lane analyses the combination of loading and delivery location can be viewed. The decrease in demand from t = 88 to t = 97, is caused by reduced demand till a production stop at the two largest lanes/customers (for this combination). This information is often not available or known in time. In case of a large customer where they have a long standing working relation with a production stop is usually announced. In such cases where demand was significant the forecast could possibly be updated to take this additional information into account. For the combination presented in figure 9, no information was available if and when this production stop was known. The head of the planning department reckons that around fifty percent of these cases is known in time or shortly after the production stop.

Another obvious low and peak in the demand is at t = 75 and 76, which corresponds to week 20 and week 21. This is probably caused by the fact that week 20 and week 22 are short weeks. But in general an adjustment for short weeks did not result in significant improved accuracy. In paragraph 6.5 adjustments are suggested based on additional information available. In this paragraph the adjusted forecast for the combination shown in figure 9 is presented. As can be seen the peak in orders at t = 76 was already known some time upfront.

Another characteristic that can be seen from figure 8, is the fact that there are ‘shifts’ in the level of demand. In the literature there are some methods presented to monitor the forecasts made, think of methods by (Trigg, 1694) and (Harrison & Davies, 1964). In the more recent literature the smooth transition exponential smoothing (STES) method was introduced (Taylor, 2004). The STES is used in this thesis. This method uses an adaptive alpha for the exponential smoothing method.

$$\alpha_t = \frac{1}{1 + \exp(\beta + \gamma V_t)}$$

$$V_t = Transition\ variable = e_t^2$$

For the transition variable the squared error at time t is chosen, this type of transition variable was recommended by (Taylor, 2004).

For the combination shown in figure 9, the STES method resulted in an almost zero value for gamma. Therefore, the alpha can fluctuate slightly depending on the error of the forecast. But the performance of the simple exponential smoothing (SES) method is almost equal. Another example of a forecast made with this method is presented in figure 10. The model had a slightly better fit in the training set than the SES model, but in the validation set the SES model performed more accurate.

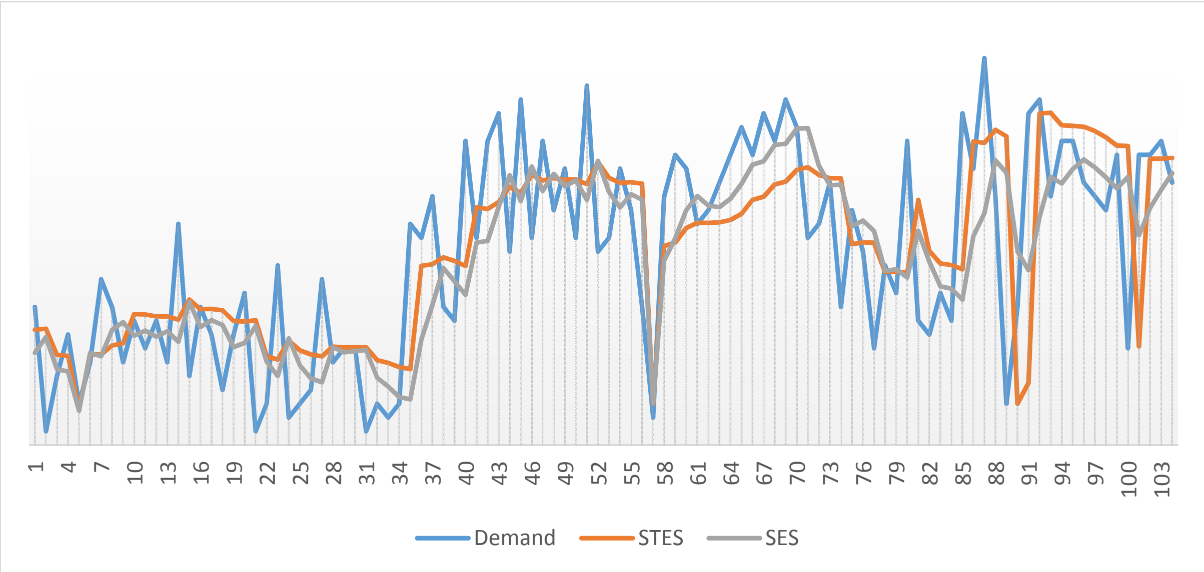

Figure 10: Forecasts of the STES and SES model on a combination with shifts in demand

In figure 11 two other special patterns are presented, at the combination presented on the left, the demand increased by a large amount at t = 29, another peak in demand at t = 43 from which the demand declined till t = 62 where it became less volatile for a short period. The forecast is made using the STES method and for week 1 adjustments are made. In the picture on the right (figure 11) the demand suddenly stopped at the start of 2015, in this case more information would have been available at DH, in equal situations the forecasts should be updated with this information in mind.

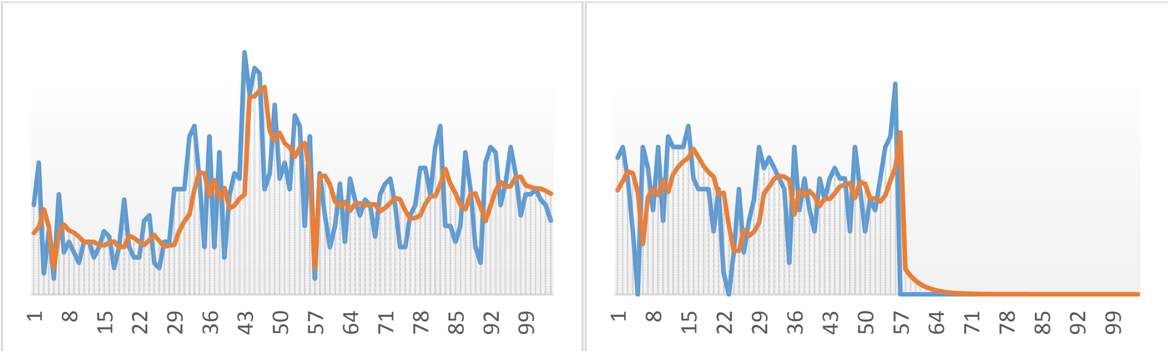

Figure 11: Shifting patterns over time.

6.4 Difference in performance between forecasting methods

As presented previously various forecasting methods will be used to forecast orders at DH. The total length of the data set is 104 weeks, where the last 16 weeks form the validation set. At DH there are numerous combinations that require forecasting. It is not possible to show every forecast made in a short paragraph therefore the results are shown per group. Table 10 shows the accuracy achieved by various forecasting methods for group: E, for a couple of error measures.

	Training			**Validation**		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
Ses	100.00	27.14	25.18	113.98	27.19	26.11
ARIMA	96.76	26.81	24.63	113.93	27.15	26.08
Ann	89.77	25.53	23.65	156.86	30.00	28.88
Ann (h1)	105.24	27.61	25.74	159.00	29.89	30.17
Hybrid	87.58	24.75	23.27	117.25	28.22	27.13
Combined(4)	88.52	25.45	23.56	114.22	26.78	25.71
STES	98.90	27.01	25.11	115.04	27.96	26.67
Combined(5)	89.60	25.67	23.74	111.65	26.71	25.64

Table 10: Overall accuracy of different forecasting methods (group: E)

In Table 10, the average result of two simple (SES and STES) methods is shown. Between these methods the SES method performs best on average but the differences are small. The STES method becomes the SES method if gamma is set to zero. Only in special cases where often shifts in demand are expected the STES method will result in improved accuracy.

Another popular method used in the literature is the ARIMA method, the accuracy of this method is slightly better than the forecasts made with the STES method but differences are only very small. Compared to the exponential smoothing method the accuracy achieved with the ARIMA method is almost equal. For the ANN method two different versions are used, one with a hidden layer size of 1 (commonly used (Turban, Sharda, & Delen, 2010)) and one with hidden layer size of 10 which is the MATLAB default. In case h = 10, the model performs more accurate in the training set compared to h = 1, in the validation set the differences are less clear. Based on the MSE, h = 10 performs slightly better, but based on the sMAPE the forecasts made with h = 1 are more accurate. Using h = 1 will result in more stable forecasts compared to h = 10.

The hybrid method uses two separate methods, first the ARIMA is used, and second the ANN method is used to forecast the residuals of the ARIMA method. As can be seen in table 11, during the training set the best performance is achieved, in the validation set this method forecasts more accurate than both versions of the ANN only, but using only the ARIMA method is superior during the validation set. Figure 12 shows a forecast made with the hybrid method for a large combination.

The average accuracy of the forecasts can be improved slightly when per combination the best method is selected. However, this result does not outweigh the increased complexity in the forecasting process. Manually selecting the ‘best’ method can therefore not be recommended.

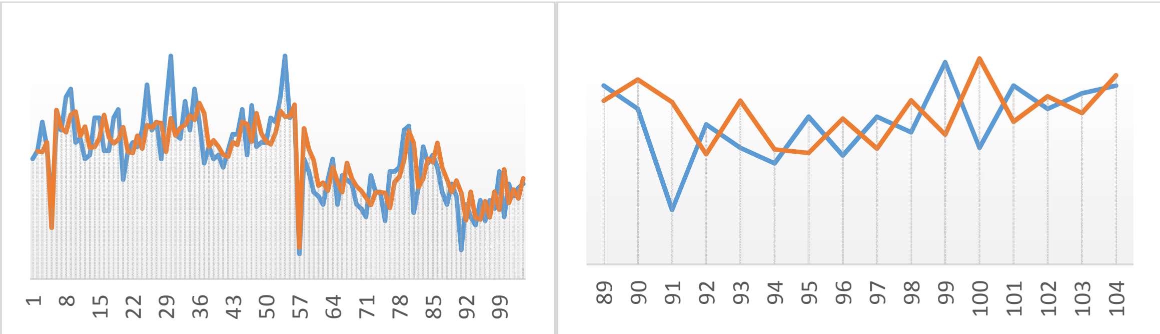

Figure 12: Forecast for a group: E combination with a shift in demand, hybrid method.

