Improving supply chain cost and hinterland modal split
an inventory theoretic approach

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Improving Supply Chain Cost and Hinterland Modal Split: An inventory theoretic approach

by

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Abstract

This study investigates the transport allocation on the inbound supply chain of a large distribution centre in the hinterland of the port of Rotterdam. More specific, the inbound supply chain costs are investigated by simulating the inventory and transport management decisions. As a result, opportunities and threats are identified for reducing supply chain cost and reducing the number of hinterland shipments by truck.

This leads to valuable insights for management at Company X and input for further research on hinterland modal split from a shippers' perspective.

Management Summary

Hinterland access is now perceived as a key success factor of European ports (Van der Horst et al., 2008). Many actors benefit from improving hinterland access including shippers. The optimal goal for shippers is to minimize costs while also minimizing the loss of speed and flexibility. Improving hinterland access by developing and scaling the barging network might fulfill the need for shippers to meet their goal. Current research on hinterland modal split does not reflect the shipper's market situation optimally (Van de Weijer, 2012). By using inventory management theories the inbound supply chain to Company X's distribution center in the hinterland of Rotterdam is simulated. By testing different scenarios of service level agreements, the relation between hinterland modal choice and supply chain service levels are approximated. This would be an extension on recent research to better reflect the optimal modal split for shippers in practice and will show the opportunity for extended gates to shift transport from truck towards barge.

Literature suggests that the focus of shippers is on supply chain excellence, with superior customer service and lowest cost to serve (Notteboom, 2008). Little is known on how the shippers manage their supply chain in practice to meet this goal and specifically how this will affect the opportunity to shift the modal split more towards barging. In this thesis we show that the inbound supply chain of the distribution center of Company X is suboptimal as different operational departments strive to meet departmental goals. Moreover, we show the need for improving coordination and communication between departments to improve supply chain performance and to shift the hinterland modal split more towards barging. The throughput time of the supply chain is long and highly variable with the factories located in Asia. We show that if transport management and inventory management decisions were aligned, then total supply chain cost can be reduced by allocating sea freight and hinterland transport differently.

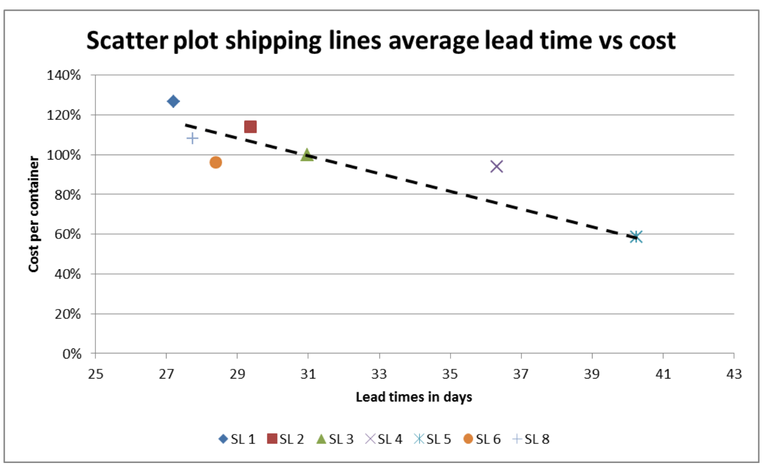


Figure 1 – Scatter plot of shipping lines' average lead times versus shipment cost

Transport management would strive to reduce cost by contracting low cost carriers, whereas inventory management tries to minimize inventory levels. If transport management would also be responsible for inventory holding cost then a tradeoff have to be made. Figure 1 shows that contracting the low cost carrier SL 5 would result in longer lead times and thus higher inventory

cost. In this thesis we develop a model to simulate the effects in practice of sea freight allocation on transport and inventory holding cost.
The model is based on a (R,S) inventory system with variable lead times and variable demand. Tyworth et al. (1996) describe a method to optimize inventory under a (s,Q) policy. We adjust this method for a (R,S) system and make it applicable for simulation by replacing the demand distribution. Tyworth et al. (1996) assume that demand distribution is constant in time, which is not the case in practice. We make use of monthly forecast data to anticipate changes in expected demand. SKUs are grouped by forecast accuracy to describe demand deviations approximated by the forecast errors.

An extra decision rule is introduced to counter the effect of the invalid assumption that the forecast accuracy and thus demand is independent in time. In case the inventory levels of specific SKUs are not in line with expected demand, the supply chain will be rebalanced by increasing the order-up-to-level with the difference between the expected inventory position and expected demand. Verification shows that despite the short term inventory shortage, the policy give a valid rough approximation of supply chain cost and hinterland model split.

The results show that the total supply chain cost mainly consists of sea freight transport cost and that this should be the key driver of transport allocation. We conclude that Company X should allocate transport of the largest flow of goods from the factories in Manila to SL 5 and optionally to SL 6 (see Table 1). This shift in transport allocation could save Company X between approximately 3.7% and 19.9% of total supply chain cost.

	SL 1	*SL 2*	*SL 3*	*SL 4*	*SL 5*	*SL 6*	*SL 7*
Total inventory cost	-1.1%	1.9%	-1.7%	6.2%	11.6%	-5.0%	-5.0%
Transport cost	3.4%	-6.4%	0.9%	-4.8%	-38.3%	-2.9%	14.6%
Total cost	1.4%	-2.8%	-0.1%	-0.8%	-19.9%	-3.7%	7.4%

Table 1 – changes in cost of simulated scenarios

By simulating scenarios with different service levels, the relation to the percentage of hinterland shipments by truck is revealed. Lower service levels increase backorders and thus the number of emergency shipments. We conclude that this relation is linear but not one to one. As the service level increases the percentage of shipments by truck decreases with factor 1.47 (see Figure 2). If Company X is able to meet the internally set service level target of 96.5% then only 4.6% of all containers will be shipped by truck from the PoR to the hinterland DC. Thus we conclude that there is an opportunity to shift the modal split of Company X more towards barging.

Lastly, we conclude that quarter end sales bonuses result in peaks in DC's turnover. The approximated extra yearly logistical cost of these peaks is 4000 dollar for trucking containers from the PoR. Moreover, the major extra cost is expressed in a decrease of service level from 90.7% to 89.8%. Therefore, the sales bonus policy should be changed to decrease the quarter end peaks. Instead of having fixed measurements each quarter, a bonus policy should be developed that measures sales team performance throughout the time to prevent sales team advancing orders.

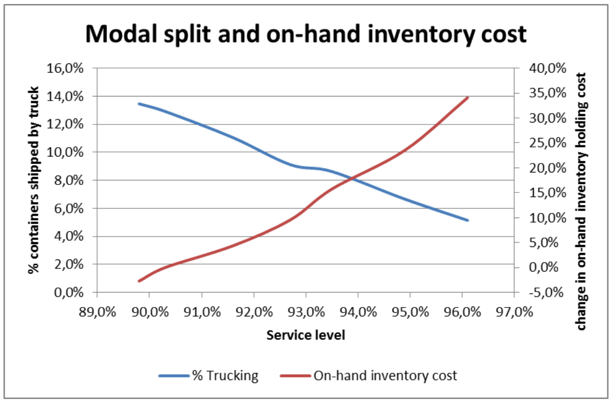


Figure 2 – Modal split and on-hand inventory cost for different service levels

Service level	*% products shipped by truck*	*% change in on-hand inventory cost*
89.8%	13.5%	-2,7%
90.3%	12.9%	0,0%
91.6%	11.0%	4,4%
92.7%	9.1%	9,6%
93.5%	8.6%	15,8%
94.9%	6.7%	23,5%
96.1%	5.1%	34,1%

Table 2 - Modal split and on-hand inventory cost for different service levels

Besides the direct recommendations from the previously made conclusions, we also recommend Company X to determine a factor to quantify the effect of the lead time distribution of sea freight transport on inventory holding cost. This factor can be used for transport management as an extra discount that needs to be negotiated in tenders.
Moreover, this study has showed that there is still room for improvement concerning the forecast accuracy. Long replenishment lead times and varying demand affect this accuracy. Nevertheless, the RAD of 44.5% and the RD of 9.3% suggest that forecasts are overestimating demand and that there is room for improvement.

Concluding, this study contributes to current research by quantifying the potential modal split from a shippers' perspective. This case study concludes that the maximum share of transport by barge is bounded by shippers' service levels and their policy to truck containers. At Company X, the percentage trucking is negatively related to their service level with a coefficient of -1.47. Further research should investigate this coefficient at different shippers to make a general conclusion on hinterland modal split from shippers' perspective. Moreover, qualitative research suggests that further research should try to quantify the relationship between warehouse capacity and modal split. This would create a better understanding of the hinterland modal split from shippers' perspective.

Preface

Eindhoven, January 2013

This report is the result of my Master thesis project which I conducted in partial fulfilment for the degree of Master in Operations Management and Logistics at Eindhoven University of Technology in the Netherlands. The project has been conducted at Company X.

During this project I finally got to chance to put the many years of study into practice. Although I had my setbacks it was a great experience to analyse and to improve the supply chain of one of the leading multinationals in business-to-business information technology electronics. I would like to thank Company X and the university for the opportunity to conduct this project in such an open minded environment. Especially the enthusiasm, interest and helpfulness will be something I will never forget.

From Company X I would like to thank my supervisor for his guidance, time and interest in me as a person. Even though you are a busy man, you always had time for me and make things happen if needed. Especially this pragmatic attitude is something I admire and hope to have learned more during my stay at the company. Your professional attitude reflects the spirit within the company which was one of my reasons to apply for a job at Company X. I hope to work with you again in the future!

Moreover, I like to thank my other colleagues at work for the amazing time and practical advice. Mario van B., who as a lean six sigma green belt expert could reflect on my work and other informal opinions. As former inbound Manager, Paolo O. was able to explain the inbound supply chain and the decision rules. I am definitely going to miss the sweets that gave me the energy to finish my work! My gratitude also goes out to everyone who made the time in their already very full days to gather data or answer my endless list of questions. Without your input I could never have finished.

From the university I would like to thank my first supervisor Jan Fransoo for his valuable inputs and feedback. Despite the setbacks, you where patient with me and always had attention for my well-being and development as a person. It took me a while to comprehend the expectations of me and my work but at the end it was the stimulation I needed to make the most of the project. Furthermore, I thank Nico Dellaert, as my second supervisor, for his time and critical reviews of my work.

With this project an amazing period as a student comes to an end. Even though I was ready to start a new journey as a working career, I am glad for the extra experience and personal growth resulting from this project. I want to thank my friends and family who were there throughout the years. Special thanks to my parents: for their interest in my work and their continuous (financial) support to make the most of my student life.

Frans van de Weijer

Contents

1. Introduction

In a search to maximize customer satisfaction and minimize operational cost, management sets KPIs to stimulate departmental performance. However, Stuart et al. (1998) show that overall supply chain performance is increased by setting mutual goals. At Company X, overall supply chain performance is suboptimal as different departments strive to fulfil KPIs set by the department of Supply Chain and Logistics management. The effects of this 'silo thinking' are reflected in the quarter end peaks in DC turnover and higher total supply chain cost as a result of sea freight transport allocation. Specifically the latest relation is extensively depicted in the literature of supply chain and inventory management. This case study is designed to better understand the departmental interdependencies and to determine opportunities for improvement by aligning departmental goals and information. Furthermore, the study will give insight into effects of supply chain management on hinterland modal split. Specifically, we look at the relation between customer service levels and the percentage of emergency shipments that are transported by truck. We will discuss why it is important to study this relation more extensively and what the contribution of this study is to the currently available literature.

1.1. Problem description

Container transport has decreased transport handling cost resulting in a significant increase of worldwide transport flows. Companies have relocated their production facilities further away to low labor cost countries in for instance Asia. The growth has also resulted in scale advantages, which in turn has further reduced transport cost. On the other hand, the increase in container transport raised the growth of congestion and air pollution in the hinterland of ports. These effects hinder future growth and thus competiveness of port hinterland with other competing ports. Ports and their hinterland transport systems can only attract port users and additional volumes if the (whole) hinterland transport network is efficient and effective. Hinterland access is now perceived as a key success factor of European ports (Van der Horst et al., 2008). Therefore, many actors benefit from improving hinterland access. Even though there have been many different initiatives to coordinate or regulate hinterland transport, there is still much room for improvement. Currently, different actors in the hinterland of the PoR are working together within the Ultimate project to substantiate opportunities for improvement.

Literature suggests that the service expectations of shippers are moving towards a push for higher flexibility, reliability and precision. It is suggested that there is growing demand from the customer for "make-to-order" or "customized" products, delivered at maximum speed, with maximum delivery reliability, at the lowest possible cost. The focus of shippers is on supply chain excellence, with superior customer service and lowest cost to serve (Notteboom, 2008). Contrary, the need for shippers to reduce their carbon emission footprint pushes them towards other modes and organization of transport. These solutions are on the expense of speed and flexibility of transport. Therefore, the optimal goal for shippers is to reduce carbon emission footprint while minimizing the loss of speed and flexibility. This need for alternative transport solution will force shippers to start collaborating closer with other hinterland actors to increase intermodal transportation.

However, in the hinterland supply chain the interest of the actors are not always aligned. While terminal operating companies (TOCs) are focused on increasing the utilization of their expensive facilities, shippers want short and reliable lead times. The frequency of services should be reasonable to satisfy the needs of shippers, but at the same time should be justified by sufficient container volume (Kiesmüller et al., 2005). Closer coordination should help to overcome this misalignment and presenting win-win solutions for both parties. Nevertheless, coordination in hinterland chains does not develop spontaneously. This may be explained by free riding problems, a lack of contractual relations, information-asymmetry, and a lack of incentives for cooperation (Notteboom, 2008). Thus, the commitment of shippers to shift their freight modal split more towards barging is an important factor to develop hinterland chains. Despite general conclusions and theoretical research on shippers' perspective, no case studies have been found that investigate the relationship between shippers' supply chain and hinterland modal choice.

However, the expected modal shift from truck and train towards barge has been approximated by Blauwens et al. (2006). Blauwens et al. (2006) analyses the effectiveness of policy measures aimed at triggering a modal shift in the freight transport market of the Rhine axis. The analysis is based on the inventory-theoretic framework that studies modal choice from a business logistics viewpoint. Thereby, this is the only currently known research that investigates the modal split from shipper's perspective in the hinterland of PoR. The crux of the inventory-theoretic approach lies in the fact that explicit attention is paid to all costs in the supply chain that are affected by the choice of transport mode. The framework is used to calculate the market shares of different freight transport modes for a hypothetical transport market. The results are shown in Table 3.

	Road transport		Rail/road transport		Barge/road transport	
	Containers	Share	Containers	Share	Containers	Share
Current situation	447 120	37.10%	200 880	16.67%	557 280	46.24%
(1) TC road transport +5%	369 720	30.68%	266 400	22.10%	569 160	47.22%
(2) TC road transport +10%	341 280	28.32%	289 440	24.01%	574 560	47.67%
(3) TC road transport +20%	284 940	23.64%	334 440	27.75%	585 900	48.61%
(4) LT rail/road −0.5 days	313 200	25.99%	401 760	33.33%	490 320	40.68%
(5) LT barge/road −0.5 days	396 540	32.90%	133 920	11.11%	674 820	55.99%
(6) LT rail/road and barge/road −0.5 days	284 580	23.61%	334 800	27.78%	585 900	48.61%
(7) TC rail transport −5%	403 920	33.51%	244 800	20.31%	556 560	46.18%
(8) TC rail transport −10%	380 880	31.60%	334 080	27.72%	490 320	40.68%
(9) TC rail transport −20%	347 040	28.79%	536 400	44.50%	321 840	26.70%

Table 3 - Theoretical modal splits in hinterland PoR (Blauwens et al. ,2006)

Applying the framework to 648 cases yields market shares of 37.10%, 16.67% and 46.24% for road transport, rail or road transport and barge or road transport, respectively. It turns out that barge or road transport has a very strong position for the low-value containerized cargoes, while road transport is very competitive for high-value goods. These results are first indications of what is theoretically economically feasible. However, because of the many assumptions, these results differentiate from practice. For instance, it is assumed that shippers will always choose the cheapest option. However, according to an extensive literature review by Cullinane and Toy (2000) the following five criteria are most often cited as having a significant impact on the freight modal choice decision: cost/price/rate, speed, transit time reliability, characteristics of the goods and service. Company X is an important shipper in the hinterland of the PoR with circa 5000 containers being imported yearly. Qualitative research is conducted at Company X as a case study to determine criteria that have a significant impact on the freight modal choice decision. Moreover, the results will give an insight into the weight of each criterion.

