NTNU – Trondheim
Norwegian University of
Science and Technology

Evaluating Lead Time Decisions

A Case Study within the General Automotive
Industry

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Sammendrag

Bedrifter har ofte problemer med å kvantifisere verdien av ledetidsreduksjoner i forbindelse med valg av leverandører. I praksis gjøres disse beslutningene kun ved å ta høyde for enhetskostnad av vare, samt kostnader knyttet til transport, kapitalbinding og lager. Leverandørens ledetid kan imidlertid ha stor påvirkning på bedriftens eksponering mot usikkerhet i etterspørsel, og siden dette kan påføre bedriften store kostnader bør dette prises inn når ulike leverandører skal evalueres. Denne masteroppgaven tar for seg et eksempelstudie innen bilindustrien for å vise effektene av eksponering mot usikkerhet i etterspørsel når ulike leverandører skal evalueres.

Denne oppgaven bygger videre på arbeidet som ble gjort i Moltu et al. [2013] ved å tilrettelegge det presenterte Excel-programmet mer for reelle situasjoner i næringslivet. Programmet er allerede utviklet for to stokastiske prosesser, geometric Brownian motion og Ornstein Uhlenbeck (OU), og blir forbedret ved å inkludere en diskret ARMA modell. Dermed er programmet mer fleksibelt med tanke på å knytte sammen etterspørsel og risiko. I tillegg har leverandørspesifikke variabler blitt lagt til for danne et mer fullstendig bilde av beslutningen om valg av leverandør.

Kongsberg Automotives fabrikk på Hvittingfoss i Norway (KA) og clutchservoen de produserer for Scania er grunnlaget for studiet. KAs etterspørselsstruktur blir analysert, og er funnet å være statsjonær, normal, og best beskrevet av en ARMA(1,3)-modell. For eksempelstudiet blir imidlertid OU-prosessen med høy reverterings rate og volatilitet benyttet. Dette skyldes likheten mellom modellene, og OU-prosessens evne til å produsere en kontinuerlig graf.

Den forventede kostnaden ved avvik i tilbud og etterspørsel sammen med realopsjonsteori benyttes for å kalkulere kostnadkurven i programmet. Kurven beskriver kostnadene som gjør deg indifferent mellom to alternativer med ulike ledetider, og benyttes for tre komponenter av clutchservoen i studiet (stempel, stempelstang og aluminium støp). På bakgrunn av kostnadskurven konkluderes det at majoriteten av etterspørselserisiko utvikles innen én uke fra levering og at lite risiko legges til ved lengre ledetid. Dette benyttes så for å bedømme om KA bør bytte leverandør for hver komponent. Konklusjonen er at KA bør enten ha ekstremt kort ledetid for å håndtere etterspørselsrisikoen, eller ha lang ledetid for å få lavere innkjøpskostnad. Andre typer risiko blir også undersøkt for å vurdere om disse vil endre utfallet av eksempelstudiet.

Preface

We have written this Master's Thesis as the concluding part of our Master's degree programme at The Department of Industrial Economics and Technology Management (IØT) at The Norwegian University of Science and Technology (NTNU). Besides the financial experience from the IØT department, we all have experience with operations management from The Department of Production and Quality Engineering (IPK) at NTNU. Our thesis combines concepts from both departments, and has therefore been a unique opportunity for us to further develop our skills within both fields of our study and synthesize our knowledge.

We would like to thank our supervisor at the IØT department, Associate Professor Verena Hagspiel, for providing us with great knowledge and experience in this specific field of research. We have taken great lessons from studying her previous and present work, and she has guided us thoroughly through the entire process of this thesis.

Furthermore, we express humble gratitude towards the Vice President of Global Sales and Marketing at Kongsberg Automotive, Hans Jørgen Mørland, for giving us the opportunity to cooperate with Kongsberg Automotive and initiating the collaboration with the plant at Hvittingfoss. We especially thank Plant Manager, Martin Jonsson, and Production Manager, Erlend Østerås, at Hvittingfoss, for valuable information and input data. The cooperation has raised the quality of this thesis.

We also wish to thank PwC for providing us with financial and intellectual support through the PwC Scholarship. We especially thank Manager Claes Halvardsson at PwC for his assistance and for sharing his professional expertise throughout the process.

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Abstract

Managers often experience problems with quantifying the value of reducing or extending lead time when assessing different sourcing alternatives. In practice, these decisions are often made considering only unit procurement cost, transportation cost, capital cost and storage cost. However, the lead time of suppliers highly influences a business' exposure to demand uncertainty. This can yield large monetary values that should be accounted for. This Master's Thesis presents a case study within the automotive industry to show the effects of exposure to demand risk when assessing different sourcing alternatives.