The sixth presented method is the combined method where, the methods, SES, ARIMA, ANN and Hybrid are combined via simple averaging. This method will result on average in the best performance (sMAPE), but differences during the validation set are very small.

For most companies it would be preferred to automate the forecasting process with a simple method, preferably implemented into Microsoft Excel. The methods SES and STES are easy to implement. They have good performance and can be easily understood by people unexperienced with forecasting.

	Training			**Validation**		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
SES	100.00	46.74	42.06	165.47	49.05	48.79
ARIMA	97.31	46.29	41.22	163.14	48.65	48.34
ANN	84.39	44.14	38.72	241.26	57.70	54.11
HYBRID	83.23	42.97	37.78	221.08	54.09	54.03
Combined	85.92	44.22	39.09	178.03	49.75	49.75

Table 11: Overall accuracy of different forecasting methods (group: D)

In table 11, the accuracy of the forecasts made for group D is presented. The simple exponential smoothing method (once Holt) performed relatively constant. The performance in the training set was based on all three error measures the least accurate, but differences are small. However, the performance at the validation set is second best. The SES method is less ‘over fitted’ than the more complex methods. The more sophisticated ARIMA method was for eight combinations an ARIMA (0,1,1) which is comparable with the SES method. The forecasts in the training set as well as in the validation set are slightly more accurate compared to the SES method. The ANN method performs most accurate in the training set, but also the least in the validation set. Therefore, the ANN method is not a good method to use in these situations. For the hybrid method, where in step 1 an ARIMA model is fitted and in step 2 the ANN method is used to forecast the residuals, the performance is again improved compared to the ANN method alone. As with group E the performance of the ARIMA method is more constant than the forecasts made with the hybrid method. Figure 13 shows a forecast made with an ARIMA model for a combination with volatile demand.

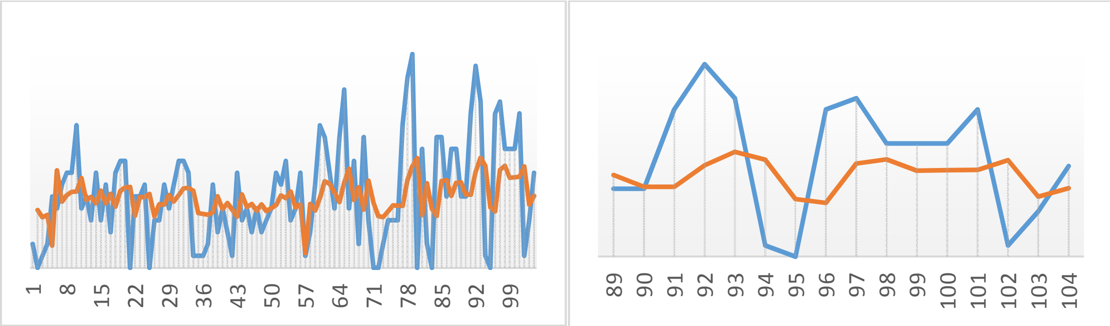

Figure 13: Forecast with an ARIMA model for a combination with volatile demand.

As can be concluded from table 10 and 11, there is not much difference in accuracy between simple and advanced methods. Therefore, the simple methods are preferred. Selecting the 'best' method for each individual time series results only in a minor improvement.

It is interesting to see how the previously used methods perform on the group C. As can be seen from table 12, in the training period the advanced methods perform slightly better than the simple methods based on the MSE criteria. In the validation set the ARIMA method is the best performing single method, the SES method became second. Selecting the best method for each time series results in a small accuracy improvement. But as posed before this cannot be recommended for DH.

	Training	**Validation**
Method/EM	MSE	MSE
SES	100.00	114.71
STES	100.00	123.53
ANN	82.35	138.24
ARIMA	88.24	108.82
Best of four	79.41	105.88

Table 12: Average MSE per method for group C (large subset)

There are also numerous combinations with less than once a week demand. All these time series have at least 24 weeks with zero orders, and can therefore be classified as having intermittent or lumpy demand. As shown in the literature chapter, special forecasting methods are recommended. One of these recommended methods is the ANN method. For this thesis the ANN method is used to set a benchmark forecast. These forecasts are presented in paragraph 6.6.

6.4.1 Answer sub question 3

Is the performance of simple forecasting methods (exponential smoothing and moving averages) equal or better than more advanced methods (ARIMA and ANN)?

This question will be answered based on the averages of groups D and E. It will also depend on which type of error measure is used. On average the performance of the ARIMA method is slightly better than the performance of the simple methods, but differences are very small. The ANN method performs better during the training set, but slightly worse during the validation set, this method can therefore not be recommended for forecasting orders at DH. Combining forecast can result in slightly improved accuracy, but instead of one forecast, various forecasts have to be made for each combination and a combination step is required.

At group D again the ARIMA method performs slightly more accurate than the simple methods. Also for this group the ANN method cannot be recommended. At group C, which is the smallest group forecasted with the 'traditional' forecasting method again ARIMA performs overall best. But differences are small.

To answer the sub question, the performance of simple methods is not better than advanced methods as ARIMA can replicate the behavior of the exponential smoothing method (ARIMA (0,1,1)). In most cases the performance of simple methods equals the advanced methods. As the name already suggests the simple methods are easier to implement. For companies like DH with only basic forecasting skills, and no advanced forecasting programs, forecasting methods such as moving averages and exponential smoothing are preferred as they can be generated even in Microsoft Excel. So no additional software packages have to be bought. Also MS Excel data can be easily loaded into other information systems, so the forecast can be automatically generated and loaded so the required information can be used without manual interference.

Another advantage of the simple methods is the fact that the t + 2 forecast equals the forecast for t + 1 (In case of MA, SES, and STES, for Holt or Winter's t + n differs). Which simplifies generating the forecasts for the company. This is an important factor, because numerous forecasts have to be generated every week. If only one forecast has to be generated sporadically, then improving a forecast by a couple of percent can outweigh the extra effort required by more advanced techniques.

6.5 Additional information (pre-orders)

Another advantage of using order types instead of actual used containers is the additional information. A significant percentage of the pre-orders is planned on the same day. There is also a reasonable amount of orders known more time upfront. At DH the planners plan orders in general two days upfront. The assumption is made that the pre-orders which are known at Wednesday with a loading in the next week/weeks are not yet fixed. Excel VBA code is written to prepare the data sets to be able to research the possibility of using pre-order information to base/update the forecasts on. (Jansen, 2014) Posed that a part of the demand is already known some time upfront. If this percentage of known demand is stable this could be used as input for forecasting. In figure 14 the fraction of known demand is shown for respectively week t + 1 (left) and t + 2 (right) (loadings). This fraction is fairly stable except for some peaks but these corresponds with the Christmas/new year period.

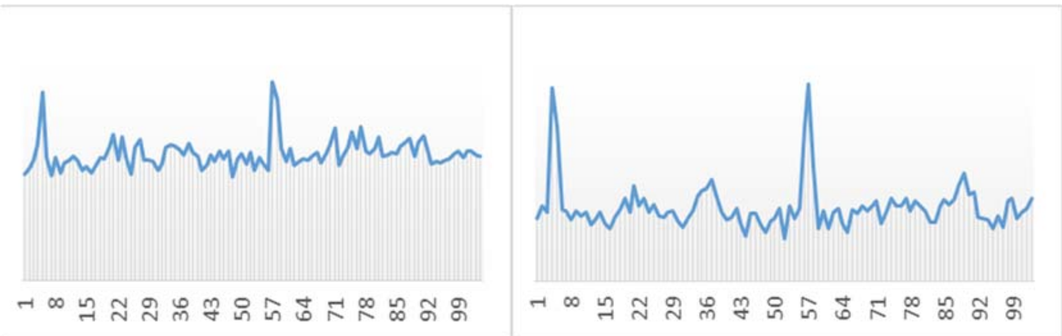

Figure 14: Left: t+1 fraction known, right: t+2 fraction known already.

Figure 14 shows the fraction known of the total demand of the network. The next step is to examine the behavior for the different combinations.

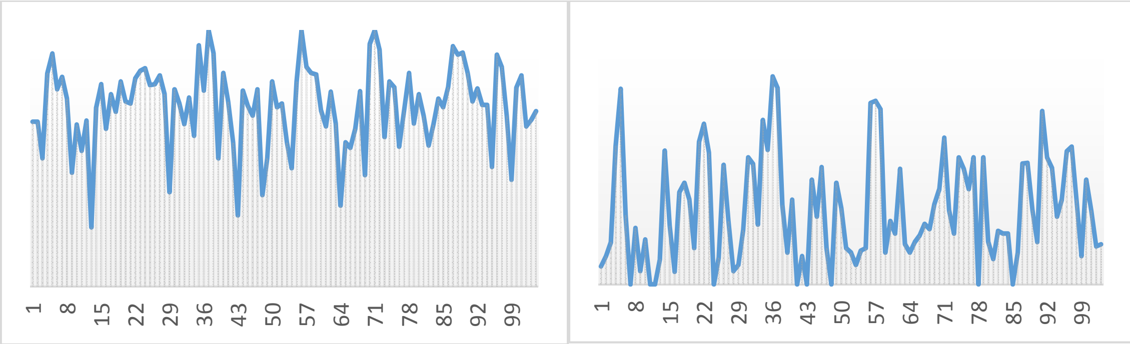

Figure 15: Left, shows the already known fraction t + 1 for a combination where already a large fraction is known upfront. R: fraction known for t + 2 at the same combination.