The standard procedure of Company X is to transport containers by barge via Inland Terminal Veghel (ITV) to the distribution center for Europe, Middle East and Africa (EMEA). Nevertheless, in 2011 13% of all containers were shipped by truck. Some containers are shipped by truck if the container terminal is too small to be called at. Nonetheless, the main reason for Company X to ship by truck is the urgency of the certain products in the container as the company tries to comply with on time delivery Company X (OTDS) of at least 96.5%; the fraction of customer demand that is delivered out of stock. Even though management is trying to minimize urgent shipments, unforeseen events will disrupt the needed product supply. First, it can take up to a week for a container to be cleared by customs, especially when the container is gassed with dangerous toxics. Secondly, the frequency of barging service affects container waiting time at the TOCs. Long delays may result in disruption of supply and have to be corrected by bringing in containers by truck. Lastly, qualitative research suggests that warehouse capacity has an impact on modal split. High capacity usage affects optimal flow of goods and off balance inventory levels. Low inventory levels will increase the change of emergency shipments, increasing the expected number of shipments by truck.
Nevertheless, the main reason for urgent shipments is the inventory shortage as a result of inaccurate supply chain management and the required service level (OTDS). Therefore, we will study the relationship of service level on hinterland modal split. Moreover, we will look at the effect of inaccurate supply chain management on the hinterland modal split as a result of quarter end peaks. This will be discussed later on in this section. Both results can be used as input for the Ultimate project to develop the hinterland barging service by better understanding shippers' perspective.

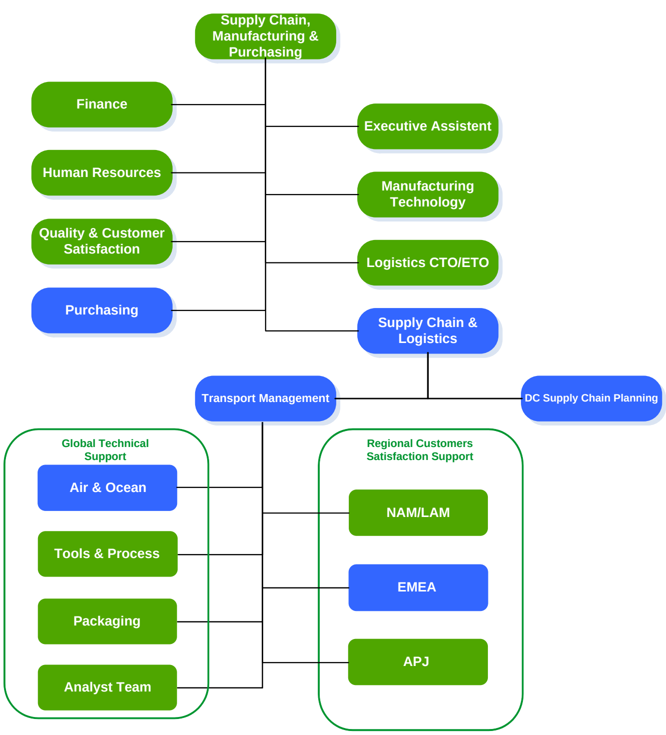


Figure 3 – Organizational diagram Supply chain, Manufacturing and Purchasing

At Company X supply chain management responsibilities are divided over different departments. Figure 3 shows these different departments in blue. Within the department of Supply Chain, Manufacturing & Purchasing, management decisions on tactical level are split up into transport purchasing and Supply Chain & Logistics. On a lower level within Supply Chain & Logistics, the DC inventory levels are planned by DC Supply Chain Planning. On the other hand transport management is further split up into Air & Ocean for global support and into the different regions of which one is EMEA. Effective collaboration between the different departments is needed to manage the overall supply chain efficiently. For instance, transport purchasing needs to communicate with the department of Air & Ocean and EMEA to discuss operational issues and performance as feedback for carrier relations and contract negotiations. Moreover, information on transport performance should be used as input for DC Supply Chain Planning to determine adequate inventory levels.

The department of Supply Chain & Logistics is constantly trying to optimize the overall supply chain by taking into account all characteristics and constraints. Both DC Supply Chain Planning and transport purchasing are induced to meet their KPIs by trying to optimize performance. This ‘silo thinking’ results in negative externalities for both parties. Supply Chain & Logistics is not aware of the magnitude of this interdependency. As a result, inventory levels and transport lead times are misaligned resulting in backorders and emergency shipments. Quantification of the interdependency between lead time distribution and inventory levels could enable Supply Chain & Logistics department to reduce total supply chain cost by balancing departmental decisions on inventory and transport differently. Thereby, it would show that departmental ‘silo thinking’ creates supply chain inefficiencies.

Figure 4 and Table 4 show that there is a significant (p=0.00) negative relation of -0.88 between the average lead time and sea freight transport cost. However, the effect of lead time variance on sea freight transport cost is smaller (-0.34) and is not significant (p=0.20). Thus, Transport Purchasing would only collaborate with the low cost carriers if the department would have no restrictions on lead time performance. Under this circumstance, safety stock levels should be increased to counter the effect of longer and more variable lead times. We will study how inventory holding cost should relate to transport allocation to meet the required OTDS by modeling different scenarios. The results will show possible opportunities of improvement by showing how total supply chain cost is minimized.

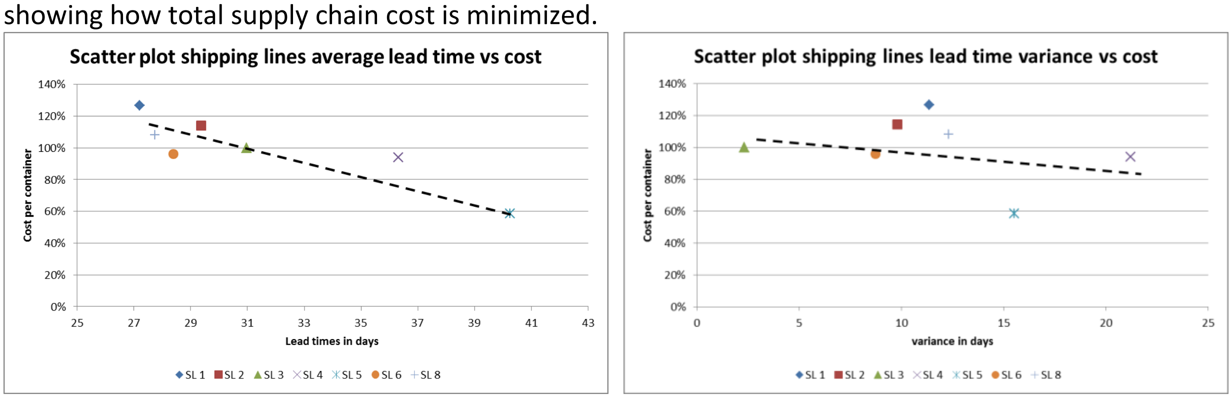


Figure 4 – Scatter plot of shipping lines’ average lead times and variance versus shipment cost

	Pearson Correlation	*Sig. (1-tailed)*
Average lead time	-0.88	0.00
Lead time variance	-0.34	0.20

Table 4 – Correlation of lead time with transport cost per container

Lastly, we will take a closer look at one of the main reasons for inventory imbalance at Company X. Again 'silo thinking' by the sales department will result in peaks of workload at the DC. Figure 5 and Table 5 show this by the difference between the turnover at the DC in 2011 and customer demand based on request date. The graph clearly shows that Company X is creating its own peaks in demand at the end of each quarter. Moreover, Table 5 shows that the CV of the quarter ends is significantly higher than other period during each quarter or during the total year of 2011. We defined the quarter ends as the last three weeks of each quarter. The sales team performance is reviewed quarterly and bonuses are acquired if sales targets are met. Qualitative research suggests that sales teams are pushed to advance orders if otherwise the bonus requirements are not met. Even though the bonus policy has a positive effect on sales team performance, the externality of quarter end peaks has a negative logistical consequence. The supply chain is not designed to manage with these large deviations in demand, resulting in extra cost of labor over hours and urgent shipments. Therefore, this study tries to quantify the effects of quarter end demand peaks on supply chain performance and hinterland modal split.

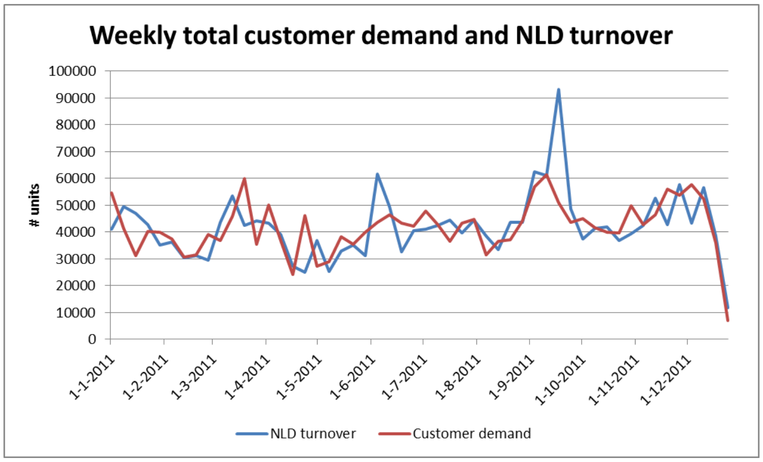


Figure 5 – Weekly total customer demand and DC turnover in units

	2011		*Quarter ends*		*Except quarter ends*	
	DC turnover	Customer demand	DC turnover	Customer demand	DC turnover	Customer demand
Average	42024	41986	47692	43728	40323	41463
standard deviation	12061	11204	19202	14089	8566	8211
CV	0.287	0.267	0.403	0.322	0.212	0.198

Table 5 - Weekly total customer demand and DC turnover in units

1.2. Company description

Ultimate

During the last decade economic growth and containerization has increased the transport volumes from and to the PoR. The PoR and its surrounding areas are reaching their limits of expansion and are getting increasingly congested and polluted. To sustain the competitive advantage, the PoR, main port and inland TOCs and scientific institutions are developing sustainable solutions.
In the Ultimate project the deployment of a hub-and-spoke network is investigated for intermodal transport by barge and truck from the container terminal ECT in Rotterdam. By bundling container volumes from road haulage into barge, it is expected to increase reliability and decrease cost within acceptable service levels. Research by Van Rooy (2010) showed that this is only feasible if shippers are willing to participate and change their order behavior to their new service. However, total replenishment lead time of inventory at the DC is predominantly determined by sea freight transport lead times. Therefore, this case study shows what the effect of Company X's service levels are on their hinterland modal choice decision. It shows that Company X does not make optimal use of barging containers as supply chain management has difficulties setting appropriate inventory levels to meet customer service levels. In light of these recent developments, it is worthwhile to quantify the opportunity for Company X to increase the use of the barging services.

1.3. Project Outline

Summarizing, this study contributes to the currently available literature by investigating the hinterland modal split from a shipper's perspective. This case study will lead to a better understanding of how Company X's customer service level relates to the hinterland modal split and to what extend shipment by barge can be increased as a result of improved inventory management. Moreover, simulation of different scenarios will show improvements in supply chain cost by allocating sea freight transport differently and adjust inventory levels accordingly.

The remainder of this report is structured as follows. In chapter 2, the research design is discussed and the research questions by which this study is led are defined. In chapter 3, the conceptual model and the input data is discussed. In chapter 4, the developed scientific model will be explained and verified with real life data. Next, in chapter 5 the research questions will be discussed by simulating different scenarios of sea freight transport allocation, customer service levels and quarter end peaks. These scenarios will give insight into the tradeoffs supply chain costs and the effect on hinterland modal split. Finally, chapter 5 presents the conclusions that can be drawn from this study, the recommendations, and interesting directions for further research.

2. Research design

2.1. Problem definition

From the problem description discussed in the previous chapter, a formal problem definition can be formulated:

At Company X, different departments are subject to silo thinking by the absence of mutual interdepartmental goal setting. Inventory and transport management partly counteract each other by disregarding the indirect effects of their pursuit to meet the set targets. Also the sales department is aiming to meet their quarterly sales targets, resulting in quarter end peaks in workload at the DC.

The company lacks the insight of the quantitative effects of this sub optimization on overall supply chain performance. Thereby, Company X is unaware of the opportunity for improvement by setting mutual goals resulting in a different allocation of sea freight and hinterland transport.

2.2. Research questions

In this study, the following main research questions will be used:

1. *How should sea freight **transport be allocated** to optimize the supply chain by minimizing inventory and transport cost under constant service level?*
2. How is the hinterland ***modal split*** related to service level agreements?
3. *What are the supply chain costs of quarter end sales **peaks**?*

2.3. Research Scope

This study will focus on the inbound transport and inventory management of the distribution center. The DC is the main distribution center for the region Europe, Middle East and Africa (EMEA). The four other business units within Company X each have their own distribution network and will not be included within the scope of this research.
The hinterland transport mode decisions of the DC are influenced by the upstream supply by sea container ships and the demand from the DC to fulfill customer orders from EMEA. Company X mainly manufactures and assembles the majority of the products. As a result, 82% of all sea containers arriving at the DC originate from the factories in Manila, Bangalore (Chennai) and

Xiamen (Figure 6). Therefore, to reduce complexity without too much loss in effectiveness, we will focus on these flows.

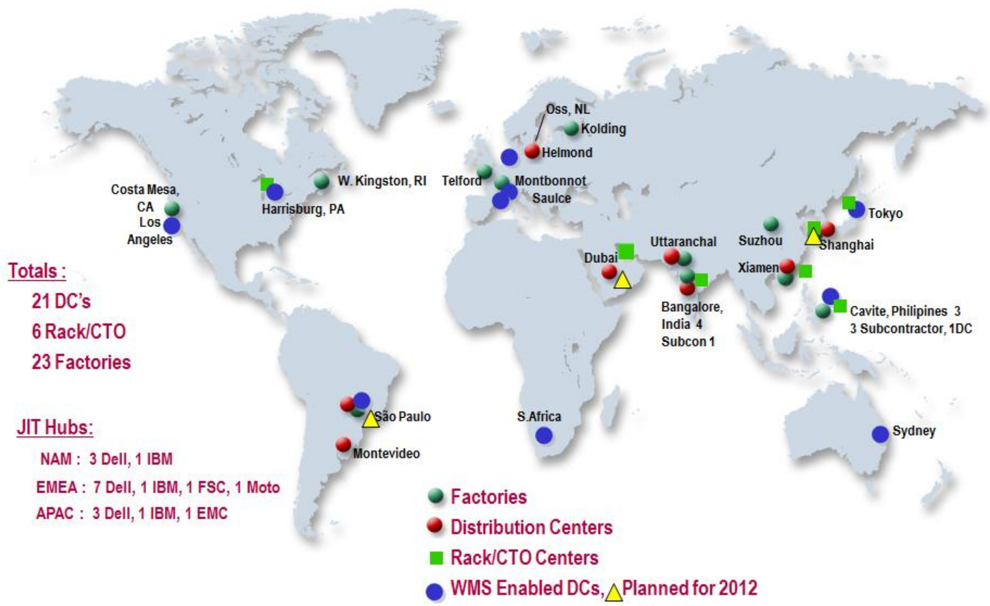


Figure 6 – Worldwide Company X facilities

To maximize the relevance of the simulation the largest timespan is chosen with the available data. Some data date back years, whereas others are only saved over previous year. Moreover, the business of Company X has changed drastically during the last decade through acquisitions. Simulating and analyzing over a too long period of time would result in difficult interpretable outcomes and the chance of making unreliable conclusions. By simulating over the period from January 2010 to June 2012, we try to balance between accuracy and relevance. With an average replenishment time of 8 weeks the simulation period should be long enough to replicate the effects of real life occurrences.

Even though nothing is fabricated in the Netherlands, server racks are assembled in the DC as well. Depending on the type of server rack and customization different components are needed. Taking into account the extra decision of production schedule it will be difficult to simulate this process adequately and balance between inventory holding cost transport cost and production cost. Therefore, the production will not be considered in our model.

2.4. Research Approach

As a backbone for the study, the research model by Mitroff et al. (1974) will be used. The model is depicted in Figure 7. It consists of four phases as cited by Bertrand and Fransoo (2002):

1. Conceptualization phase: In this phase, a conceptual model is made. Decisions are made about what variables have to be included and the scope of the problem is.
2. Modeling phase: The actual quantitative model is built and causal relationships between the variables are defined.
3. Model solving phase: The model is solved.
4. Implementation phase: Conclusions are drawn and results are implemented.

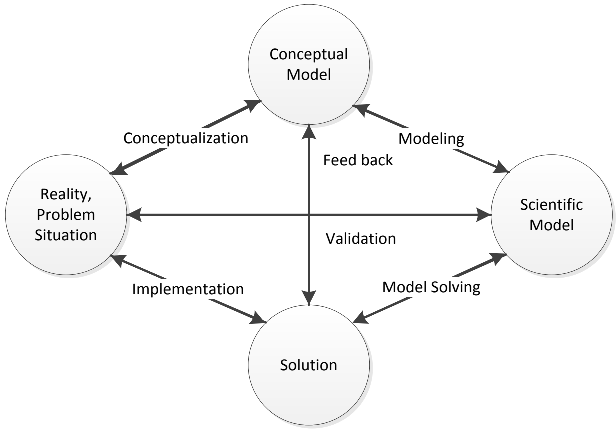


Figure 7 – Research model by Mitroff et al. (1974)

3. Conceptual Model

To conduct supply chain cost analysis, first data on cost, lead times and demand is gathered. This is discussed in section 3.1. In section 3.2, we define a replenishment strategy to replenish inventory to keep the service level on target.

3.1. Data collection

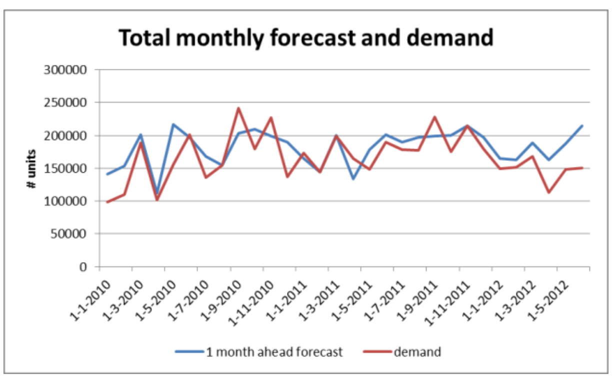
Data to simulate the current supply chain are gathered from different internal and external sources of Company X. Oracle information systems is the main internal source of data as it registers the operational status of all orders and products. Assumptions are made for data that are not available.

Demand

Data on customer demand is extracted directly from order management section in Oracle. Each order is assigned to the geographical region. We only look at orders for the EMEA region which are handled by the DC. The request date in the data is the date and time at which the order should be delivered. The order should be delivered within 6 days after the order is released at the DC. Because there is no data available on the lead time distribution we assume that all orders take exactly 6 days to be processed and delivered if the product is available in inventory. Therefore, we use the request date as the moment customer demand occurs.

Forecast

Monthly forecasts are made to anticipate customer demand. Every month, sales are predicted for one, two and three months ahead. For example, Figure 8 shows the total one month ahead forecast of all selected SKUs for simulation. The accuracy of these forecasts have a direct effect on operational efficiency as overestimating demand may result in abundant inventory whereas underestimating may result in backorders. The latest problem can be resolved by holding safety stock. Nevertheless, more accurate forecasts will result in lower supply chain cost.



	Forecast	*Demand*
Monthly average	181671	166236
Standard deviation	26671	36351
CV	0.147	0.219

Figure 8 – Total monthly forecast and demand

Forecast accuracy of demand can be measures in many ways. The most commonly used methods are mean absolute percentage error (MAPE) and mean percentage error (MPE):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_{t,t+1} - \hat{x}_{t,t+1}}{\hat{x}_{t,t+1}}\right| * 100 \; and \; MPE = \frac{1}{n}\sum_{t=1}^{n}\frac{x_{t,t+1} - \hat{x}_{t,t+1}}{\hat{x}_{t,t+1}} * 100$$

$where,$

$x_{t,t+1} = cummulative\ demand\ from\ time\ month\ t\ to\ t+1$

$\hat{x}_{t,t+1} = forecast\ of\ cumulative\ demand\ at\ time\ t\ to\ t+1$

A problem arises with these measures when the denominator is zero. Certain SKUs have sometimes zero demand, making this method unsuitable. The problem is solved by measuring the mean absolute deviation relative to the mean forecast; Relative Absolute Deviation (RAD):

$$RAD = \frac{\sum_{t=1}^{n}\left|x_{t,t+1} - \hat{x}_{t,t+1}\right|}{\sum_{t=1}^{n}\hat{x}_{t,t+1}}$$

The disadvantage of this method is the lack to comprehend with trend as the deviation is divided by a singular number representing the entire timespan. Nevertheless, this method gives the best practical results.

Applying this method to the collected data will result in the graphs in Appendix A. The average relative absolute deviations are 44.5% for all SKUs for one month ahead forecast, 37.6% for two months ahead forecast and 34.6% for three months ahead forecast. These percentages are calculated by dividing the sum of all absolute deviations by the sum of all forecasted values. The increase in accuracy might be unexpected as it will be more difficult to predict an event that lies further away in the future. However, increasing the forecast window will increase the cumulative demand. Consequently, forecast errors partly cancel each other out and the denominator will increase. Thus, the forecast accuracy of cumulative demand will increase. The overall forecasts accuracies are rather high, meaning that supply chain management will have to hold sufficient safety stock when managing inventory levels. The inaccuracy can partly be explained by the fluctuating demand and the timeliness of the forecast. It is difficult for Company X to predict a sudden increase in demand even though it is expected to happen. Consequently, the mismatch between forecasted peaks and actual demand peaks will result in an overestimation and underestimation of demand.

To determine the bias of the forecasts the relative deviations (RD) have to be determined:

$$RD = \frac{\sum_{t=1}^{n} x_{t,t+1} - \hat{x}_{t,t+1}}{\sum_{t=1}^{n}\hat{x}_{t,t+1}}$$

The relative deviations are 9.3% for one month ahead forecast, 8.8% for two months ahead forecast and 8.1% for three months ahead forecast. This means that Company X is overestimating demand on a structural basis. However, the difference between RAD and RD also implies that often demand is higher than forecasted.

Appendix A shows the distribution of RD and RAD per SKU for the three forecast time windows. The graphs of RAD look gamma distributed with some outliers at the end of the tail. These outliers result from low moving SKUs of which almost no forecast is expected. As a result every unit demand has a large effect on the forecast accuracy. The tail of deviations larger than 200% only make up 0.9%, 2.7% and 5.8% of total demand for one, two and three months ahead

forecast respectively.
As explained, RD is more centered on the zero percent. The spread growths along the forecast window because of the difficulty to predict events further away into the future. The increase in -100% forecast deviation can be explained by new SKUs being introduced at the beginning of 2012. Because these SKUs are new, only one and/or two months ahead forecasts are available.

We can conclude that Company X has difficulties with predicting demand, especially SKUs with more variable demand patterns. In total the company is overestimating demand, but has difficulties predicting when sudden changes will happen. Therefore, extra safety stock is needed to absorb the sudden peaks in demand and still be able to fulfill customer orders.

SKU selection

During the period from January 2010 to June 2012 4029 different SKUs were sold. However, in the electronics business, demand changes rapidly over time and products get quickly outdated. Demand of 56% of all SKUs are not forecasted as these products are only sold incidentally because the products are already phased out. For these SKUs remnants are still in stock. Otherwise a special order will be created with different service agreements which we will not include in our scope. Because the total volume is only 3.2% of all products sold in this period, we will exclude these 2271 SKUs from our research. From the remaining 1758 SKUs only those originating from Bangalore, Manila or Xiamen are of our interest. Again 138 SKUs (7.8%) will be excluded from our analysis.

	Demand data	*Selection steps*			*Simulation data*
		Phased out	Origin	CV <1.33	
# SKUs selected	4029	1758	1620	396	396
# SKUs removed		2271	138	1224	
% SKUs left	100.0%	43.6%	40.2%	9.8%	9.8%
% turnover in # left	100.0%	96.8%	96.6%	76.6%	76.6%

Table 6 – SKU selection steps

There are also SKUs that are sold seldomly. As discussed, customer demand changes rapidly in the electronics business. Certain new product introductions turn out to be a success and will grow into the maturity stage of the product lifecycle. Other product introductions fail to fully grow into the maturity stage and customer demand will diminish quickly after product introduction. If the product lifespan is shorter than six months, we will not be able to determine the demand characteristics and the required inventory levels. The product lifespan is measured by the difference between the first month and last month of forecasted or realized demand. Therefore, all SKUs that have a lifespan shorter than six month will be excluded from our analysis.

Besides, from an inventory theoretic perspective highly fluctuating demand cannot be efficiently controlled at the customer order decoupling point (CODP). As the DC is the CODP, we have to decide which SKUs will be managed from the DC and which should be controlled differently by for instance outsourcing. Van Wanrooij (2012) explains that in historical demand data the CV of demand is the major cause for lack of controllability at the CODP. She identifies a threshold value for the CV that indicates that a stock point becomes uncontrollable. Van Wanrooij (2012) states that the CV is used more often to indicate volatility, but it has not been related to the controllability of stock points yet. There is no clear indication in the literature about an exact maximum value; in fact the mentioned maximum ranges from 1 to 2. Where these values originate from however, is unclear. In this thesis we choose the same value in between these borders that is used in the manufacturing context: 1.33 (Hopp et al., 2008). Thus SKUs with a CV of demand during lead time of more than 1.33 will be excluded from the analysis. 75.6% of all remaining SKUs are removed from the data set, resulting in 396 SKUs that will be used for our analysis. Table 3 displays the selection steps. Even though more than 90% of all sold SKUs are removed from the analysis, the remaining 9.8% account for 76.6% of total sold products. Thus we can conclude that the selected SKUs still account for the majority of sales. Figure 9 shows how the turnover of the selected SKUs varies over time.

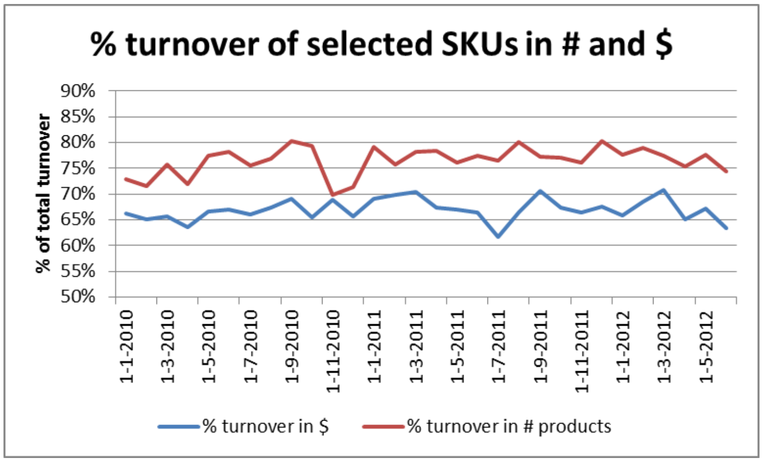


Figure 9 – Percentage turnover of selected SKUs

Lead times

The replenishment lead time at the DC consists of four elements:

- Preprocessing
- Processing
- Sea freight transport
- Hinterland transport

Figure 10 shows the inbound supply chain of the DC and the shipping lead times. As discussed, we will focus on the green marked chain. On the left side are the different sources of supply with segregate origins of Manila, Bangalore and Xiamen. Even though only Manila has a separate distribution center, each factory has a stock point after the production process to decouple manufacturing and distribution decisions. The number on the arrows represent the assumed average lead time. In the case of direct trucking from the PoR to the DC this is zero days as trucking will only take 3 hours and can be neglected. The barging lead time from the PoR to ITV deviates around one day. Because of the long and variable lead times of sea freight transport, we simplify the model by assuming a constant barging lead time of one day.

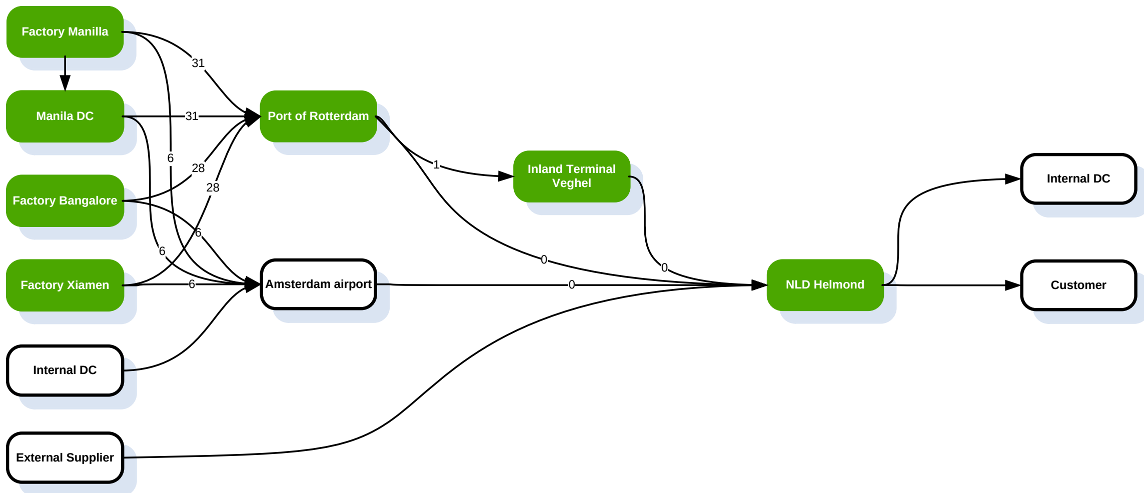


Figure 10 – DC inbound supply chain and transport lead times

The lead time distribution of sea freight transport depends on the shipping line and origin. In 2011 Company X worked with 44 different logistical parties to ship the products from the other internal DCs and factories to the DC. 80% of total flows are shipped by eight carriers. Figure 11 and Table 7 show the port to port lead time characteristics of these shipping lines over 2011.

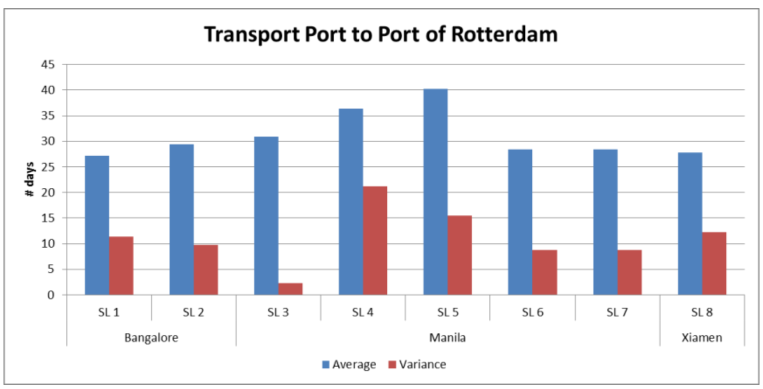


Figure 11 – Sea freight transport lead times 2011

Origin	*Bangalore*		*Manila*					*Xiamen*
Shipping line	SL 1	SL 2	SL 3	SL 4	SL 5	SL 6	SL 7	SL 8
Average	27.20	29.37	30.97	36.33	40.25	28.39	28.43	27.74
Standard deviation	3.37	3.13	1.51	4.60	3.94	2.95	2.97	3.51
CV	0.124	0.107	0.049	0.127	0.098	0.104	0.104	0.126

Table 7 - Sea freight transport lead times 2011 in days

We excluded outliers of lead time shorter than two weeks and longer than 100 days. Considering the sailing speed at which shipping lines operate, it normally takes 20 days from Chennai to Rotterdam (see Appendix B). The used samples contain shortest lead time of 20 days from Chennai and longest lead time of 59 days from Manila. Appendix C shows the distributions of each individual shipping line. Data on lead time distributions over 2010 were not available. Therefore, we will use the distributions over 2011 for the simulation.
There are significant differences between the shipping lines operating from Manila. SL 6 and SL 7 have both low average lead time and variance, whereas SL 4 and SL 5 have high and strongly

fluctuating lead times. The cost figures in Figure 12 show that there is a tradeoff to be made between transport and inventory cost. The cheapest service from Manila is slower and more variable which have to be compensated by higher safety stock levels to maintain the same service level.