The left graph presented in figure 15, shows the fraction known for combination X, for week t+1, the right picture shows the fraction known for week t + 2. The combination shown in figure 15 represents a fairly large combination. As can be seen in figure 15, the fraction of demand known is far from stable. It is less stable than the actual demand, therefore using PO data as input for forecasting will in general not improve the accuracy of the forecast. In this report only one combination is presented, for this thesis, this information is generated for all combinations. In figure 16 for two large combinations the actual orders vs. the already known pre-orders for week t + 1 are presented.

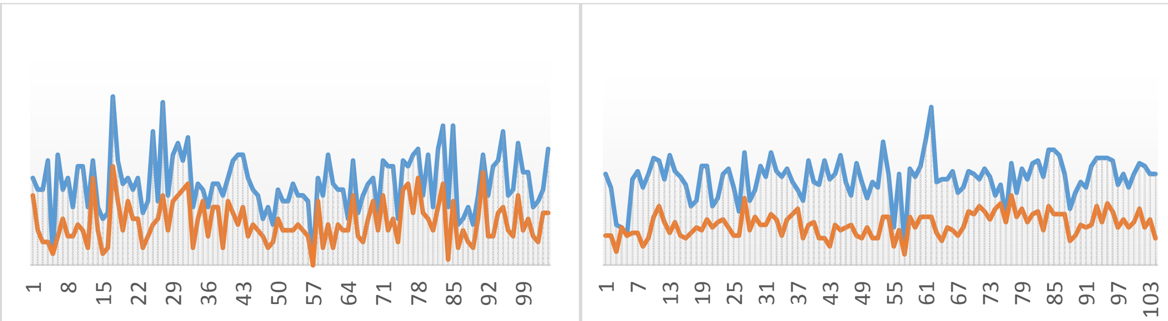

Figure 16: Already known pre-orders for week t + 1 for a large combination

As can be seen some peaks are already known some time upfront, if the forecast is lower, then the forecast could be updated with this information in mind. (Nahmias, 2009) posed that a forecasting method should not exclude known information. Therefore the forecasts should be updated with known information. By updating the forecasts, the accuracy improves. In the next paragraph, the effect on group E, earlier presented is discussed.

For week t + 2 not much information is already known, but in some cases, where peaks occurred, a large percentage of the orders was already known. Therefore, also for the t + 2 case, forecasts could sometimes be updated by using the already known pre-orders. Figure 17 shows the known orders for week t + 2. In most cases the forecast will do a better job, but for example at t = 58 the forecast could be lower than the already known pre-orders. Therefore, forecasts should always be checked against the already known pre-orders, and updated if necessary.

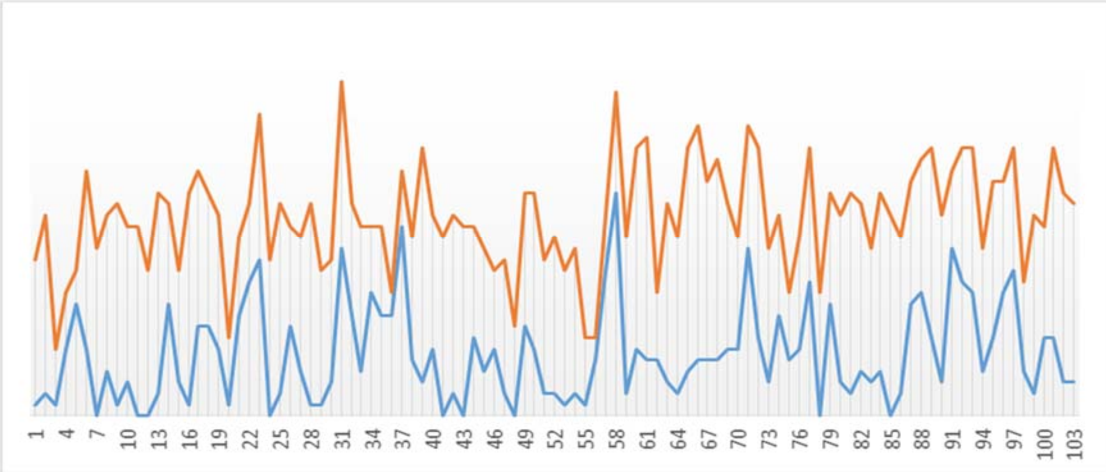

Figure 17: Pre-orders known for week t + 2 for a large combination

6.5.1 Fraction forecast

For some combinations using the fraction of known orders as input for forecasting instead of actual demand can lead to improved accuracy. As posed in the previous sub paragraph, in most cases the fraction of demand known for week t + 1 is less stable than the actual demand. For week t + 2 the forecast has to be based on historical demand. The forecasts presented in figure 18 are generated with the simple exponential smoothing method (based on the fraction of known orders).

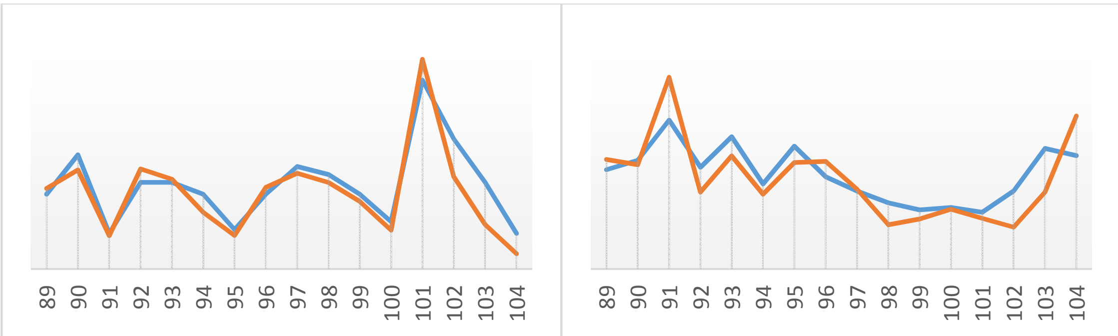

Figure 18: Two examples of forecasts based on the fraction of known orders.

Forecasting based on the fraction of known demand, is more volatile. It is important to monitor the forecasts. So in case of large errors, the forecast can be adjusted manually. In general, the fraction known on combination level, is not stable enough to be used as input for forecasting. Using the fraction of known orders can therefore not be recommended as input for forecasting.

6.5.2 Updated forecasts

Based on the pre-order information the forecasts can sometimes be adjusted upwards if in special cases more demand is already known than forecasted. In table 13 the effect on group E is presented for forecasts made with the SES method. For this group the smallest effect is gained.

	Training			**Validation**		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
Ses	100.00	27.14	25.18	113.98	27.19	26.11
SesUpd	91.23	25.57	23.69	100.29	25.97	24.66
Difference (%)	-8.77	-5.78	-5.92	-12.01	-4.49	-5.55

Table 13: Difference in accuracy after updating the forecast with pre-order information (group E)

These updates can be simply made by setting a max function on the forecasts and already known pre-orders. In almost all cases the fraction of the orders already known cannot be used to accurately forecast the actual number of orders. Even for a couple of cases where the accuracy is more accurate based on the accuracy measures, the forecasts are very volatile and therefore hard to use in reality. An example of the differences between a fraction forecast and an updated simple exponential smoothing forecast is presented in figure 19.

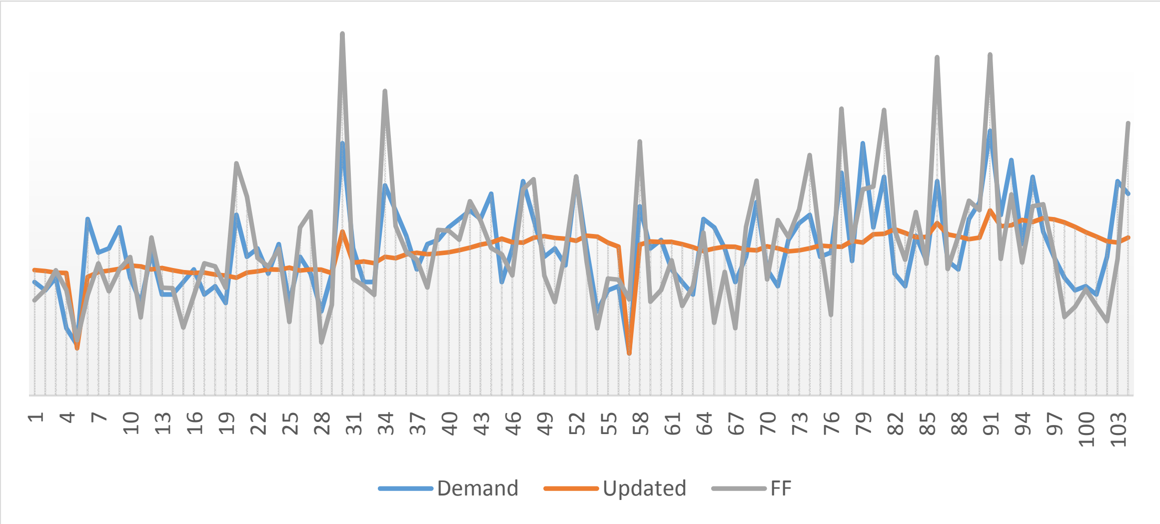

Figure 19: Demand, SES-updated and fraction forecast for combination X

For most of the smallest combinations (group A) the 'forecasts' will be solely based on the pre-order information because statistical methods cannot forecast most of these combinations accurately. These will not be actual forecasts, this information is already known and is the lowest number of orders which can be expected for the next week. Therefore, these forecasts will be biased downwards on average.

The effect of updating the forecasts for week t + 1 for group D, is shown in table 14. The SES method is used, updating the forecasts with pre-order information results in approximately a six percent reduction of the sMAPE.