Besides the transport lead times, the handling time at the origin needs to be considered. The preprocessing time for each order is three days. This is the time needed to book and plan the order. Also a fixed processing time is set in which the SKU might be produced, picked and be shipment confirmed. This means that the shipment is custom cleared and ready to be sent to the harbor where it will be loaded. These processing times vary between 5 and 20 days depending on the type and origin of the SKU.

Each replenishment of an individual SKU has a variable lead time due to lead time distribution of the sea freight transport. Depending on the SKU a fixed pre- and processing time is added and one extra day of hinterland transport. Therefore, the replenishment lead time can vary between 26 days and 84 days.

Transport cost

Transport costs at the end of the second quarter of 2012 are based on contractual agreements and rate sheet applicable at that moment in time. As discussed for the shipping lines, SL 5 is significantly cheaper per container than other shipping lines, which is partly explained by the long and variable lead times. Moreover, we suspect that the service of SL 5 will be less frequent to reduce cost. This also affects inventory control but this will not be included in the model.

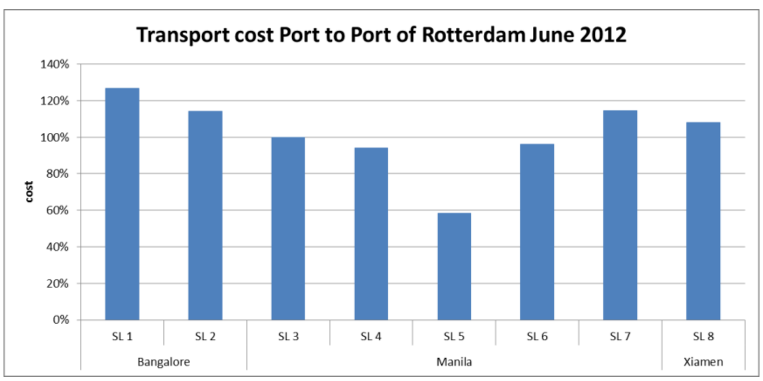


Figure 12 – Transport cost per container to PoR in June 2012 relative to SL 3

Origin	*Bangalore*		*Manila*					*Xiamen*
Shipping line	SL 1	SL 2	SL 3	SL 4	SL 5	SL 6	SL 7	SL 8
Transport cost	127%	114%	100%	94%	58%	96%	115%	108%

Table 8 - Transport cost per container to PoR June 2012 relative to SL 3

The transport cost in Figure 12 and Table 8 is a single measurement in time and does not reflect the cost per container throughout the period of simulation. Inflation and increasing oil prices have resulted in an increase of transport cost during the last years. Unfortunately, we were not able to collect data on the development of sea freight transport cost during the period from January 2010 to June 2012. For convenience, we use the same factor at which the product value increases in time. Thereby, we will make the same tradeoff in cost during the simulation period.

In chapter 5 we will conduct a sensitivity analysis to determine the effect of this assumption on the simulation results.

As Company X only ships full loaded 40 feet containers to the DC, we use the 'Full Loading Meter' (FLM) list to allocate the transport cost per container to the actual products that are shipped. Transport cost is reduced by using container space efficiently. However, product and package characteristics impede Company X from loading each container optimally. For example, certain products cannot be stacked leaving an unused space above the pallet with products. The FLM list shows how much products fit into one container. Only when each pallet is fully loaded reality and theory coincide. In practice pallets are not always fully loaded or certain combinations of products are less than optimal. This inefficiency will be displayed in the difference between the containers shipped in practice and the simulated number of containers shipped to the DC. The relative difference will be used as an extra factor on transport cost.

Inventory holding cost

Inventory holding cost is based on the value invested to manufacture and transport the products to the DC times the requested return on investment (ROI). Data on June 2010 suggest that the weighted average cost of transport is 4.4% of total product cost. The ROI is a fixed percentage set by the company which reflects the ROI required by the stakeholders. The specific risk of inventory is not considered as the sustainability is assumed to be sufficient to neglect the extra risk of holding inventory. In practice, some products such as batteries exceed their expiration date or become unsellable and have to de obliterated. Nevertheless, finance department is determining inventory holding cost based on the same standard yearly percentage of 8.5%.

Even though the holding cost rate stays the same over time, the internal cost of each SKU does change in time. With the available information Figure 13 can be drawn. The data is based on the average value of the SKU per month. The dotted line shows the trend of the average value of all SKUs relative to the benchmark of June 2012. Thus the average value of a SKU was 7% lower on March 2011 than on June 2012; a yearly increase of 5.36%.

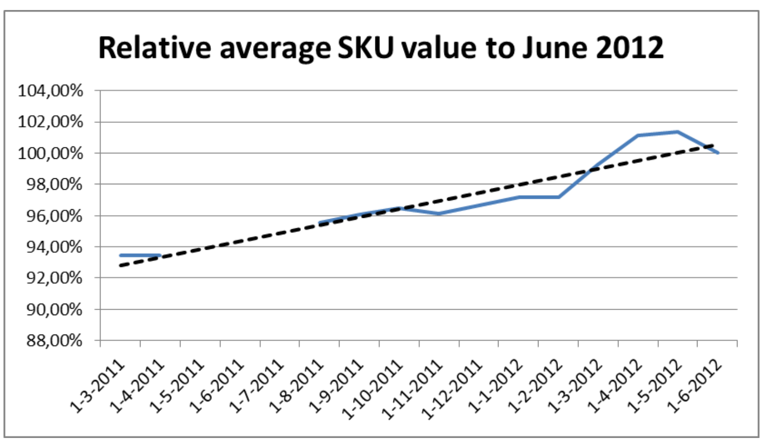


Figure 13 – Relative average SKU value to June 2012

To trend was described linearly as exponential trend would result in large differences when used in long time spans. Even though time series of the data sample is small, so is the simulation time period of 2.5 years. With no better data to our availability we assume that the SKU value have increased linearly with 5.36% per year resulting in the last known values at June 2012. As discussed, the same rate will be used to simulate the increase in transport cost.

3.2. Inventory Management Policy

The collected data will be used as input for an inventory theoretic model to simulate supply chain operations. The inbound supply as shown in Figure 11 can be redesigned into the goods flow diagram in Figure 14. As discussed, we will only focus on the supply chain highlighted in green. Thus, we will not look at shipments by air or from other internal DCs. The detailed goods flow diagram is shown in Appendix E.

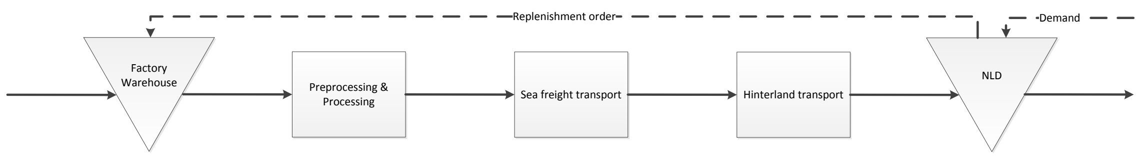
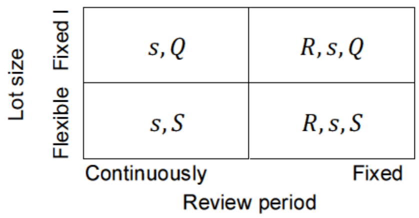


Figure 14 – Goods flow diagram

The factory warehouse is a stock point to decouple distribution scheduling from production scheduling. Occasionally it might happen that inventory levels are insufficient to handle all replenishment orders. Especially before the year end closing of the factories in Asia, the supply chain changes from a pull system by replenishment orders from the DC to a push system in which the factories are scheduled to maximize output. Consequently, production batches increase which will result in an imbalance of abundant and shortage of supply of certain SKUs. Because this happens only rarely, we assume that replenishment orders at factory warehouses can always be directly delivered from stock.

The DC is the customer order decoupling point (CODP) at which orders become customer specific. The CODP cannot be moved upstream the supply chain because of the long and variable lead times of sea freight transport. The customer order promise date is six days after the order is released at the DC. Inventories at the DC have to be replenished to guarantee an OTDS within six days of 96.5%. We will discuss the appropriate inventory policy next to accomplish this service level.

Silver et al. (1998) give an overview to determine the appropriate inventory policy to be used. Depending on the possibility to review the stock periodically of continuously, different forms of inventory policies can be considered. As Information technology at Company X enables the company to monitor the stock levels continuously, a (s,Q) or (s,S) system suits the situation the best. However, information on shipping lead time is used which does not take into account the frequency of shipments. Therefore, we will use a weekly periodically reviewed system as shipping lines will be able to ship products weekly. This is in line with Silver et al. (1998) which state that periodically reviewed systems are found in practice where R is selected largely for convenience even when point-of-sale equipment permits continuous review of the inventory position. The weekly volumes from the factories in Asia to the DC are sufficiently large to assume no ordering cost or penalty. Company X has only identified eight SKUs that require a minimum order size, which are on average 2.5 weeks of demand. A (R,s,S) system would consider these minimum required order size but is more complex to determine than a (R,S) system. A (R,S) system is a special case of a (R,s,S) system where the reorder level and order-up-to-levels are equal to S. Because the minimum order size is relatively large in comparison to the average weekly demand and there are only eight SKUs with minimum order sizes, we will use a (R,S) system to determine the order-up-to-levels. However, after determining these levels the minimum required order size will be taken into account during simulation.



Where:
$s \coloneqq reorder\ point$
$Q \coloneqq lot\ size$
$S \coloneqq order-up-to-level$
$R \coloneqq review\ period\ in\ number\ of\ periods$

Figure 15 – Replenishment strategies

Company X has a customer service policy where the OTDS should be at least 96.5%. This is equal to the fill rate (P_2), which is the fraction of customer demand that is met routinely; that is, without backorders or lost sales. The key time period over which protection against these stock outs is required is of duration R+L. In selecting the order-up-to-level at time zero we must recognize that when we have ordered the second order a week later, no other later orders can be received until seven days plus the lead time (R+L). Therefore, the order-up-to-level must be sufficient to cover demand through a period of duration R+L (Silver et al, 1998).

Silver et al. (1998) states that the reorder point for a (R,S) system can mathematically be determined as follows:

$$S = E(D) + SS = E(D) + k\sigma_L$$
$$SS = \int_0^{\infty} (S - x) f(x) dx$$
$$where\ 1 - P_2 = \frac{\int_S^{\infty} (x - S) f(x) dx}{E(D)}$$

In these functions f(x) is the probability density function of the demand assuming constant lead time. As we know, the supply chain has variable demand and lead times making this method unsuitable. As a (R,S) system is a special case of a (s,Q) system, we will use Tyworth's method in the next chapter to design the scientific model. Specifically, the (R,S) system is exactly equivalent to the (s,Q) system if one makes the transformations in Table 9.

(s,Q)	*(R,S)*
s	S
Q	DR
L	R+L

Table 9 – transformation steps

4. Scientific Model

4.1. Variable lead time

Tyworth et al. (1996) purpose is to present a nonlinear programming approach for analyzing (s, Q) inventory systems in a gamma-demand and random lead time setting. The expected total annual cost can be formulated as:

$$ETAC(s,Q) = \frac{AD}{Q} + \left(\frac{Q}{2} + s - \mu_x\right)vh$$

With ordering cost A, annual unit volume D, holding cost h, unit value v, reorder quantity Q and lead time demand X with mean μ_x. We assume that there are no ordering costs and that the (s,Q) system is replaced for a (R,S) system. Therefore, the expected total annual inventory cost is:

$$ETAC(s,Q) = \left(\frac{DR}{2} + S - \mu_x\right)vh$$

As the demand over lead time is not set as a conditional probability distribution, the conditional distribution is determined per lead time and is given by T=t, for t=1,2,…,m G(tα,β), where m is the maximum lead time.

$$ES_t = E(S|T = t) = t\alpha\beta\big(1 - G_1(s)\big) - s\big(1 - G_0(s)\big)$$

Where $\mathrm{ES_t}$ is the expected shortage during lead time t, $\mathrm{G_0}$ and $\mathrm{G_1}$ are the cumulative demand distributions of gamma functions $\mathrm{G(t\alpha, \beta)}$ and $\mathrm{G(t\alpha + 1, \beta)}$, respectively. The expected number of units short per replenishment cycle can then be calculated as followed:

$$ES = \sum_{t=1}^{m} P_t ES_t$$

To optimize expected total annual cost we have to determine reorder point s under the restrictions that:

$$ES \leq (1 - P_2)RD$$
$$s \geq 0$$
$$RD \geq 1$$

Tyworth et al. (1996) show how this problem can be solved by using the solver function in MS Excel. To implement this theory in the specific situation of Company X the use of a demand distribution has to be changed. The theoretical model is only using one demand distribution for the entire timespan of modeling. As we know demand changes over time because of quarter end peaks, trend and because SKUs phase in and out during the simulation period. To encounter this problem we use the demand forecast to anticipate changes in demand. The forecast accuracy will be used as the possible deviation of demand in practice of what is forecasted. Thus, the demand distribution will be determined by the sum of the forecasted cumulative demand and the forecast deviation as shown by the blue line and the normal distributions in black respectively in Figure 16 .

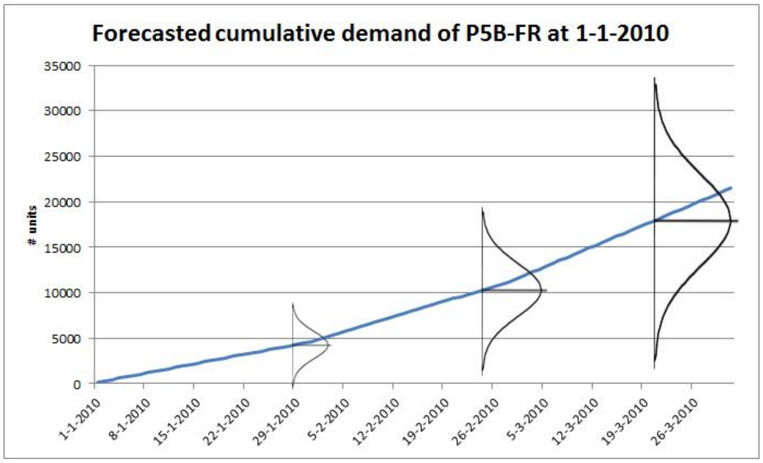


Figure 16 – Example of determining demand distribution

Variable Demand

To determine the demand distribution the data forecast has to be rewritten from monthly to daily forecasts intervals. We assume that monthly forecast is equally distributed over each day. Depending on the forecast time window, the forecast is variable in the forecasted amount and in the predetermined forecast deviation distribution for x days ahead. The forecast can be searched in the rewritten daily forecasts. Determining the deviation is more difficult. In theory we do not know anything of forecast deviations of individual SKUs at the start. In practice, management has experience and even has older data to estimate the forecast deviation. Since we lack this information and knowledge, we try to imitate this by generalizing the forecast deviations to a level at which picking a deviation from the same product sample is smaller than 5%. 5% is our aim because generalization makes the deviation less specific to the individual SKU. Thereby we will become less accurate in forecasting actual daily demand and thus create extra supply chain cost.

Thus groups of SKUs are created with same forecast accuracy. As was mentioned before, the absolute deviation (AD) is only interpretable with knowing the mean demand. Therefore the forecast deviations will be grouped by mean demand and deviation as can be seen in Table 10. The numbers of the mean and AD represent the maximum of each group. The minimum is zero or based on the maximum of the lower group.

Mean					
15,5		231.9		>231.9	
Group	AD	Group	AD	Group	AD
11	475.3	21	4193.6	31	29157.4
12	950.8	22	7180.4	32	48970.8
13	1606.1	23	11965.3	33	73603.1
14	2441.2	24	18340.4	34	131661.1
15	4035.4	25	31558.3	35	264473.3
16	>4035.4	26	>31558.3	36	>264473.3

Table 10 – Forecast deviation groups

Each deviation group contains 22 SKUs. Depending on the lifespan of the products there will be at maximum 660 forecasts as we have 30 times 1 month ahead forecasts per SKU. With this solution we now have a new method to determine the demand distribution for 1 to 92 days ahead. The major disadvantage of this method is that the highest deviation groups are not bounded by an upper limit. Therefore it may occur that two SKUs are placed in the same group while the demand and forecast accuracy is significantly different. Consequently the model will derive too high order-up-to-levels for SKUs with high forecast accuracy and too low levels for SKUs with low forecast accuracy. This is an undesirable side effect that will result in higher inventory cost and backorder levels.

4.2. Additional decision rules

Another negative side effect is the dependency of forecast accuracy over time. In the model we assume that deviations are independent in time. However, there are two reasons why the forecasts are dependent in time. First, the daily forecast is derived linearly from the monthly forecast. An error in the monthly forecast will therefore have an effect on all estimated demand for all days in that month. Secondly, because of the long forecast window, management will only be able to adjust the forecast after feedback of realized demand. Therefore predictions up to three month ahead are made at time zero and cannot be changed any more. As new information comes in each month, the forecast can be adjusted. Nevertheless, the correction will come with a delay.

Appendix D shows that the forecast deviations of one, two and three months ahead are strongly correlated (0.310 to 0.425) and significant (p=0.000). In practice, this correlated effect of under- or overestimating demand can be corrected by increasing the replenishment orders. The (R,S) system automatically does this when demand is overestimated by diminishing the replenishment order. On the other hand, when demand is underestimated, the on hand inventory level will decrease and the chance of backordering will grow as the demand for upcoming months is likely to be underestimated as well. A decision rule is introduced to decrease the chance of these stock outs as a result of underestimating demand in the upcoming months. In the optimal situation the cycle stock should be sufficient for the expected demand during lead time and the safety stock should buffer against the variation. When the inventory position is insufficient to cover the expected demand for the upcoming month, the supply chain is imbalanced. Automatically the (R,S) system will place a replenishment order to bring the inventory position back to the order-up-to-level. However, the inventories became imbalanced by underestimating demand during previous month. Because of the correlation in forecast errors, we expect that the used forecast for upcoming month will again be an underestimation of the demand during the upcoming month. Therefore, extra units have to be ordered on top of the already determined replenishment order to anticipate the underestimation of demand. Hence, the order-up-to-level will be further increased by the difference between the expected demand for the upcoming month minus the inventory position for that same month. The decision is only applicable for one month as the inventory position for the upcoming month is reviewed at the beginning of each month as new forecasts are available. The mathematical representation is shown below.

$$S_{new} = S_{old} + \left(E\left(D_{t,t+1}\right) - E\left(IP_{t,t+1}\right)\right)^{+}$$

$, where$

$S_{old} = \text{determined order} - \text{up} - \text{to} - \text{level at the beginning of the month based on the new forecast estimates}$

$S_{new} = \text{new order} - \text{up} - \text{to} - \text{level after correcting for correlated underestimation of demand}$

$D_{t,t+1} = cumulative\ demand\ from\ month\ to\ to\ t+1$

$IP_{t,t+1} = inventory\ position\ for\ the\ period\ from\ month\ t\ to\ t+1$

$= on\ hand\ inventory\ at\ time\ t\ and\ incoming\ product\ during\ upcoming\ month$

The decision to review the expected shortage over a time window of one month ahead is substantiated by the fact that forecasts are revised at the beginning of each month. Reviewing the expected shortage over the upcoming two months will have little effect because the relevant lead time distributions and (R,S) system will result that almost all products on-order will be received at the DC. Therefore, the determined order-up-to-levels should already be sufficient to handle the expected demand during the upcoming two months.

The decision to increase the replenishment order with the full difference between the expected demand and the inventory position is more subjective. The chosen factor is exactly one instead of the determined correlation factor, because the extra ordered units should compensate the underestimation of demand for several months ahead. As discussed, due to the long replenishment lead time the extra ordered items will only sort effect after at least one month. Only ordering the expected difference based on the correlation factor would result in constantly lacking behind by only compensating the underestimation of the upcoming month. The factor one remains a rough estimation. Therefore, extra testing is needed to improve the accuracy and effectiveness of the decision rule.

4.3. Simplification

As discussed, the current model will determine the new order-up-to-levels at the beginning of each month as new forecasts are available. Much calculation power is needed to find this optimal level. Only simplifications that reduce the needed calculation power without a loss in model quality will be implemented. The most straightforward improvement is to approximate demand by a probability density function. Unfortunately, to determine the expected shortage the same calculations have to be made in MS Excel; the probability density function describes the deviation and not the expected demand as this depends on the forecasted demand. The second opportunity for simplification is to recalculating only the safety stock each quarter. As the distribution of forecast deviation is independent in time, the only difference in order-up-to-level stems from the cycle stock. The cycle stock is equal to the expected demand. Therefore, we will evaluate the order up-to-level at the beginning of the second and third month of each quarter. The change in one month forecast ahead will be added to the order-up-to-level, which is shown in the equation below:

$$S_t = S_{t-1} + \hat{x}_{t,t+1} - \hat{x}_{t-1,t}$$

$, where$

$S_t = order - up - to - level\ at\ the\ beginning\ of\ month\ t$

$\hat{x}_{t,t+1} = forecasted\ cumulative\ demand\ of\ month\ t$

4.4. Illustration

In this example we use a SKU to illustrate how the order-up-to levels are determined. The SKU characteristics are listed in Table 11.

SKU	*Group*	*Origin*	*Preprocessing*	*Processing*	*Barging*
X	36	Manila	3 days	10 days	1 day

Table 11 – SKU characteristics

To determine the order-up-to-level at the start on the first of January 2010, we have to find the distribution of the demand during lead time. Since the SKU originates from Manila the lead time distribution is as shown in Figure 17.

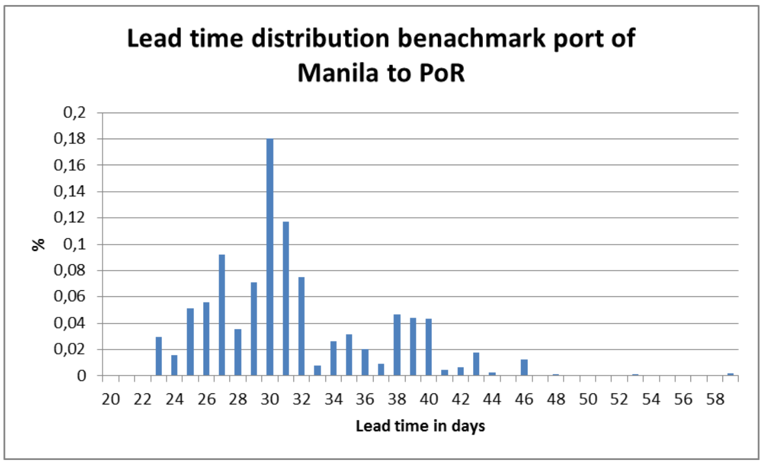


Figure 17 – Lead time distribution Port of Manila to PoR

Figure 18 shows the demand distribution during lead times of 36, 52 and 73 days. These are the minimum, the modus and the maximum lead times respectively.

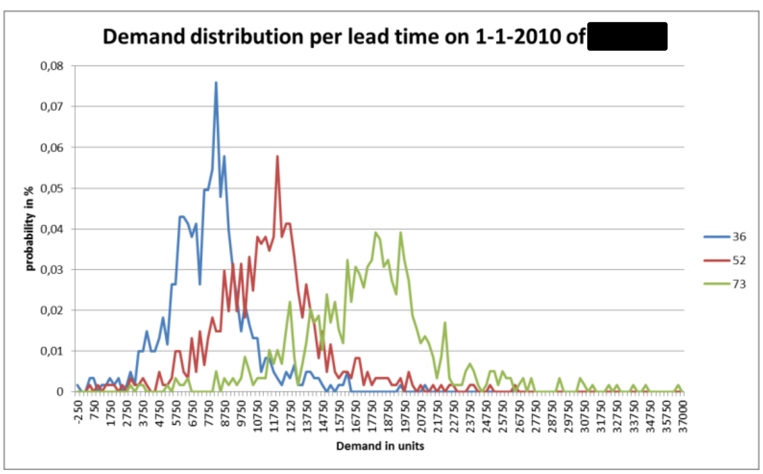


Figure 18 – Demand distributions

The model uses the demand of all the possible lead times by y combining the demand weighted the lead time probability. Thereby we derive the DDLT distribution as shown in Figure 19. Next, the order-up-to-level is determined by optimizing S under the condition that the expected shortage is 9.2% of total expected demand. The 9.2% is equal to the percentage backorders at Company X during 2011. To optimize S, we first have to determine the expected demand. As can be seen, the left tail has negative expected demand and will be excluded from our calculations. The red line shows the required order-up-to-level of 15959 units to get an expected shortage of 9.2%.

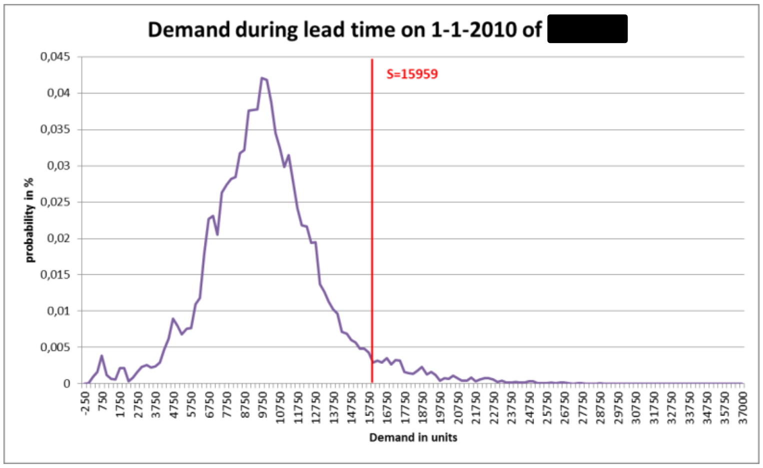


Figure 19 – DDLT on 1-1-2010 of P5B-FR

The calculations will be repeated quarterly to determine the new order-up-to-levels. As discussed in the paragraph Simplification, at the beginning of the second and third month of each quarter the new order-up-to-levels will be determined. The change in order-up-to-level is determined by the difference between the forecasted demand over the upcoming month and previous month. Appendix F shows the results.

4.5. Verification

Net, the discussed model is programmed in MS Excel Visual Basics. We are interested if the theory works in practice by comparing the KPIs of the supply chain in practice and in the simulation. These KPIs are backorders, transport cost and inventory cost. Moreover, we will look at the number of products shipped by truck as an indicator of the hinterland modal split.

Key Performance Indicators

To make a comparison of our model accuracy and our research results, we use inventory and transport data as a benchmark of the current situation at Company X. After determining the order-up-to-levels of all 396 SKUs, the process from January 2010 to June 2012 is simulated. The variable lead times make it impossible to draw conclusion out of one simulation run. Considering the calculation power and available time, each simulation will run three times to increase reliability. The result for the simulated benchmark is shown in Figure 20.

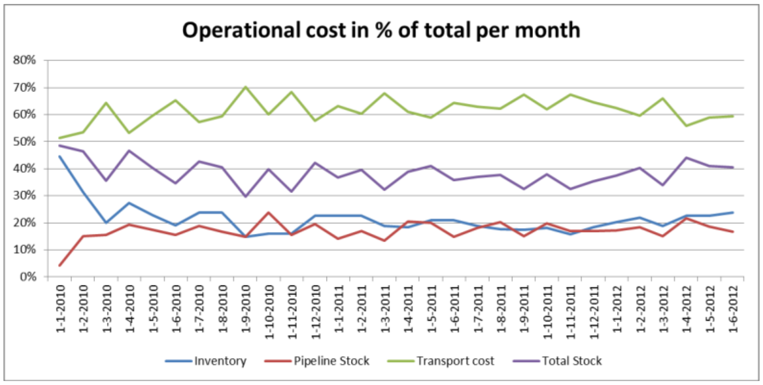


Figure 20 – Simulated percentage costs of total supply chain cost of benchmark

The graphs show no suspicious patterns except for the increase and decrease during the warm-up period of the on-order inventory cost and the on-hand inventory cost respectively. By using the moving average technique of Welch (1981, 1983), we determine that the warm-up period is 18 weeks, i.e. the first four months of 2010. We will exclude this warm-up period from our analysis.

	Backorders	*On-hand stock*	*On-order stock*	*# imported containers*	*Trucking*
Benchmark	9.2%	censored	censored	3106	12.8%
Simulation	9.7%	censored	censored	2769	16.7%
% difference	5.4%	-11.8%	-13.6%	-10.8%	30.4%

Table 12 – KPI comparison between benchmark and simulation

Table 12 shows the KPIs of the benchmark and the simulation results. In general we can conclude that the magnitudes of the simulated KPIs are similar to the benchmark. However, there are differences that need to be explained. First, the percentage backorders in the simulation is 5.4% higher than calculated. Because the forecast inaccuracy is dependent in time, we used a decision rule to rebalance the supply chain by increasing to order-up-to-level. Nevertheless, the decision rule will rebalance the inventory with a delay resulting in higher backorders than calculated.

Secondly, the on-hand stock is 11.8% lower than the benchmark. The simulated on-hand stock should be lower than the benchmark since it does not take into account certain operational inefficiencies. For instance we have assumed infinite uninterrupted supply from the factories in Asia. In practice, this is not the case as the factory closes at the end of the year. Moreover, the broader supply chain is optimized by also taken production scheduling into account.

Thirdly, the simulated on-order inventory is 13.6% lower than in practice. On-order inventory depends on the lead time and customer demand. In the long run customer demand and ordered items are almost equal except for unsold products that are amortized. Figure 21 shows the relative on-hand and on-order inventory value of the simulation results compared to the benchmark per month. As can be seen, we only have data on inventory levels for a short period of time. Nevertheless, extrapolation would suggest that the simulated on-order inventory value is significantly lower than in practice. Therefore, we conclude that the assumed lead times are too short. We suspect that the difference is predominantly due to delays at the origin port that are not taken into account. Even though customer clearance is included in the processing time, waiting time at the container terminal is neglected. Therefore, to improve the accuracy of the results we will correct the on-order inventory holding cost with the measured difference.

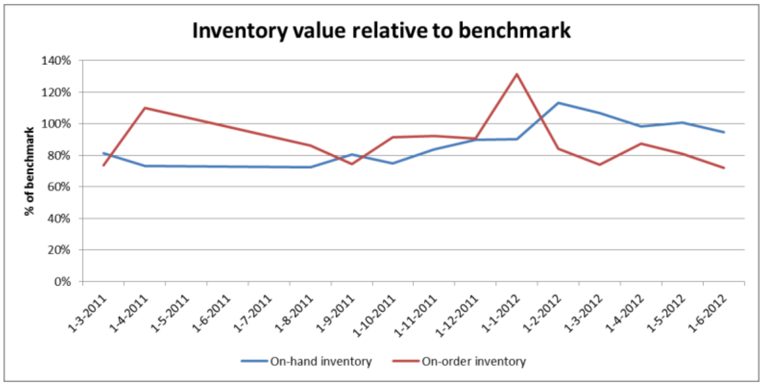


Figure 21 – Inventory value comparison

The fourth KPI suggest that the number of simulated shipped containers is 10.8% lower than in practice. A discussed, we need to take into account that not every container is filled optimally. 10.8% of the containers are needed extra to ship the same amount of products in reality. This factor is added to the transport cost to improve the quality of the model to estimate supply chain cost.

Lastly, the decision rule to truck containers from the PoR result in 30.4% more containers shipped by truck. This difference is related to the decision rule to counter the assumption of independent forecast accuracy by increasing the order-up-to-level if the supply chain is unbalanced. The unbalanced supply chain will result in more shipments by truck. We suspect that Company X proactively holds more safety stock instead of reacting when imbalances occur. Nevertheless, the model gives a rough estimate of the effect of supply chain management on the hinterland modal split.

Individual SKU performance

In this section we will investigate the distribution of backorders on group level and SKU level to look for extreme cases. Appendix G shows how the backorders are distributed. The percentage of total backorders is skewed with only 11.1% of all SKUs making up 80% of total backorders. Moreover, Appendix G shows that 10.1% of all SKUs have a backorder level higher than 20% and make up 25% of total backorders. Even though all order-up-to-levels are determined based on an expected service level of 90.8%, we would have expected a lower spread in backorder levels. A part of the spread can be explained by the varying demand and lead times. However, the other part of the total backorders can be explained by the product groups. By generalizing the forecast deviation into forecast groups, the forecast deviation distribution becomes less applicable for the specific SKU. As mentioned, the distributions of forecast deviations for higher product groups become less applicable for a specific SKU. Especially groups 16, 26 and 36 show this problem as the absolute deviation is not bounded by an upper limit. This can be seen in the increase in CV for these groups. Nevertheless, Appendix G shows that the average backorder levels per product group are rather similar.