	Training			**Validation**		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
Ses	100.00	46.74	42.06	165.47	49.05	48.79
SesUpd	83.41	43.61	38.15	137.58	46.18	45.03
Difference (%)	-16.59	-6.70	-9.30	-16.86	-5.85	-7.72

Table 14: Difference in accuracy after updating the forecasts with pre-order information (group D)

In paragraph 6.3, special patterns, a non-updated forecast was presented for a combination with a special pattern. With the additional information from this paragraph the forecast is updated, as can be seen in figure 20, a couple of large peaks were already known some time upfront. The sMAPE of the training set is reduced from 30 till 25 percent. During the validation period only one minor update was possible, therefore the sMAPE did not significantly change. Because of the sudden decrease in demand during the validation set, the accuracy is low, with a sMAPE of more than 50 percent. As posed in paragraph 6.3, the decline in demand is caused by the reduced number of orders till a production stop at the two most important customers for this combination. If it was known if and when this information was known by DH, this could be used to adjust the forecast and thereby likely improve forecast accuracy.

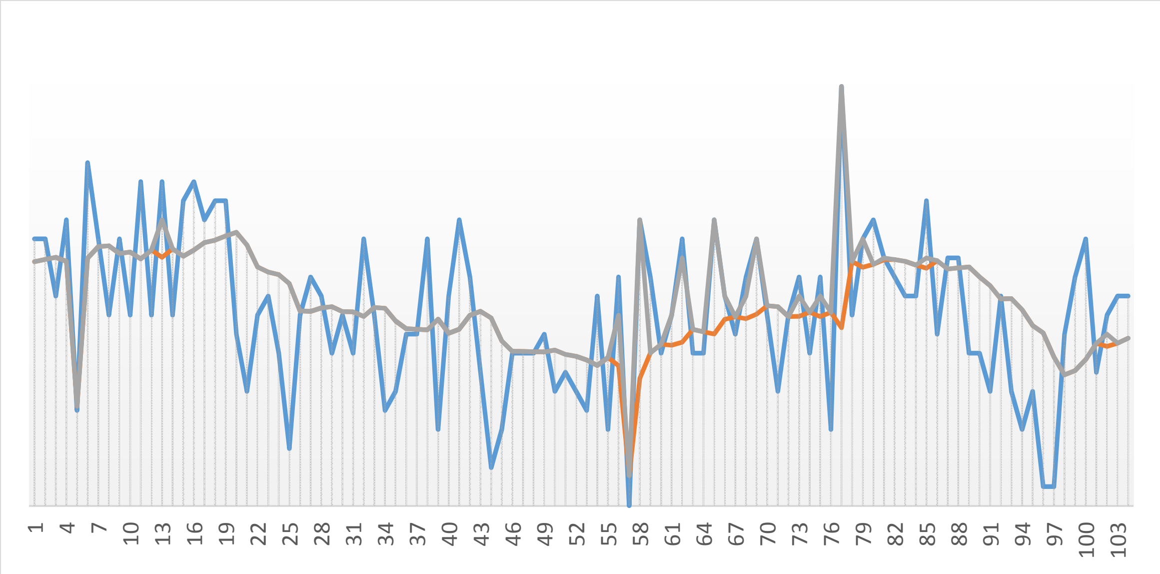

Figure 20: Example of an updated forecast (combination earlier presented in figure 9)

6.6 Sporadic or Intermittent demand

More than 800 different combinations (loading and delivery) are created. Numerous of those have only a low number of occurrences. The accuracy of traditional statistical methods on time series with sporadic or intermittent demand patterns is limited. As presented in the literature section, there are some methods which are specially designed to forecast time series with intermittent or lumpy demand. In this thesis the ANN method will be used to generate the forecasts.

A time series is classified sporadic or intermittent if at least 24 percent of the time there is zero demand. For various combinations made, at least 90 percent of the time zero demand was received. If these are forecasted with statistical forecasting methods this almost always results in a forecast of zero orders. As seen in paragraph 6.5, if there are already some pre-orders known, the forecast can be updated. In figure 21 an example is presented.

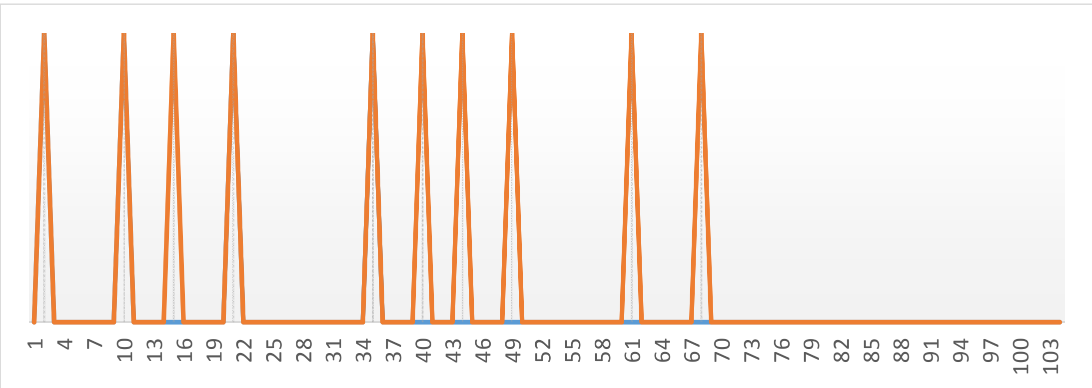

Figure 21: A combination with only ten orders over time.

As can be seen in figure 21 there is ten times one demand. The traditional method forecasted zero orders. With the pre-order information taken into account, four out of ten orders were already known for week t + 1. For week t + 2 no additional information was available, therefore the forecasted demand was just the statistical forecast which is zero in this case.

Group A can be classified as having sporadic or intermittent demand. The performance of traditional statistical methods is poor. Artificial Neural Networks are fitted on these datasets, but in most cases the result is not promising. For some combinations ANN resulted in better performance than just taking the known pre-orders.

For most of the loading combinations of group A, the forecast is zero, if additional information is available the forecast is updated. This means that most of the demand that occurred in these combinations was not forecasted and therefore not anticipated.

By using the pre-orders as input for the expected demand, the 'forecasts' are never too high (so the error will be zero or positive). For the t + 1 'forecast' on average 45 percent of the orders (loadings) of these combinations a pre-order is already known. Fortunately, these combinations account only for a small percentage of the included orders. For the delivery part of the combinations more is already known.

The week t + 2 'forecast' is again set at zero, if there is more information known then this forecast can be updated. Not much orders are already known with loadings in week t + 2. 15.3 percent of the orders is already known for week t + 2. The remaining 84.7 percent of the orders is not forecasted/known for the second week.

There are more deliveries combinations with a low number of occurrences. But there is already more information available than for the loadings. The forecasts can help to gain a better overview of which container types are likely to become available in a region. For the t + 1 forecast, the accuracy achieved (for these low occurrence combinations) with statistical methods was poor. Therefore, the t + 1 prediction, will be the number of known pre-orders of a combination. On average 88.2 percent of the deliveries is already known for week t + 1. As can be expected the percentage known for week t + 2, is lower, 47.1 percent of the deliveries are known. In paragraph 6.9, the deliveries for larger combinations are discussed.

6.6.1 Group B

The combinations at group B have a low number of orders and often periods with zero demand. The demand pattern of these combinations can be categorized as intermittent. For the loading combinations of this range, 47.4 percent of the (pre-) orders is known for week t + 1. Twelve percent is known for week t + 2. These values do not differ much from the smaller combinations. For the deliveries, on average 83.4 percent is known for week t + 1. For week t + 2 this percentage decreases till 47.6 percent.

For most cases no pattern can be found by the ANN or other traditional methods for combinations in group B. However, for a couple of the combinations clear patterns are found. Figure 22 shows an example, the forecast is made with the ANN method, however an ARIMA model performed equally.

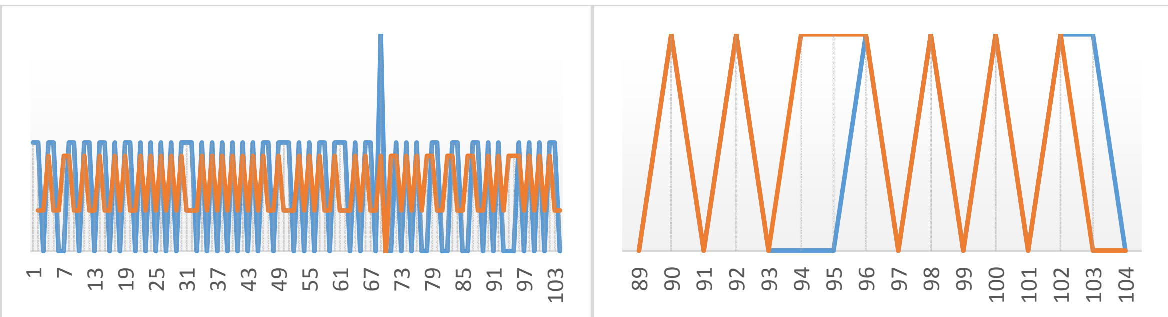

Figure 22: L: Forecast made with ANN. R: rounded forecast, validation period

In most cases the pattern at a small combination is less clear. Therefore, using statistical forecasting methods does not result in accurate forecasts. Figure 23 shows on the left the original ANN forecast and on the right the rounded forecast. In figure 24 the same combination is presented as in figure 23, but for the left graph only the pre-orders are used, whereas for the right graph the rounded ANN forecast is updated with pre-order information.