4.6. Conclusion

In this chapter we have developed a scientific model to approximate supply chain cost and management effects by simulating replenishment decisions based on a (R,S) system. The DDLT is estimated by using the available monthly forecast and generalizing forecast deviations into product groups. The magnitude of the simulation outcomes is in line with the benchmark. Specific differences occur because of made assumptions to limit the scope of this research to the inbound flow of 9.8% of the SKUs which originate from Bangalore, Manila and Xiamen. Moreover, the decision rule to counter the effect of assumed independent forecast accuracies, result in higher percentage of shipments by truck. Nevertheless, the model gives a rough estimate of the effect of supply chain management on the hinterland model split. The limited availability of data on inventory levels impedes the ability to make a detailed comparison between the benchmark at Company X and the simulation results. However, we conclude that the lack of data decreased the accuracy of the model, especially because of missing data on lead time distributions. Nevertheless, we can use the model to investigate the tradeoff of different management decisions and the effects on supply chain cost.

5. Results

In this chapter we will try to answer the proposed research questioned with the simulation model described in the previous chapter. First we will look at the allocation problem of sea freight transport. We will show improvements in supply chain cost by considering both inventory and transport cost. Next we investigate the possible hinterland modal split under different service level scenarios. We show how these are related and what the potential is for a shift in modal split in the hinterland of the PoR. Lastly we will discuss the effects of the DC turnover peaks on supply chain performance.

5.1. Sea freight transport allocation

In the simulation model we only make use of eight carriers. The shares of total volume shipped by these carriers are shown in Table 13. The second row shows the weight adjusted shares if Company X would only contract these carriers. These shares are used to determine the results of the simulated benchmark.

	Chennai		*Manila*					*Xiamen*
	SL 1	SL 2	SL 3	SL 4	SL 5	SL 6	SL 7	SL 8
% of total volume	57.9%	30.6%	17.4%	14.9%	10.7%	17.4%	35.5%	85.9%
Adjusted % of total volume	65.5%	34.5%	18.2%	15.5%	11.2%	18.1%	37.0%	100.0%

Table 13 - % of total volume shipped per origin in 2011

Because we control both transport and inventory decisions we can investigate the effect on supply chain performance of scenarios in which transport is only allocated to one carrier per origin. Thus, with these eight carriers we can make ten different combinations which we will simulate. In these scenarios the service level will be kept constant at 90.7%. The results of the total supply chain cost of the benchmark and the ten different scenarios are shown in Figure 22 and Table 14.

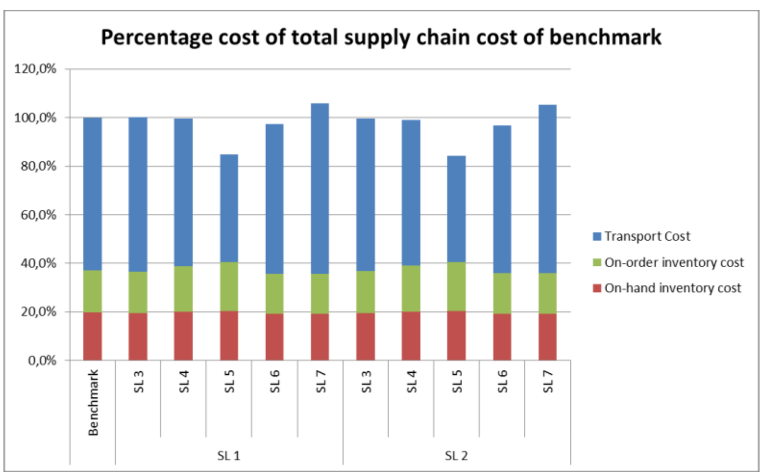


Figure 22 – Total supply chain cost per combination of shipping line

Carrier Bangalore	*Carrier Manila*	*Transport cost*	*On-hand inventory cost*	*On-order inventory cost*	*Total cost*
Benchmark	Benchmark	62.7%	19.7%	17.5%	100.0%
SL 1	SL 3	63.5%	19.4%	17.3%	100.2%
SL 1	SL 4	60.7%	20.0%	18.9%	99.6%
SL 1	SL 5	44.5%	20.3%	20.1%	84.9%
SL 1	SL 6	61.7%	19.2%	16.5%	97.4%
SL 1	SL 7	70.1%	19.2%	16.5%	105.9%
SL 2	SL 3	62.6%	19.4%	17.5%	99.5%
SL 2	SL 4	59.8%	20.0%	19.1%	99.0%
SL 2	SL 5	43.6%	20.4%	20.3%	84.2%
SL 2	SL 6	60.8%	19.3%	16.7%	96.7%
SL 2	SL 7	69.2%	19.3%	16.7%	105.2%

Table 14 - Supply chain costs per combination of shipping line in comparison to the benchmark

It can be seen that transport cost make up the majority of total cost (62.7% for benchmark). Even though the inventory holding cost increases, transport cost remain the key driver of total cost. Table 15 summarizes the difference in cost specifically for the flows from Bangalore or Manila. The best opportunity for improvement is by shipping all products from Manila with SL 5. Despite the increase of 11.6% in inventory cost, a reduction of 19,9% of total cost might be realized. To increase the frequency of shipments and also for strategically reasons, Company X prefers to work with multiple shipping lines. SL 6 would then be a good second choice. In practice, 35.5% of all shipments are handled by SL 7. Simulation outcome suggests that this has negative effect on total cost because of the high transport cost. Thus we recommend to work more closely SL 5 and optionally with SL 6 and try to reduce the number of shipments by SL 7.

	SL 1	*SL 2*	*SL 3*	*SL 4*	*SL 5*	*SL 6*	*SL 7*
Total inventory cost	-1.1%	1.9%	-1.7%	6.2%	11.6%	-5.0%	-5.0%
Transport cost	3.4%	-6.4%	0.9%	-4.8%	-38.3%	-2.9%	14.6%
Total cost	1.4%	-2.8%	-0.1%	-0.8%	-19.9%	-3.7%	7.4%

Table 15 – changes in cost of simulated scenarios

The scenario outcomes of the supply chain cost for the flow from Bangalore are more similar than Manila. Still an expected cost reduction of 2.8% might be realized by shipping all products with SL 2. Considering this relatively small differences, we recommend Company X to make both shipping lines preferred carriers. Company X should be aware of the shift in cost as a result of transport allocation. Supply chain management should be informed of changes in transport allocation, such that they can adjust the order-up-to-levels. Otherwise, inventory management will be unable to prevent abundant inventory levels or shortages, both implying extra cost in inventory holding cost and extra cost of emergency shipments respectively.

Appendix H summarizes the total supply chain cost based on the product safety groups set by Company X. The first table shows the cutoff of each category based on the cumulative percentage of total dollars of sales. The graph below shows the total cost of the cheapest scenario with SL 2 and SL 5 per SS group. It is peculiar to see that SS-B has higher total inventory holding cost than SS-A. The main reason for the difference is that the cutoff is based on sales turnover and not on product value. Thus, SS-A has more faster moving products of lower average value than SS-B. The last table in Appendix shows the cost savings per SS group for all ten scenarios. It can be concluded that regardless of the SS group transport cost can be saved by contracting only SL 2 and SL 5.

Sensitivity analysis

In chapter 3.1 we have discussed several assumptions to approximate the input parameters of the simulation model. The accuracy of these assumptions will influence the reliability of the simulation results. Because we have limited data on the growth of SKU value and transport cost in time, we will conduct a sensitivity analysis to determine the impact of the assumptions made for these parameters.

We assumed that both the transport cost and the SKU value increase with 5.36% each year. Data shows that transport cost is only 4.4% of total weighted average SKU value. Thereby, changing the transport growth rate will predominantly influence transport cost. Moreover, under current supply chain practices transport cost makes up 62.7% of total supply chain cost. The results of setting different yearly growth rates while keeping the other yearly growth rate at 5.36% are shown in Figure 23.

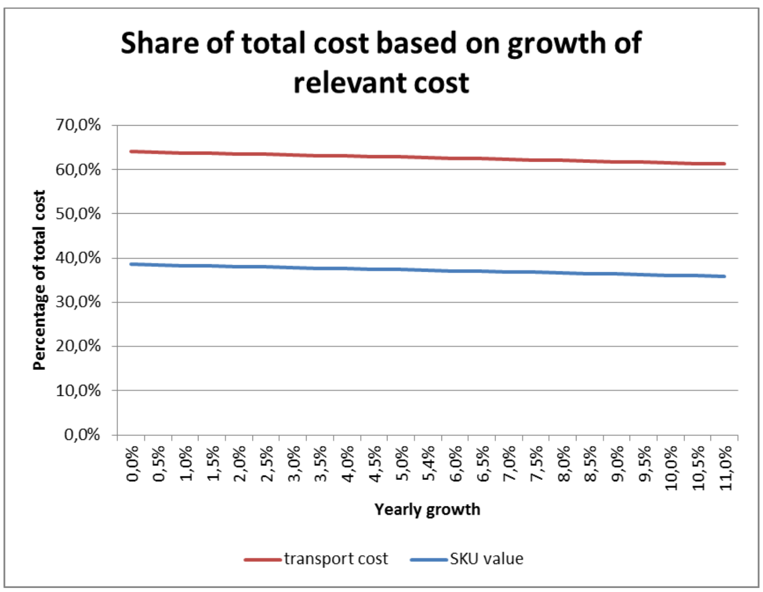


Figure 23 – Growth rate sensitivity analysis

The SKU Value in the graph refers to the SKU value minus the invested transport cost. The graph shows that share of total cost does not change drastically if one of the yearly growth rates is changed. Increasing yearly transport growth from 5,36% to almost double at 10% would result in transport cost of 61.3% of total supply chain cost; a decrease of only 1.46%. Increasing the yearly SKU value growth from 5.36% to 10% would result in inventory holding cost of 36.1% of total supply chain cost; a decrease of only 1.41%. Thus, we can conclude that growth rates do not have a large impact on the distribution of transport cost and inventory holding cost. Therefore, the assumptions have only little effect on sea freight transport allocation.

Besides the assumed growth rates, we also used the inventory holding cost rate of 8.5% which is used by the finance department of Company X. We explained that we have doubts if the rate resembles the required ROI of Company X's stakeholders because of the extra risk of amortizing stock. We would expect inventory holding cost rates in the electronics business to be around 20%. We showed that allocating sea freight transport from Manila to SL 5 would result in the lowest total supply chain cost. However, higher inventory holding cost rates would increase the transport cost of this shipping line the most because of the long and variable lead time distribution. Therefore, we will conduct a sensitivity analysis to determine the effect of inventory holding cost rates on the allocation of flows from Manila.

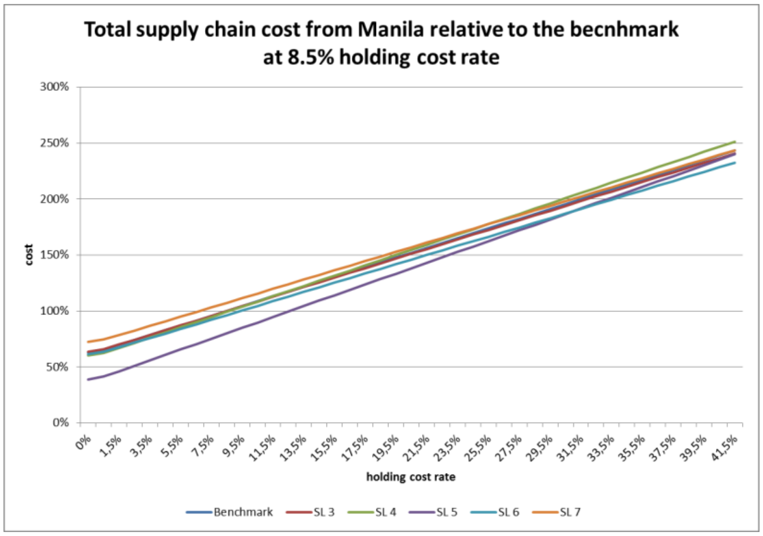


Figure 24 – Inventory holding cost rate sensitivity analysis

Figure 24 shows that under higher inventory holding cost rates SL 5 remains the best carrier to minimize total supply chain cost from Manila. The cost savings by allocating all sea freight transport to SL 5 reduces with 0.21% per percent increase of the inventory holding cost rate. However, at a rate of 31.15% the total cost of SL 5 and SL 6 are equal. However, this is an unrealistically high holding cost rate. Table 16 shows all costs if the yearly holding cost rate is 20%. Under this circumstance, the yearly cost savings by allocating all sea freight transport to SL 5 would still be approximately 1.3 Million dollar.

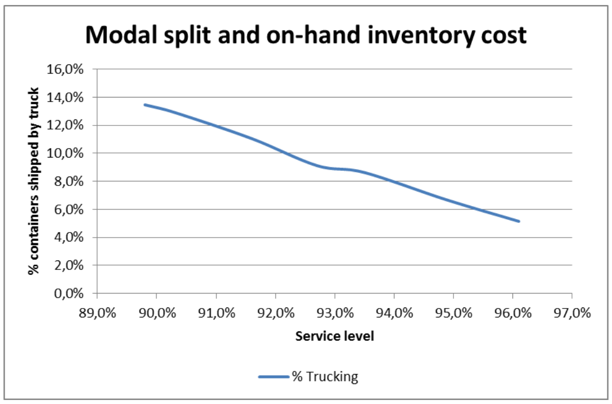
	Benchmark	*SL 3*	*SL 4*	*SL 5*	*SL 6*	*SL 7*
On-hand inventory cost	30.8%	30.2%	31.4%	32.1%	29.9%	29.9%
On-order inventory cost	27.1%	26.8%	30.1%	32.5%	25.2%	25.2%
Total inventory cost	57.9%	56.9%	61.5%	64.6%	55.0%	55.0%
Transport cost	42.1%	42.5%	40.1%	26.0%	40.9%	48.2%
Total cost	100.0%	99.4%	101.6%	90.6%	95.9%	103.3%
Total cost saving	0.0%	0.06%	-1.6%	9.4%	4.1%	-3.3%

Table 16 – Costs from Manila in comparison to the total cost of the benchmark at 20% yearly holding cost rate

Summarizing, we can conclude that the choice of cost parameters has little effect on the cost reduction by allocating sea freight transport to SL 5. The total cost reduction will decrease with 0.21% for every percent increase in yearly holding cost rate. Only when the holding cost rate is increased to 31.15%, then SL 6 would perform equally well. The results on hinterland modal split will not be affected by these price changes as the choice to ship containers by truck is based on the backorder levels. This will be discussed in the next section.

5.2. Hinterland modal split

Regardless of the sea freight transport allocation, the hinterland modal shift should stay the same as the service level is kept constant in each scenario. However, increasing the service level should result in fewer shipments by truck as there will be fewer products in backorder. Figure 25 shows that this is the case. Moreover it shows that the modal split is linearly related to the service level with a coefficient of -1.47. This means that as the expected backorders grow the number of shipments by truck increases 47% faster. As explained, the average modal split is lower in practice because we introduced the rebalancing decision rule to counter the effect of assuming forecast error independence. Nevertheless, the percentage of shipments by truck will be larger than the percentage backorders.



Service level	*% products shipped by truck*
89.8%	13.5%
90.3%	12.9%
91.6%	11.0%
92.7%	9.1%
93.5%	8.6%
94.9%	6.7%
96.1%	5.1%

Figure 25 – Modal split and on-hand inventory cost for different service levels

This relationship can be explained by the fact that more products are shipped by truck than there are products in backorder. Especially when there are only few backorders, bringing in a large replenishment order by truck would result in a relative high percentage of products shipped by truck in comparison to the percentage backorders of total demand. Figure 26 shows this relation for product BR120G-FR. The percentage backorders of total demand is 9.4% and the percentage of products shipped by truck of total demand is 14.1%.