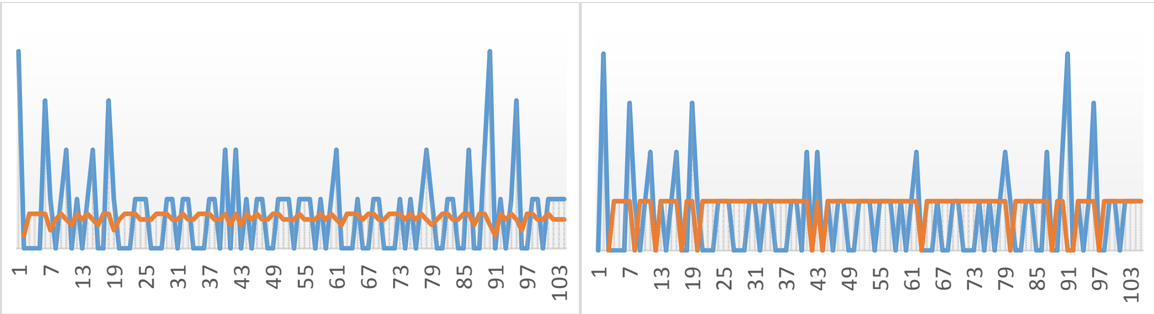

Figure 23: L: Non-rounded and R: rounded forecast for a combination with a low number of orders

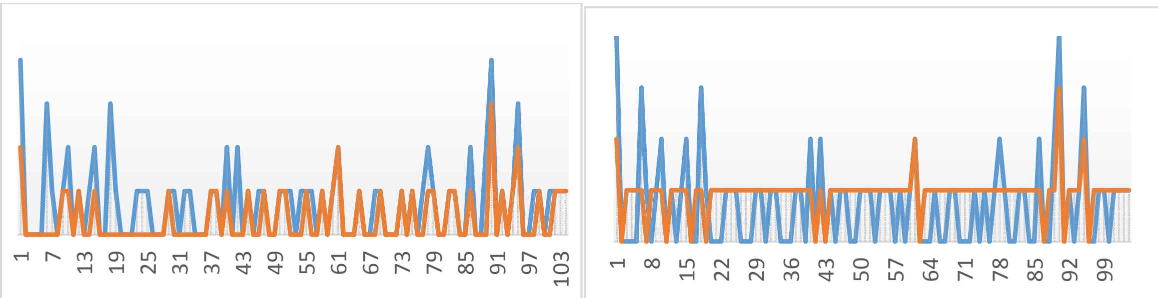

Figure 24: L: Only pre-order information, R: updated and rounded forecast (ANN)

6.7 T + 2 forecast

The accuracy measures presented in the previous paragraphs are based on the t + 1 forecasts. DH is also interested in forecasting the orders for t + 2. Depending on the data structure and method chosen the t + 2 forecast can be equal to the t + 1 forecast (SES). However, updating the forecasts with known pre-order information will be less relevant. Only for special cases this is possible. The pre-orders should always be checked however. Table 15 shows the accuracy achieved by the simple exponential smoothing method. As can be seen there is only a slight difference in overall accuracy between the non-updated forecasts for group E, but on average the forecasts are slightly less accurate. For the smaller combinations the differences are expected to be larger. For these combinations updating the forecasts with known pre-order information occurs more often at week t + 1 than for group E.

	Training			Validation		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
SesT+1	100.00	27.14	25.18	113.98	27.19	26.11
SesT+2	111.96	27.79	26.03	127.10	28.08	27.11

Table 15: Accuracy forecasts T + 1 and T + 2 (group E)

6.8 Starting/ending of combinations

The demand/orders at DH have a flexible nature. There are numerous spot orders. Also DH works with tenders which are valid for a certain length of time. Because of this flexibility, the forecasts should be monitored. Figure 25 shows two examples of combinations where demand suddenly dropped. If a department has additional information about this, the knowledge should be shared, so the forecast can be updated. For the examples presented in figure 25 it is likely that additional information was present. The picture on the right (figure 25) the drop occurred after the year 2014 ended, most likely a tender ended and no new one is agreed on or the new orders had some different requirements and therefore belongs to a different order type.

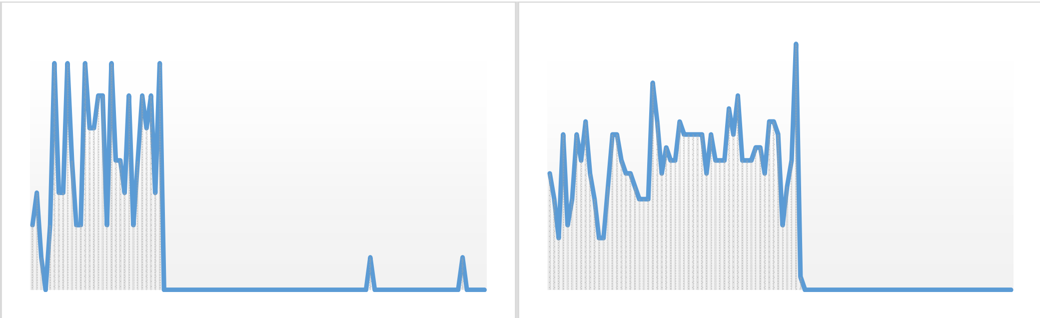

Figure 25: Example combinations where demand dropped/ended

A problem with this is for example, a combination has on average a demand of five orders but also five different account managers. Also the account managers do not yet know the order types, but only know the historical orders by their customers.

For the network it is of importance that the different departments work closely together. If an information system could be developed to share important information easily with the different involved departments this could be helpful. In the current situation information about losing a customer, will likely only happen in case of a large customer. Monitoring forecasts is therefore of importance.

In the examples of figure 25, the demand suddenly (almost) ended. The other way around is also possible, figure 26 shows a combination where no forecast was made for. Only at the end of the training set demand occurred. It is thus possible that demand will start at new combinations.

Most forecasting methods are based on the assumption of stationarity. Also to make a reliable forecast the data is split into a training and validation part. For these situations where a combination just starts having demand, it is not possible to make use of the traditional methods. The known pre-order information could be used to acquire an indication of the number of orders. Depending on the pattern of the demand, a mean or random walk model could be used to estimate future demand. Till a certain moment in time where enough historical data points are gathered to use another method.

Figure 26: Combination where demand starts

As presented in paragraph 5.2, order types, not all possibilities are generated. Only the 24 largest order types are used. It is not very likely that the demand will shift far outside these 24 order types. But the fraction of the total demand categorized as one of these 24 order types should be monitored.

6.9 Deliveries

DH is also interested to know the number of deliveries of each order type in a region. For this type of forecast already a large fraction is known, therefore for week t + 1 this will not really be a forecast. As can be seen in figure 27, the week t + 1 'forecast' has a high accuracy. There are a couple of options, first fit the statistical method on the time series, and if necessary update the forecasts upwards.

After some research the best way to 'forecast' deliveries in week t + 1, is by using the already known pre-orders. More than 86 percent of the orders on average is already known/planned. It should be kept in mind, that for numerous of these orders the actual TC is already assigned to the order. But in this way a clearer overview of incoming order types/TCs into a region can be obtained.

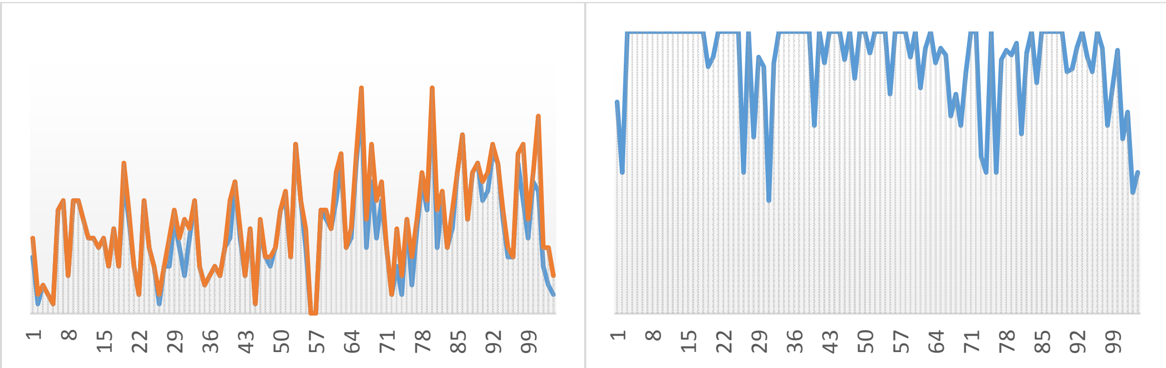

Figure 27: Delivery combination X vs. already known pre-orders t + 1, fraction known.

The expected deliveries in week t + 2, cannot be based on the already known pre-orders as done with the t + 1 forecast. Therefore, these will be based on the forecasts made with statistical methods. If possible updated upwards with information from the pre-orders. An example of the deliveries known for week t + 2 is presented in figure 28.

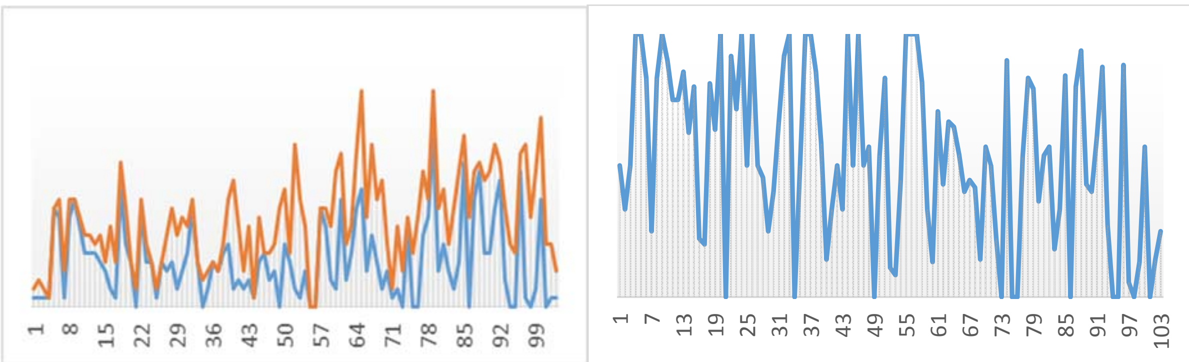

Figure 28: Delivery combination X vs. already known pre-orders t + 2, fraction known.

In table 16 the t + 2 forecasting results are presented for group E. Table 17 shows these results for group D. These results are achieved with the use of the simple exponential smoothing method. In table 16 and 17 the accuracy for the updated forecasts is also presented. On average 86.4 percent of the deliveries for week T + 1 is already known (pre-order and a part already planned). For week t + 2, this is approximately 48 percent.

	training			Validation		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
SesT+2	100.00	29.29	26.90	106.51	27.80	27.07
SesT+2Adj	90.78	26.87	24.03	98.36	26.36	25.46

Table 16: Accuracy of the T + 2 forecast, with the SES method (group E)

	training			Validation		
	MSE	sMAPE	gMAPE	MSE	sMAPE	gMAPE
SesT+2	100.00	48.37	43.35	117.86	45.43	42.38
SesT+2Adj	81.33	44.67	39.07	90.22	41.96	37.88

Table 17: Accuracy of the T + 2 forecast, with the SES method (group D)

6.10 Achieved accuracy of the forecasts

In paragraph 6.4 the forecasting accuracy for two largest groups (D and E) is presented. Group C consists of several combinations. Not all methods could be fit without violating some statistical tests. For those combinations using the pre-order information can help to gain some insights. For some combinations there are a couple of weeks with zero demand, if the forecast is higher than zero, the sMAPE has value 200. So this influences the overall statistic. The MAPE by (Gilliland, 2002) however takes the total error in a set dividing by the total demand. Which results in an easier overview. The average gMAPE for the t + 1 forecasts for the total group (group C) is approximately 50 percent for the updated t + 1 forecast. For the non-updated forecasts this value ranges between 60 and 70 percent, depending on the method used and training versus validation set.

For the smallest combinations in general no useful forecast can be made. To have some information the pre-orders will be used. For these orders, for week t + 1 on average 45 percent of the orders are known, this will result in an average gMAPE of 55 percent. Keep in mind that this information is on average biased downwards. Also large differences per combination are present. There are combinations where already a large percentage of the orders are known in advance, and combinations such as the one presented in figure 29, where almost no pre-order information is present.

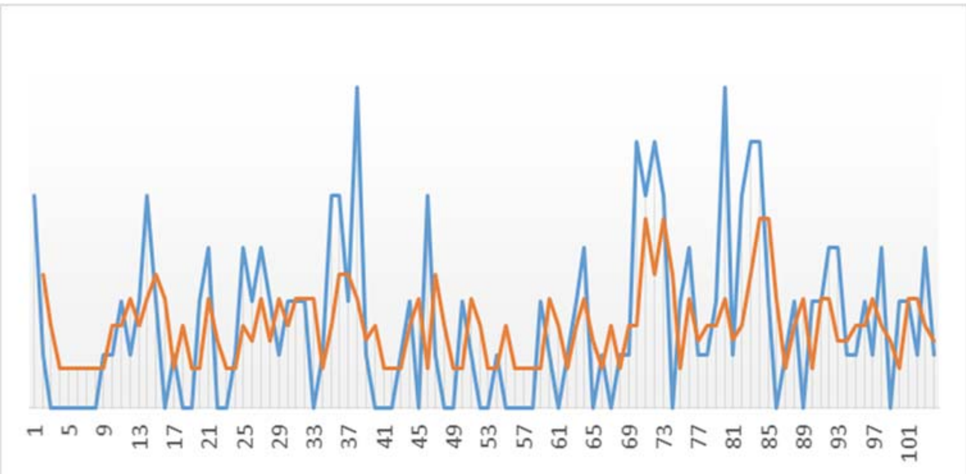

Figure 29: Forecast made with ANN for a combination with a low number of orders (almost no pre-order information was available for this order).

Sub question 4: How accurate can demand be forecasted at the company and what steps can be taken to improve forecast accuracy? To answer this sub question, the demand is categorized in order types/regions. For these combinations weekly forecasts are made. The average error achieved (t+1) with the available information and methods used is around 36 percent based on the (g)MAPE. This is a relatively high error and therefore a relatively low accuracy can be achieved. As shown before DH has numerous different combinations, therefore total demand is divided by a large number. This results in numerous small combinations which are hard to forecast. The variance of the demand at DH on combination level is high. The overall pattern for the larger combinations can be followed/predicted by statistical methods, but the fluctuations around this level are in most cases difficult to predict. For the smallest groups the forecasts made have a very low accuracy. For the t + 2 forecasts the (g)MAPE will be higher, because less information is available to take into account.

The following steps could be taken to improve forecast accuracy. If information about a production stop at an important customer becomes known, this should be saved. The date and time of the production stop and when this became known is relevant. This information could be used to manually update the forecasts. Important information should be saved, also the date and time this information became known is relevant. For example, if new orders are acquired via a new tender and a shift in demand can be expected. The other way around is also possible in case a large customer is lost, for example because the tender has ended and no new quote is agreed on. In this case additional information is available and should be used. As posed before relevant information should be saved for future use. If this information can be used, the forecasting accuracy can be improved slightly.

In paragraph 6.4 the accuracy of group E is presented. This group is split in half based on the number of orders per combination. The first half represents the combinations with the lowest number of orders. The second half represents the largest combinations. The accuracy of these different sets is presented in table 18. The forecast accuracy presented is achieved with the simple exponential smoothing method. The overall accuracy is expected to significantly increase when the number of orders (per combination) increases.

	Training		**Validation**	
	sMAPE	gMAPE	sMAPE	gMAPE
Group	27.14	25.18	27.19	26.11
1stHalf	34.42	31.47	35.23	34.03
2ndHalf	23.89	22.38	23.61	22.58

Table 18: Difference in accuracy of larger and smaller half of group E, method = SES.

6.11 Notes on seasonality

As posed before, DH is a specialized LSP for the chemical industry, a large percentage of their work is flexible. Tenders are often valid for one or two years. During this time the customer can use DH services for the requested type of transport for a certain amount. A customer is not obligate to use the services of DH, therefore the number of orders placed during the validity period of the tender can fluctuate much. However, a yearly indication is given. Besides these tenders numerous spot orders are present.

The dataset by DH had a length of two years, 104 weeks. The minimum data required to calculate seasonal factors is two years (Nahmias, 2009). At DH besides the Christmas period there are no clear seasonal patterns. Also seasonality with N = 52 is not common in the literature. Often seasonality is used in cases where monthly demand is used, and forecasts are made for seasonal affected products.

Per combination, various different products are transported. For some combinations more than 300 different lanes are present. If demand for the two years is analyzed, no real seasonal pattern can be found. However, some peaks or lows correspond. From an analysis with three years of data (acquired at the end of the project), the accuracy of group E can probably be increased by 1 or 2 percent. For group D the same level of performance increase can be expected (2 percent). This by selecting a

Winter's method for some of the combinations and the best other method for the combinations where Winter's method performed poorly. For group no significant difference in performance was found. For the combinations in group A and B seasonality is not relevant.

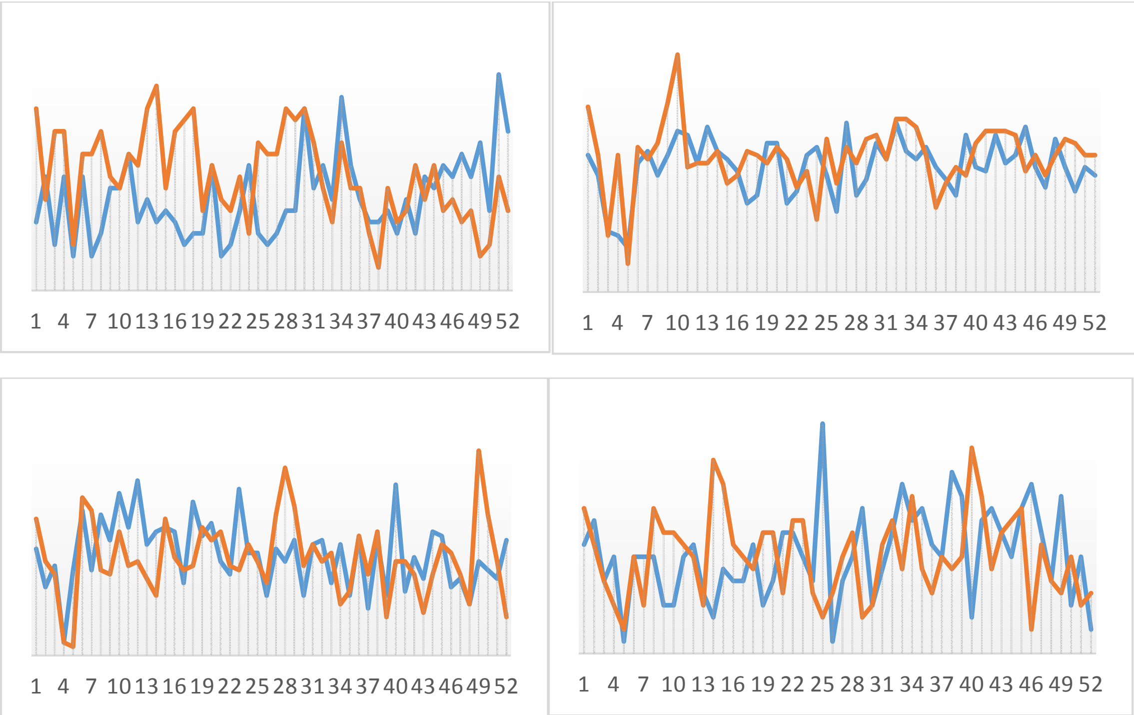

Figure 30: Four example graphs of two years of data for large combinations, seasonality check.