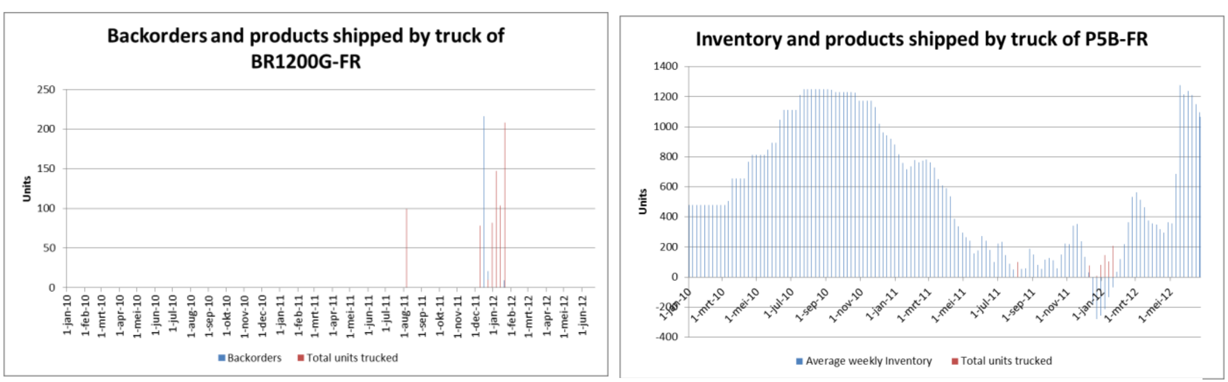


Figure 26 – Relation between backorder level and shipments by truck

If Company X accomplishes to meet the target of 96.5% OTDS, the expected percentage of shipment by truck will be 4.6%. Thus we can conclude that there is an opportunity to increase the relative volume of shipments by barge.

5.3. Quarter end peaks

Lastly we want to show what the effect of the DC turnover peaks are on supply chain cost and hinterland modal split. The monthly forecasts are a prediction of customer demand and not the turnover at the DC. Therefore, we expect that the artificially created turnover peaks at the DC will create shortage in inventory and will increase the number of shipments by truck. We only have the DC turnover data of 2011 available. However, this should be enough as the first month of simulation is excluded because of the warming-up period and the underestimation of demand will affect the decision the truck shipments several months after the inventory shortage occurs. The results are shown in Table 17.

	Backorders	*Trucking*
Benchmark	9.7%	16.7%
Quarter end peaks	10.2%	17.1%
Difference	0.5%	0.4%

Table 17 – percentage backorders and shipments by truck

As expected, the percentage backorders has increased with 5.7% to 10.2%. Consequently, the shipments by truck grow with 2.5% to 17.1%. Company X pays a fixed rate to the expeditor for bringing in the container from the PoR regardless of the mode of transport. However, by saving cost for the expeditor, future lower transport rates might be negotiated. Therefore, we assume that the extra cost of shipping a container from the PoR by truck instead of barge is 100 dollar. In that case transport cost will increase with 4000 dollar due to the quarter end peaks in turnover. However, the major increase in cost is due to the higher backorder levels.

6. Conclusions and Recommendations

In this chapter, the main findings of this study are presented. Section 5.1 presents the conclusions drawn from this study. Section 5.2 presents the recommendation. Finally, Section 5.3 presents possible areas for further research.

6.1. Conclusions

This study has been led by the following research questions:

1. How should sea freight transport be allocated to optimize the supply chain by minimizing inventory and transport cost under constant service level?
2. How is the hinterland modal split related to service level agreements?
3. What are the supply chain costs of quarter end sales peaks?

To address these research questions, sales forecasting and supply chain decision rules have been investigated. Existing theory on inventory management is customized to develop a model to simulate supply chain flows through the period from January 2010 to June 2012. Extra decision rules were added to counter the effect of the invalid assumption that the forecast errors are independent in time. We concluded that the model can generate rough estimates of the supply chain cost and hinterland modal split. Considering the simulation outcomes, the general conclusions drawn from this study are:

1. The majority of the total supply chain cost consists of transport cost. Thus, the focus of transport purchasing management on reducing sea freight transport cost will not lead to a sub optimized supply chain. However, current sea freight transport allocation results in supply chain inefficiencies. By allocating more transport to SL 5 and SL 6, between approximately 3.7% and 19.9% on supply chain cost can be saved yearly. This is only possible if the department of DC Supply Chain Planning is aware of these transport allocation decisions and act accordingly by changing the inventory order-up-to-levels. Therefore, closer collaboration and communication is needed to align decision to maximize supply chain performance.
2. The percentage of hinterland shipments by truck is linearly correlated to the service level at the DC with factor -1.47. Increasing the service level from 90.7% in 2011 to 96.5% would result in a decrease of shipments by truck from 12.8% to 4.6%. Thus, the maximum modal split is bounded by the service level and the factor that depends on the company policy when to bring in products by truck. The possible decrease of shipment by truck will only be feasible if Company X improves their supply chain control.
3. The quarter end sales bonuses result in peaks in DC’s turnover. The approximated extra yearly logistical costs of these peaks are 4000 dollar for trucking containers from the PoR. Moreover, the major extra cost is expressed in a drop of service level from 90.7% to 89.8%. Therefore, Company X should change the sales bonus structure to prevent sales team from advancing sales orders to meet bonus targets.

Limitations

The validity of our conclusions is limited by the accuracy of the simulation results. First, this is mainly affected by the invalid assumption of independent forecast errors in time. The introduction of an extra operational decision rule diminishes this effect but has the negative side effect of increasing the shipment by truck as more inventories are temporary imbalanced. Secondly, the research scope on the inbound supply chain from the factories in Asia to the DC exempts the model from supply disruptions and replenishment orders from other internal DCs. Thirdly, missing data requires extra assumptions to approximate reality and slightly hinder to review simulation validity on a detailed level. Nevertheless, verification shows that the model is valid to make rough estimates.

The impact of our research on transport allocation is limited by neglecting any constraints on transport capacity or DC's warehousing capacity. It is expected that these limitations hinder the possibility to implement improvements to the fullest. The DC capacity usage is already maximal with occurrences of 95%. Also the shipping line capacity and frequency of service will influence the possibility to shift transport from Manila more towards SL 5.

This study of the relation between supply chain management and the possible hinterland modal shift is limited by focusing on the relationship between service level and hinterland modal split. In practice, many different factors influence the modal split, namely the frequency of the barging service, DC capacity and customs. Moreover, Company X has fixed contract rates with expediter DHL which diminishes the incentive for Company X to ship more containers by barge.

Implementation

During this project attempts were made to generate a tool to estimate the effect of sea freight transport allocation on total supply chain cost. The simulation model gives a rough estimate of the distribution of cost under different scenarios of transport allocation. However, Trend and seasonality make it impossible to approximate DDLT accurately by fitting a distribution, hence the model complexity increases to incorporate monthly forecast demand into the model. Therefore, further simplification or extra testing of the model is needed to generate a simple approximation of the tradeoff between transport cost and inventory holding cost. Supply chain management can use these approximations to better tune inventory levels to transport allocation on operational level.

Alternatively, the model can be used to analyze carrier offers during a tender. The model can determine the extra cost of holding more inventories to meet the service level agreements. This extra cost should be used as a required discount when negotiating sea freight transport rates.

6.2. Recommendations

Simulating current inbound supply chain operations have resulted in the following recommendations:

1. Allocate more sea freight transport from Manila to SL 5 by making this shipping line the preferred carrier. To limit the dependency on one carrier, SL 6 can be added as second preferred carrier.

2. Company X should determine a factor to quantify the effect of the lead time distribution of sea freight transport on inventory holding cost. This factor can be used to develop an extra KPI for transport management of as an extra discount that need to be negotiated in tenders.
3. Company X should further investigate the effect of shipping products by air. Determining the required inventory levels to reduce the chance of air shipments would show the tradeoff and possible opportunity to reduce supply chain cost.
4. The customer order decoupling point (CODP) of all SKUs with a coefficient of variance higher than 1.33 should be redefined. Theory suggests that is impossible to efficiently control these products from the DC as CODP.
5. The sales bonus policy should be changed to decrease the quarter end peaks. Instead of having fixed measurements each quarter, a bonus policy should be developed that measures sales team performance throughout the time to prevent sales team advancing orders.
6. This study has showed that there is still room for improvement concerning the forecast accuracy. Long replenishment lead times and varying demand affect this accuracy. Nevertheless, the RAD of 44.5% and the RD of 9.3% suggest that forecast are overestimating demand and that there is room for improvement.

6.3. Future Research

This study contributes to current research by quantifying the potential modal split from a shippers' perspective. This case study concludes that the maximum share of transport by barge is bounded by shippers' service levels and their policy to truck containers. At Company X, the percentage trucking is negatively related to their service level with a coefficient of -1.47. Further research should investigate this coefficient at different shippers to make a general conclusion on hinterland modal split from shippers' perspective.

Besides, we concluded that this study was limited by neglecting warehouse capacity constraints. Quantitative research suggests that warehouse capacity has a large impact on modal split. High capacity usage affects optimal flow of goods and off balance inventory levels. As a result, shippers will pay extra demurrage cost for containers waiting at the inland terminal. Low inventories will increase the change of emergency shipments increasing the expected number of shipments by truck. Further research should try to quantify this relationship to better understand the hinterland modal split from shippers' perspective.

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Abbreviations

AD	Absolute Deviation
APC	American Power Conversion
CODP	Customer Order Decoupling Point
CV	Coefficient of Variance
DC	Distribution Center
EMEA	Europe, Middle East, Africa
FLM	Full Loading Meter
ITBU	IT Business Unit
ITV	Inland Terminal Veghel
KPI	Key Performance Indicators
MAPE	Mean Absolute Percentage Error
MPE	Mean Percentage Error
DC	Distribution center Helmond
NLF	Assembly Helmond
OTDS	On Time Delivery Company X
PoR	Port of Rotterdam
RAD	Relative Absolute Deviation
RD	Relative Deviation
ROI	Return on Investment
SKU	Stock-keeping Unit
TOC	Terminal operating company

List of Figures

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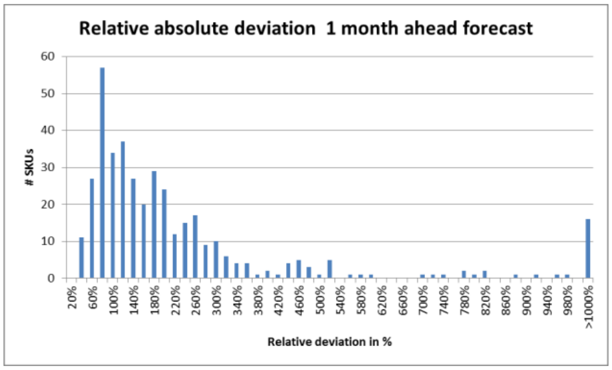
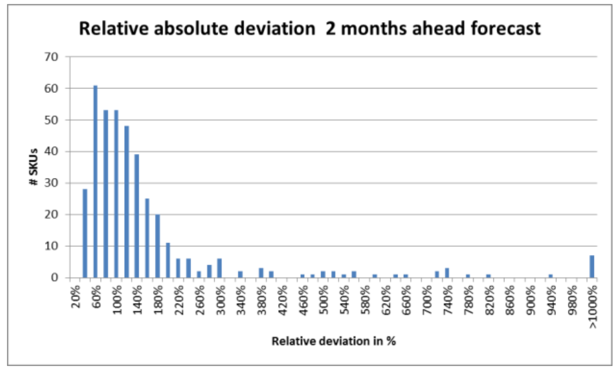
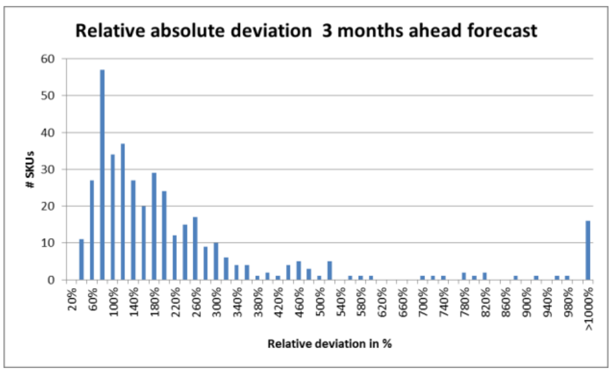
Appendix A

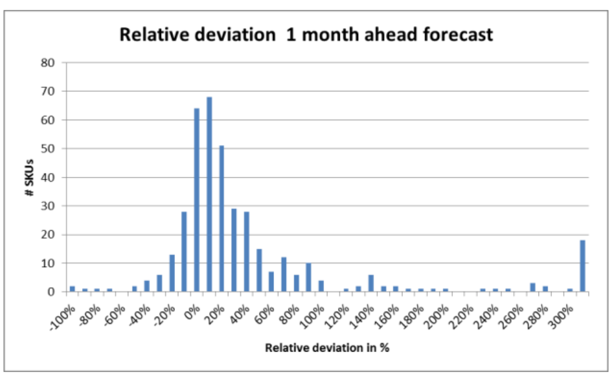
Relative absolute forecast deviation:

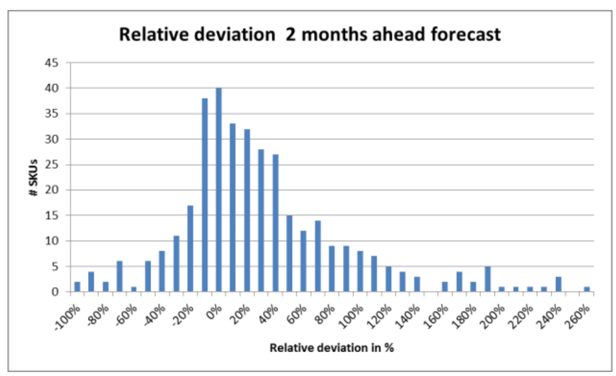


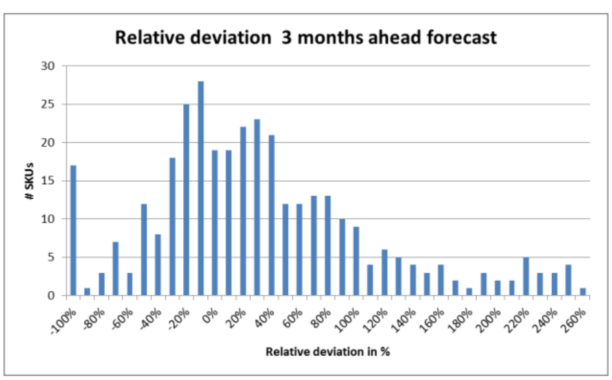




Relative forecast deviation:







Appendix B

Port to port distances

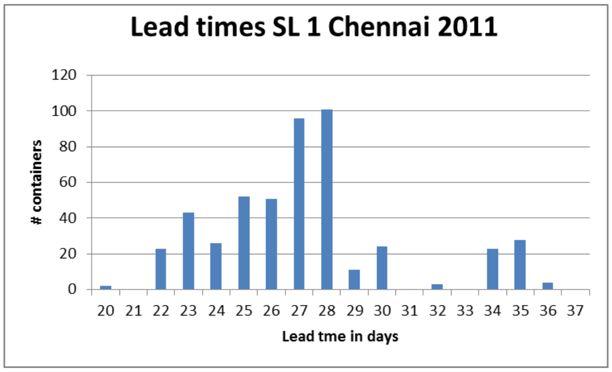
Calculation results

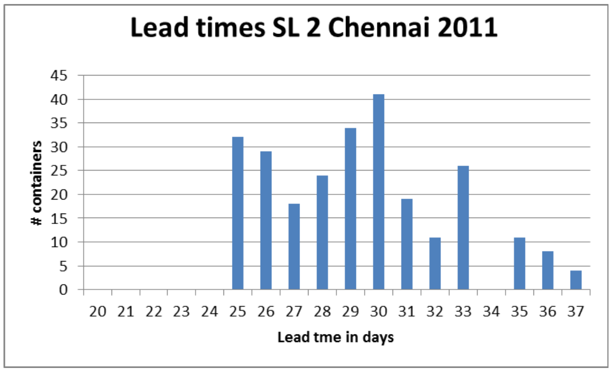
Port of loading: Chennai, IN
Port of discharge: Rotterdam, NL
Distance: 6970 nautical miles
Vessel speed: 14 knots
Time: 20 days 18 hours