The presented graphs in figure 30 show the possibility of using seasonality. There are some equalities, but also large differences.

Conclusion: Taking seasonality into account does not result in real improved accuracy. There are no clear seasonal patterns (except Christmas), but for some combinations taking this historical 'pattern' into account seems slightly more accurate than the used methods. However, for most of the combinations seasonality resulted in comparable or reduced accuracy. To take seasonality into account more data would be preferred, but only for a part of the combinations this could lead to slight improvements. Taking more data into account can also have negative effects, because of the changes in the network over time. Sometimes large peaks occur. If these are known to be one time only then these should not be taken into account.

To use seasonality more data should be available, it should be carefully checked whether seasonality can help to improve forecast performance. There are also combinations where demand ended last year. The opposite is also seen, combinations where demand recently started. Examples of these situations can be found in paragraph 6.8: Starting/ending combinations.

7 Discussion, Insights, Limitations

7.1 Discussion

DH intends to use the forecasts to improve the process of assigning a tank container to an order. By improving this process the number of empty repositioning's will reduce. It should be noted that in the current situation various empty repositioning's are required to be able to complete the orders. One of the reasons is the distribution of chemical companies over the regions. There are more trips from the core regions to other regions than the other way around. These minimal repositioning's cannot be reduced by using forecasts in the planning process. However, the gained information can be used to give inside into the flows/order types through the regions. The goal of using forecasts is to reduce the “unnecessary” empty repositioning’s and overall save costs.

Region A has numerous orders where only tank containers of a certain type X can be used. If another region has orders with delivery in region A and has ample type X TCs in the region then one of those could be used (if allowed) to complete the order. If another TC type was used instead then it is more likely that a type X TC has to be repositioned empty.

7.1.1 Example interchangeability effect in a small region

In this section the forecasts (week t + 1) are discussed for a small region. This region is a region where in general a shortage of TCs is. Therefore, TCs from other regions have to be send to this region, to be able to complete demand. Which TC types to send depends on the loadings and deliveries.

	OrderType / Week t	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Forecast	1	2	1	1	1		4	4	2
Actual	1						5	6	2
Error	1	-2	-1	-1	-1		1	2	
Forecast	2	6	4	5	4	5	9	6	4
Actual	2	1	5	4	5	4	9		3
Error	2	-5	1	-1	1	-1		-6	-1

Table 19: Forecasted, actual and error for loadings of order types 1 and 2 in region X.

Table 19 shows the forecasted and the actual demand for order types 1 and 2. What should be noted is that every TC type anticipated for OT2 can be used to complete an order of OT1. The other way around, 95 percent of the allowed containers for OT1 could be used to complete OT2 (based on the used characteristics, in reality additional restrictions could be present). This interchangeability results in more flexibility. On page 20 (table 6) the allowed container types (and explanation) per order type can be found.

OT/Week	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
4	1	1		3	1	1	2	2
5	12	10	19	12	14	12	12	8
6	1	3	2	2		1	1	4
7	9	4	7	12	12	9	9	11
8	1		1		2	1	1	1
9	1	2	2		2	2	2	3
10	1		1			1	2	1

Table 20: Actual loadings, OT 4-10 in region X.

OT/Week	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
4	1	1	1	2	1	1	1	1
5	14	13	14	14	13	14	13	13
6	2	2	2	2	2	2	1	1
7	9	9	9	9	9	9	9	9
8	1	1	1	1	2	1	1	1
9	1	2	2	2	2	1	2	2
10	1	1	1	1	1	1	1	1

Table 21: Forecasted loadings, OT 4-10 in region X.

OT/Week	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
4			-1	1			1	1
5	-2	-3	5	-2	1	-2	-1	-5
6	-1	1			-2	-1		3
7		-5	-2	3	3			2

8	-1		-1				
9			-2		1		1
10	-1		-1	-1		1	

Table 22: Error forecasted loadings, OT 4-10 in region X.

OT4 are large orders where all types of heating systems can be used but the tank container can only have one compartment. These orders can be categorized as ‘hard’ orders (only two allowed tank types), and are one of the hardest orders of the OTs presented in table 19-22. For these only TC types 6 and 7 can be used. At t = 4 the forecast for OT4 is one order too low, as are the forecasts for periods 7 and 8. For those ‘hard’ order types a buffer should be available (or these special TC types should be saved if possible). Every TC type allowed for OT6 can be used for OT5, OT7, OT8, OT9 and OT10. In case of OT5, 89 percent of the allowed TCs can be used to complete orders of OT6 and 8. Whereas every TC allowed for OT5 can be used to complete orders of OT7, 9 and 10. For OT5 and 6 it is thus not really problematic if these are forecasted too high, these TC types can be used to complete various other OTs.

The other way around is of course also possible. As can be seen in table 22, for t = 2 the forecast was 5 orders too high for OT7. For OT7 twelve different TC types could be used. OT6 has one more order than forecasted. Overall the forecasts for week 1 in region X where two orders higher than the actual number of loadings. However, order type 12 was forecasted seven orders too low. For this OT only 22 percent of the allowed TC’s for OT5 could be used. So some interchangeability is possible but only to a small degree.

In appendix III a matrix can be found with an overview of the interchangeability of the allowed containers for order type X over the different order types.

7.2 Insights

The accuracy of the forecasts is not as good as hoped. The accuracy however does not tell the whole story, because of the flexibility in the process of assigning TC’s to an order. If some order types are forecasted too high, these anticipated TC’s can to a certain degree be used to complete other orders which were forecasted too low. More problematic is the case when ‘hard’ orders are forecasted too high in one region and too low in another region which can result in required empty repositions.

Also other insights can be gained by this research. The distribution of loadings and deliveries of various order types per region can be analyzed. This information can be used to make important network decisions. Which orders (from A to B) can reduce costs. For example, if region A needs TCs of type one, and region B has an overshoot of TC’s of type one then it could be useful to make more competitive quotes. Maybe no direct profit will be made on these trips, but these will reduce the empty travel costs.

Other insights gained are the variability of the demand. Aggregated to the whole company the demand is relatively stable. This aggregation level is however not helpful for the planners to make planning decisions. Therefore, the data is represented as order types (so flexibility is maintained) and as location regions are chosen. This still is a simplification of reality but represents a good tradeoff.

This research also shows how the orders can be classified in order types, this will be helpful to give different departments a better understanding of the possible container types that can be used.

In the current situation the empty repositioning’s (from a region with an overshoot to a region with a shortage of TCs) are chosen by the planners. Based on their estimates of demand they redistribute the TCs over the different depots. Their estimates are likely based on a mean, trend or random walk model. The forecasts made are more accurate on average then forecasts by one of those models. Also more consistent repositioning's could be made when they are made based on forecasts. In the current situation DH has no order types included in their system. Therefore, these should be included first.

The order types/forecasts can also help (new) planners to gain useful information on which type of orders (and an indication of the number) occur in which region. This can help in deciding which TC can be best assigned to an order. Also the time it will take to get a new planner acquainted with the order process can be reduced.

When a new request to transport a certain product in quantity X and from location A to B comes in, the quote department can look at the current flow of order types over the regions and take this into account when making the quote. If for example in region A various orders of type X start and these end in region B. If there are not enough orders from B to A where a TC can be used which also can be used for orders of type X, then empty reposting's are required. For some orders it can be useful to quote a more competitive price than normal. The chance of receiving these orders will be higher, it can be the case that this trip will even cost money, but the costs saved because no empty repositioning have to occur will result in an overall benefit. This effect should be taken into account when making the quotes.

It is also important that the quote department keeps track of the number of orders a customer placed over the length of the tender. If for example the tender ended at the end of the year and the customer did not accept a new quote, the forecast should be updated with this information. The other way around is probably less predictable, but if for a certain combination previously only two tenders were valid, and for the next year there are five tenders valid, some additional information is available.

For DH it is of interest to gain (improved) insights in the balance of available TC (types) in a region and the expected orders in a region. If for example at the account management department a new order for twenty trips next week comes in and in the loading region a shortage of the allowed tank types is expected, this should be communicated to the planning department. Maybe it is possible to change some requirements for example the volume, so it will fit in other (available) TC types. If a good overview is available the communication between the different departments and the customer can be improved.

Research question: *Can forecasting demand reduce costs for a specialized logistic service provider with a complex network?*

This study is a pilot study into the possibilities of forecasting. From (Jansen, 2014) DH knows that if demand was known four weeks upfront, a saving of approximately seven percent could be achieved. For the largest group reasonable accuracy can be achieved, if the integration of InterBulk is completed the forecasting accuracy is likely to improve further. There are however various combinations with a low number of orders, for these combinations the forecast accuracy is on average low. Often no clear pattern is present. For some order types some interchangeability is possible as shown for an example region. The most important orders are therefore the 'hard' orders, at these order types not much interchangeability is possible (OTx -> OThard). The number of allowed TCs is limited and if in one region these 'hard' orders are forecasted too high and in another region forecasted too low, empty repositions can be required.

In the current situation the algorithm makes suggestions based on the optimized costs over a time horizon of two days. When a larger time horizon is taken into account, the costs will be optimized over the longer horizon based on forecasted information. These forecasts can also change over the weeks. Based on information from the study of (Jansen, 2014), discussion with planners and my supervisor we concluded that adapting the algorithm to take into account the forecasts will not result in reduced costs. Also planners often assign a different TC to an order than was recommended by the MMP algorithm. Planners have various other information to base their decision on.

This research can also help to gain insights in the different order types and the number of loadings and deliveries per region based on the order type categorization. The order types/forecasts can help to get new planners easier acquainted with the orders over the different regions. The empty repositions are currently executed by the planners based on what they estimate to be required in a region. They will likely use a mean or random walk model to base their decision on. The accuracy of the forecasts made with for example a simple exponential smoothing model is on average higher than forecasts made with a simple mean or random walk model. The forecasts made are however on a different aggregation level, currently DH does not work with order types yet. To answer the research question, forecasting is not expected to reduce costs for a specialized logistic service provider with a complex network. For the case where forecasts are used in the planning algorithm compared to short term planning based on known orders.

7.3 Limitations

As posed before, a limitation of this research is the fact that it was not possible to check to what degree an order of a certain order type can actually be completed by the 'allowed' TCs. Some characteristics used for the order types were only available based on the standard pre-order where sometimes differences between the standard pre-order and the actual pre-order are possible.

The forecasts are based on a data set of 104 data points, 2 years. For the large combinations some minor improvements are probably possible if four or five years of data was available. But this should be carefully researched.

It was not possible to actually check the effect of using forecasts in reality. To do this two models should be formed, one which replicates the behavior of the actual MMP algorithm (the actual MMP algorithm does not use container types and order types yet, also orders which are excluded from the order types are taken into account with the MMP algorithm), and a second model which takes the forecasts into account. This is a very complex and time consuming step. Black and green lists are involved, thousands of start end ending locations, decisions on how to use the order types, interchangeability between order types, hard orders, numerous different costs, etc.

Forecasting accuracy could be improved if knowledge about known production stops (at important customers) can be used to update the forecasts. The forecasts can also be adjusted and thereby improved if information is/can be used when a tender of an important customer ends and no new agreement is made.

8 Conclusion & recommendations

8.1 Conclusion

DH is interested in whether it is possible to 'accurately' forecast demand. The first step was to determine how to represent the demand (orders). To achieve this order types are created, every order type represents a unique set of allowed TC types. Based on these order types and the regions where the locations are distributed over, the forecasts are made. The overall accuracy (gMAPE) had a deviation of around 36 percent. Because of the order type interchangeability, the actual result in practice will be somewhat better. But still large errors can be expected. This type of business, with numerous different customers with different products, a number of different competitors and a short horizon, is hard to forecast. The size of the different order type/region combinations differs greatly, which complicates the forecasting process. There will be various factors which have an impact on the demand, but not much knowledge is available over these factors.

The most important order types (to forecasts accurately) for a company like DH are the 'hard' orders, orders which can only be completed by a small percentage of the total resources. Because of the limited resources it is more important to know this type of demand a longer time before/more accurate. DH was interested to know how accurate demand (order types) can be forecasted, and if it would be possible to save costs by adjusting the MMP algorithm to take forecasts into account. With the achieved forecasting accuracy, it is not likely that costs can be saved when taking forecasts into account with the MMP algorithm and thereby taking a longer horizon into account.

Based on this research, a good overview of the demand and supply of order types in each region is gained. This information can be very useful in making future decisions for the network.

At the end of the project it became known that DH bought the company InterBulk. The company recently started to integrate InterBulk. At the second half/end of the year more information about the orders will become known. By acquiring another large company DH has become a top 3 player in their sector. The fleet of tank containers and thereby the distribution over the TC types is likely to change. Thereby the distribution over the order types will also change. This study was initialized as a pilot study. It shows how to create order types, the difference in performance between the different forecasting methods. The difficulties of the different 'sizes' of the combinations. Also indications of the achievable forecasting performance for different groups are shown. Because the number of orders will likely increase the average accuracy is expected to improve.

8.2 Recommendations

How can DH improve the accuracy of the forecasts? The first step is already taken by them, increasing the number of orders. They bought InterBulk, a large LSP and thereby DH will become a top 3 player in their field. By the end of the year the integration is expected to be finished. It is likely that the overall accuracy will improve because of the increased number of orders in the network. It is expected that the number of combinations will not change much. So a larger number of orders, results in more orders per combination. As shown in chapter 6, combinations with a higher number of orders, have on average a better forecasting accuracy.

The order types made for this project should be checked for the new situation, if necessary minor changes should be made. The combinations can then be formed by dividing the order types over the different regions. For the combinations with intermittent/lumpy demand patterns on average no accurate forecasts can be made. For these the already known pre-order information can be used. Keep in mind that the actual orders will be equal or higher than the pre-order information.

For the combinations of groups C, D and E, the difference between simple and more sophisticated methods is small. Therefore, a good indication of the achievable forecasting accuracy can be generated by using the simple exponential smoothing method. If it is possible to use four or five years of data, Winter's method could be compared to the SES method. Only small differences are expected on average (for group E).

In this thesis is shown that more advanced methods do not significantly improve forecasting accuracy. Combining forecasting methods could lead to small improvements (group E), but multiple forecasts have to be made for each combination. For the largest combinations Winter's method can be compared against the simple exponential smoothing method. By using the simple exponential smoothing method, a good indication of the possible accuracy can be found. Some improvement in accuracy can be gained by complicating the forecasting process.

The forecasts made should be monitored, and updated with relevant known information. Such as a known production stop at an important customer (this information should be saved). In general orders are planned which are due in two days. The forecasts should be updated for week 1. Other important information is the number of already known pre-orders. For the largest combinations, some small improvements are possible if the already known pre-order information is taken into account. For combinations < group E, some additional improvement is possible by using the pre-orders. For the smallest combinations, the statistical forecast will be zero. Therefore, only the pre-order information will be used. Rule: use the pre-order information, this is the minimum number of orders.

The possibility of updating the forecasts is mainly for week t + 1. For week t + 2 only in case of special large orders more information is known. The forecasts for week t + 2, will be comparable/slightly less accurate than the non-updated forecasts for week t + 1. This because in most cases no trend or seasonality is available. For the updated forecasts the differences between week t + 1 and t + 2 accuracy increases.

To forecast demand, it is important that the different departments communicate relevant information to the one keeping track of the forecasts. For example, if an account manager knows that an important customer has a production stop for the next six weeks. This information could be used to manually adjust the forecast. Important information should be saved, also the data and time that this information became known is relevant. For example, if a large customer (tender) is acquired and a shift in demand can be expected. The other way around is also possible in case a large customer is lost, for example because the tender has ended and no new quote is agreed on. In this case additional information is available and should be used. As posed before relevant information should be saved for future use. The forecasts should be monitored and adjusted if necessary.

As seen in paragraph 6.8, demand can suddenly stop or start at a combination. It is important that the forecasts are monitored and/or that the methods used have some flexibility. Also not all possible order types are included. The distribution of orders over the order types can shift over time. It is therefore also important to monitor the percentage of orders categorized as one of the included order types. If the number of different (relevant) order types reduce over time, the accuracy of the forecasts is expected to improve. This not only depends on the order requirements but also on the available tank container types.

Another future possibility to increase forecast accuracy is making the fleet more homogeneous, which will reduce the number of order types, and therefore the number of orders per order type will increase.

If 'hard' orders can be known more time in advance the network can be planned more efficiently. 'Hard' orders can only be transported by a limited number of containers, and are therefore difficult to complete. Various 'hard' order combinations (order type/region) have a relatively low number of orders and are therefore more difficult to predict.

The incoming and outgoing flow of order types (possible container types) can be seen more detailed. In the current situation only the actual used TC (type) can be seen. For the quote, sell and account management departments this knowledge can be used to make more informed decisions and thereby improve the efficiency of the network. Also these departments should directly share the knowledge of gaining/losing a large customer, production stops, etc. when this becomes available.

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10 Appendices

Appendix I: Tank container types at DHLL Rotterdam

Container type	Volume
Chem|>2Comp|EG	M
Chem|>2Comp|Steam	M
Chem|1Comp|EG|Medium+Large	M
Chem|1Comp|EG|Small|iso	S
Chem|1Comp|EG|Small|noniso	S
Chem|1Comp|Steam|Large	L
Chem|1Comp|Steam|Large|Baffles	L
Chem|1Comp|Steam|Medium	M
Chem|1Comp|Steam|Medium|Baffles	M
Chem|1Comp|Steam|Small|iso	S
Chem|1Comp|Steam|Small|iso|Baffles	S
Chem|1Comp|Steam|Small|noniso	S
Chem|2Comp|EG|Medium+Large	M
Chem|2Comp|EG|Small	S
Chem|2Comp|Steam|Medium+Large	L
Chem|2Comp|Steam|Small	S
Chem|HighInsulated	M

Appendix II: Order Volumes

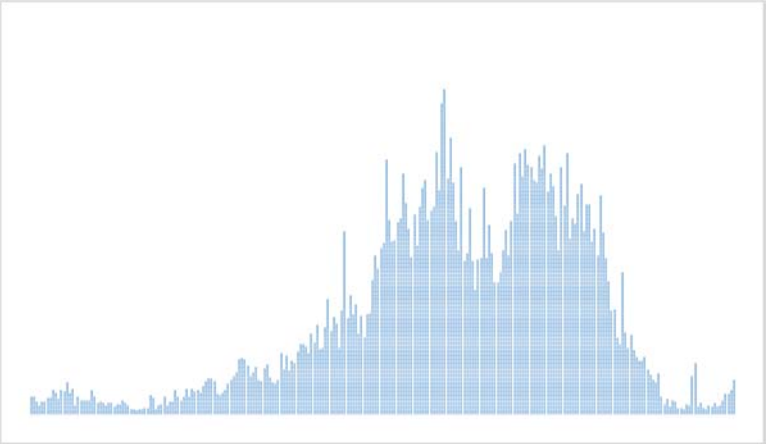

Figure 31: Volumes for 99% of the orders

Appendix III: Interchangeability Matrix

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