Figure 27 – source www.searates.com

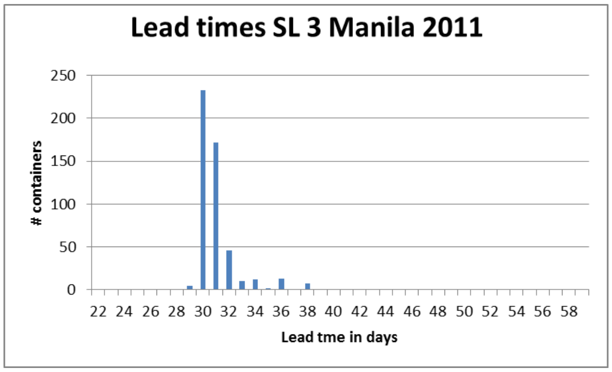
Appendix C

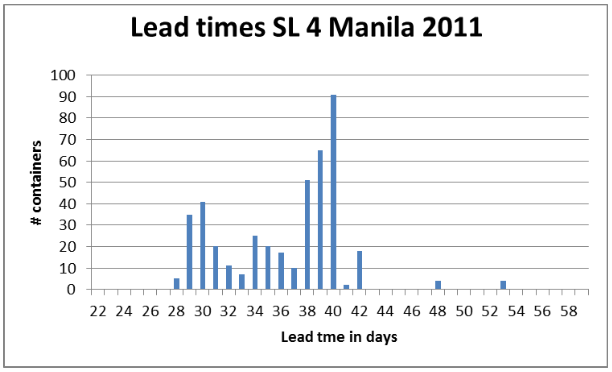
Lead time distributions Chennai

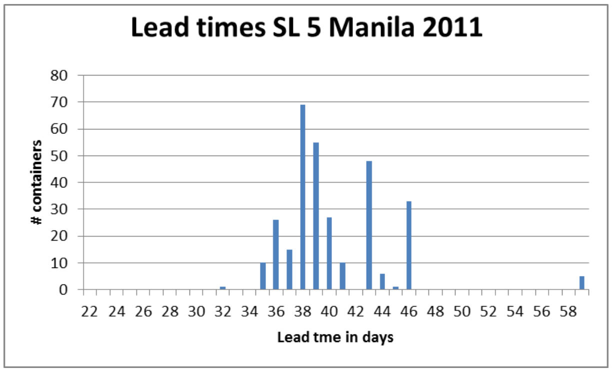


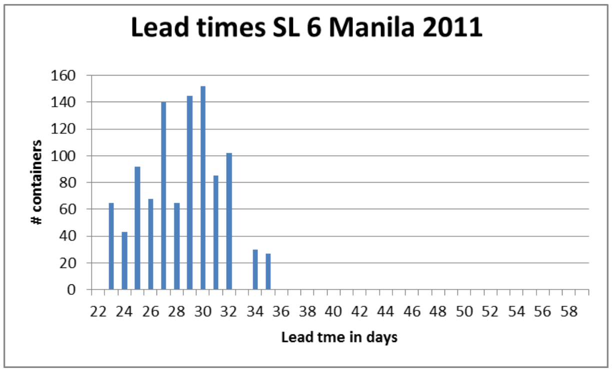


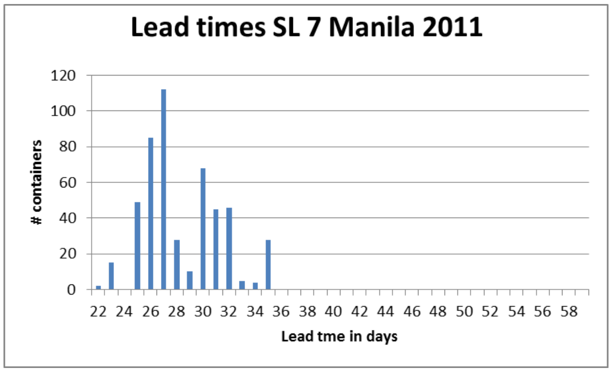
Lead time distributions Manila



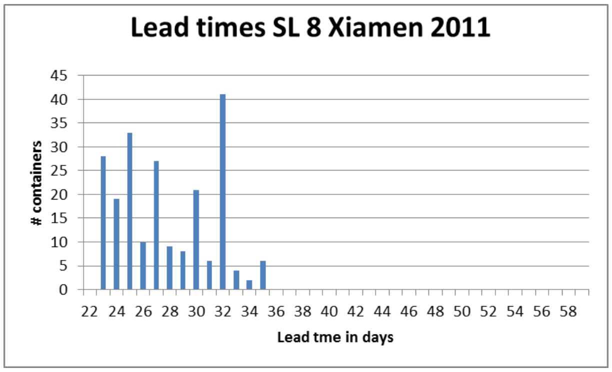






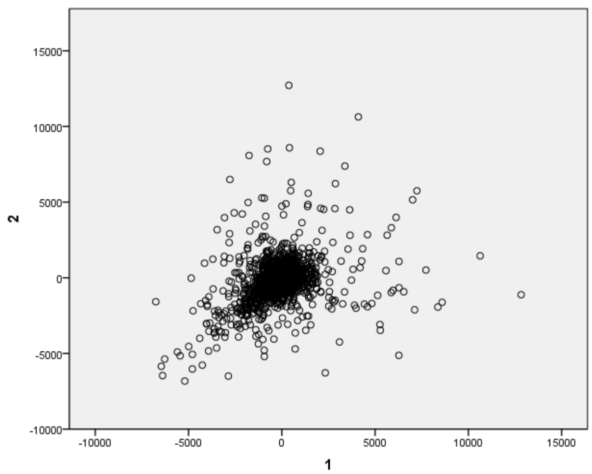


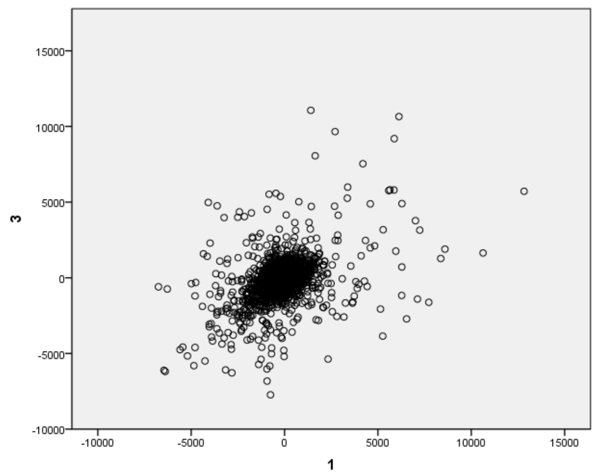
Lead time distribution Xiamen

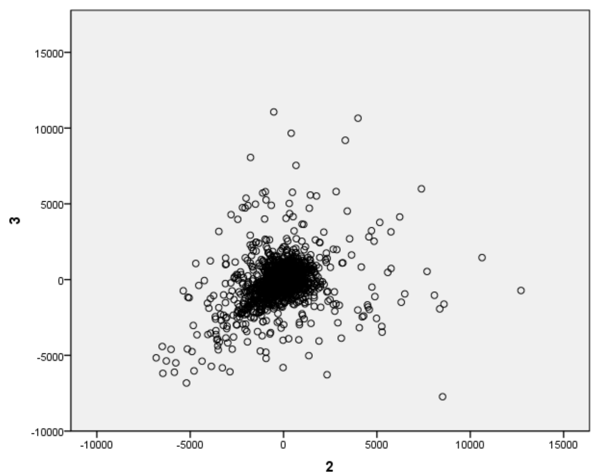


Appendix D

Scatterplot and correlation matrix of 1, 2 and 3 months ahead forecast deviation







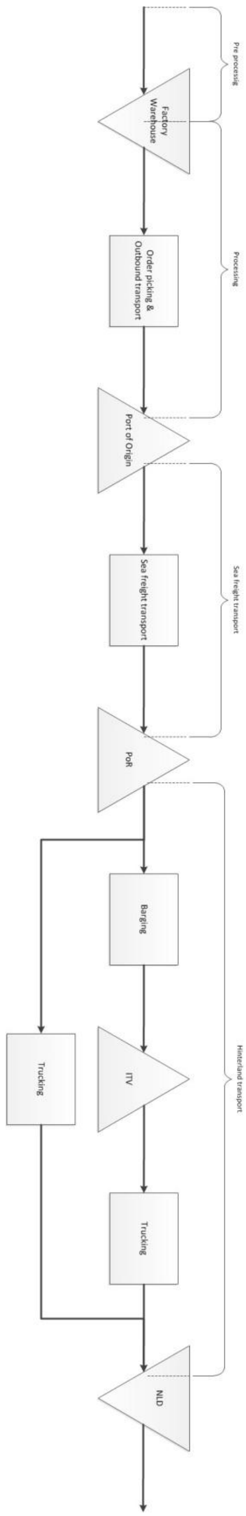
Correlations

		1	2	3
1	Pearson Correlation	1	.328**	.425**
	Sig. (2-tailed)		.000	.000
	N	10568	10568	10568
2	Pearson Correlation	.328**	1	.310**
	Sig. (2-tailed)	.000		.000
	N	10568	10568	10568
3	Pearson Correlation	.425**	.310**	1
	Sig. (2-tailed)	.000	.000	
	N	10568	10568	10568

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix E

Detailed goods flow diagram



Appendix F

Illustration of determining order-up-to levels

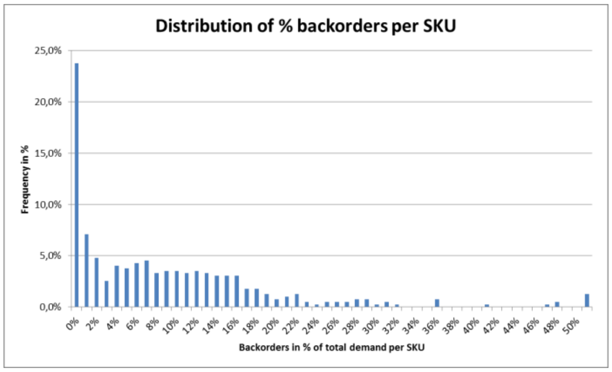
	1-1-2010	1-2-2010	1-3-2010	1-4-2010	1-5-2010	1-6-2010	1-7-2010	1-8-2010	1-9-2010	1-10-2010	1-11-2010	1-12-2010
S based on Safety Stock	15959			15923			10168			13844		
Forecast one month ahead	6599	10242	6313	8142	11363	6011	3926	3999	3887	6742	6496	8932
difference in forecast		3643	-3929		3221	-5352		73	-112		-246	2436
S based on Cycle Stock	15959	19602	15673	15923	19144	13792	10168	10241	10129	13844	13598	16034

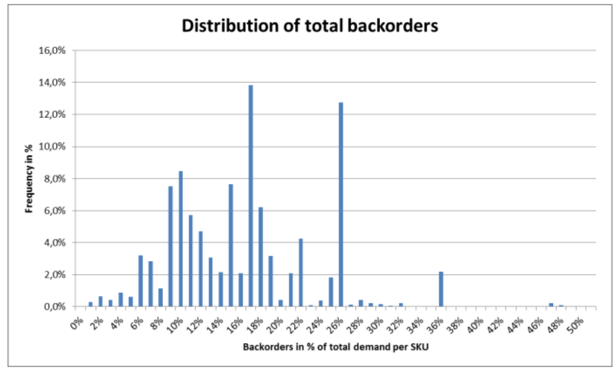
	1-1-2011	1-2-2011	1-3-2011	1-4-2011	1-5-2011	1-6-2011	1-7-2011	1-8-2011	1-9-2011	1-10-2011	1-11-2011	1-12-2011
S based on Safety Stock	17434			15255			16467			16216		
Forecast one month ahead	7654	10988	7145	6396	9974	6503	9425	8300	8500	8500	8500	7273
Maximum forecast		3334	-3843		3578	-3471		-1125	200		0	-1227
S based on Cycle Stock	17434	20768	16925	15255	18833	15362	16467	15342	15542	16216	16216	14989

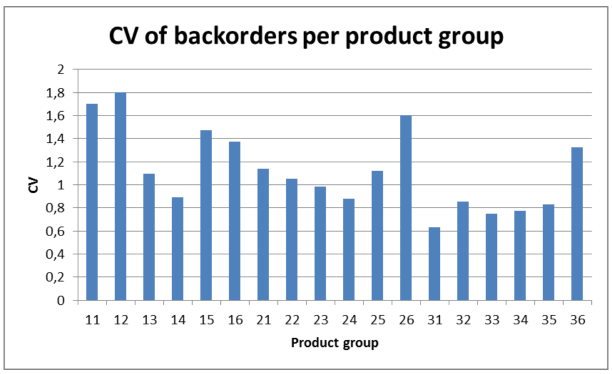
	1-1-2012	1-2-2012	1-3-2012	1-4-2012	1-5-2012	1-6-2012
S based on Safety Stock	15859			16150		
Forecast one month ahead	6101	10946	7243	7121	8391	
Maximum forecast		4845	-3703		1270	-8391
S based on Cycle Stock	15859	20704	17001	16150	17420	9029

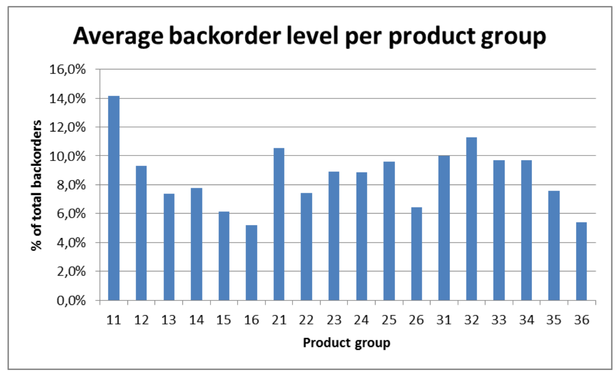
Appendix G

Distributions of backorders per SKU and product group







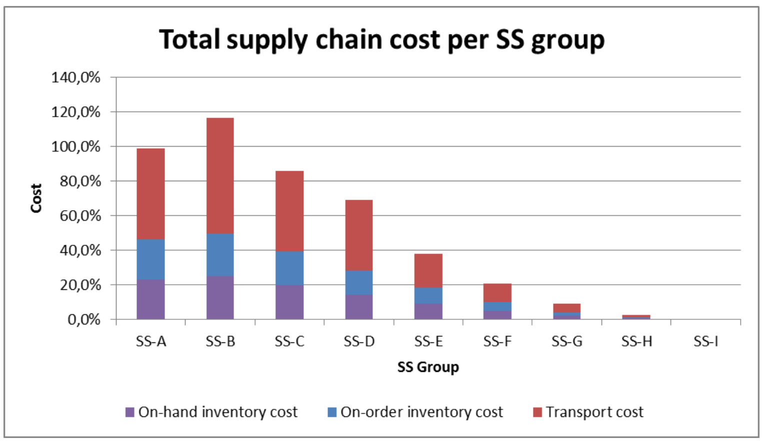


Appendix H

SS groups

Group	% of total volume in $
SS-A	22.22%
SS-B	41.67%
SS-C	58.33%
SS-D	72.22%
SS-E	83.33%
SS-F	91.67%
SS-G	97.22%
SS-H	99.99%
SS-I	100.00%

Total supply chain cost per SS groups for SL 2 from Bangalore and SL 5 from Manila relative to total cost of SS-A



Total supply chain cost savings per SS group in comparison to benchmark

Carrier Bangalore	*Carrier Manila*	*SS-A*	*SS-B*	*SS-C*	*SS-D*	*SS-E*	*SS-F*	*SS-G*	*SS-H*	*SS-I*	*Total*
SL 1	SL 3	0.2%	0.1%	0.3%	0.2%	0.1%	-0.2%	1.7%	0.3%	0.6%	0.2%
SL 1	SL 4	-0.3%	-0.5%	-0.7%	-0.6%	-0.5%	0.3%	1.8%	0.3%	-1.6%	-0.4%
SL 1	SL 5	-16.8%	-15.6%	-15.6%	-15.8%	-16.5%	-11.5%	-2.8%	-7.4%	-11.9%	-15.1%
SL 1	SL 6	-2.8%	-2.6%	-2.3%	-2.5%	-2.9%	-2.8%	0.6%	-1.2%	-2.0%	-2.4%
SL 1	SL 7	6.6%	6.0%	6.1%	6.1%	6.4%	4.5%	3.3%	3.3%	6.3%	6.0%
SL 2	SL 3	-0.7%	-0.4%	-0.5%	-0.5%	-0.5%	-0.8%	-3.4%	-0.8%	0.8%	-0.7%
SL 2	SL 4	-1.3%	-1.1%	-1.4%	-1.3%	-1.1%	-0.4%	-3.3%	-0.8%	-1.1%	-1.3%
SL 2	SL 5	-17.8%	-16.2%	-16.3%	-16.5%	-17.1%	-12.1%	-7.8%	-8.5%	-11.8%	-16.0%
SL 2	SL 6	-3.7%	-3.2%	-3.0%	-3.1%	-3.4%	-3.4%	-4.4%	-2.3%	-1.1%	-3.3%
SL 2	SL 7	5.7%	5.5%	5.4%	5.5%	5.8%	3.8%	-1.7%	2.2%	6.4%	5.1%