Building on the work done in Moltu et al. [2013], the computer program is further developed to better fit real life applications. Extending the existing geometric Brownian motion and mean reverting process, a discrete ARMA model is incorporated allowing for more flexibility in connecting demand to demand risk. Additionally, new case specific variables are added to give a more holistic view of the sourcing decision.

Kongsberg Automotive's plant in Hvittingfoss, Norway (KA), and their clutch servo produced for Scania is analyzed. A thorough assessment of KA's demand structure shows that the demand is stationary, normally distributed and best described by an ARMA(1,3) model. However, due to the similarity between ARMA(1,3) and the mean reverting Ornstein-Uhlenbeck process, the latter is used for the case study because of its continuous nature. The mean reversion rate and demand volatility is found to be high.

Utilizing the expected supply-demand mismatch cost and real options theory enables for calculation of the cost curve - an indifference curve showing the costs at which you are indifferent between lead times. Three components of the clutch servo is evaluated - the piston, piston rod and aluminum casting. Based on the cost curve, this thesis concludes whether KA should change their supplier for each of them. The cost curves show that the majority of demand risk develops the last week prior to delivery, and little risk is added at longer lead times. Therefore, KA should either acquire a short lead time to mitigate this uncertainty, or choose a long lead time to benefit from the low obtained procurement cost. An assessment of other sources of risk that potentially could alter this conclusion is also presented.

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1 Introduction

Making good sourcing decisions is an essential undertaking for most large corporations. The most obvious reason for this is that the cost of purchased raw materials and sub-components accounts for more than 60% of the cost of goods sold for manufacturing companies [Gencer and Gürpinar, 2007], hence the supplier selection has a great impact on the company's performance. However, the incentive for a sourcing decision can differ, and consequently the foundation for which the decision is based on varies. For example, some sourcing decisions are primarily a question of price, while others depend on quality or service level. Regardless of the basis for the sourcing decision, most sourcing alternatives have, to some extent, an effect on the company's lead time. However, the effect of changes in lead time is often a difficult component of a sourcing decision to evaluate. Thus, practitioners often tend to omit accounting for these effect. In order to build a complete picture of the situation and to reach the correct decision, it is therefore important for companies to analyze the effects of lead time.

Real options theory has recently been proposed as a way to assess and evaluate reductions in lead time [De Treville et al., 2012]. The underlying concept is that as lead time increases, companies need to determine their production quantity longer before the actual demand is known. As an effect, they might over- or underproduce, which will consequently reduce their profit. Hence, as lead time increases, exposure to demand risk also increases. By modeling demand as a stochastic process, these dynamics can be captured and real options theory can be used to evaluate a reduction in demand risk. This way of analyzing lead time changes was first introduced by De Treville et al. [2012].

Moltu et al. [2013] have developed a computer program that utilizes this theory to evaluate different sourcing alternatives. The program features two different stochastic processes for modeling demand; geometric Brownian motion (GBM) and mean reverting Ornstein Uhlenbeck process (MRP). By using this software, companies are able to evaluate different sourcing alternatives that reduce lead time.

The aim of this thesis is to use this program to test the theory on a real life case study. Hopefully, this will reveal weaknesses with the current theory and detect areas of improvement. Further, it is believed that a case study will help practitioners see the value of incorporating demand risk exposure into their sourcing decisions. Also, earlier case studies within the field have only focused on reducing lead time. The case study presented here will take a more holistic approach, enabling both lead time reductions and extensions. This way, the theory can not only be used in cases where the lead time is reduced but also in cases where lead time extensions is the alternatives. As a result, the computer program developed in Moltu et al. [2013] will have to be further developed to incorporate lead time extensions.

The automotive industry has been chosen for the purpose of this case study. This industry features several characteristics that make it especially interesting. Companies in the industry tend to outsource a lot of their components and their current contracts are often reevaluated at expiration. Further, the industry has several layers of producers that complicate the demand structure the further upstream one goes. The company analyzed in this thesis is Kongsberg Automotive; a car part manufacturer that serves as both a third, second and first tier supplier to the original equipment manufacturers (OEM). Kongsberg Automotive's plant at Hvittingfoss, Norway, will be considered in this thesis, and is hereafter referred to as KA. When referring to the entire corporation of Kongsberg Automotive, KA Corporation will be used. The clutch servo that KA produces for Scania, for now on referred to as the clutch servo, is chosen as the product of interest. This product is produced directly for the OEMs and consists of 46 parts sourced from different second tier suppliers. The company has recently, and is currently, working on evaluating their different sourcing contracts for this product. This thesis will consequently use the presented theory to assess current sourcing decisions. Through this case, practitioners will hopefully understand and recognize the importance of taking demand risk exposure into account when assessing sourcing decisions. A key aspect of the analysis used is the assumed underlying stochastic process for demand. An extensive data analysis with the aim of determining a suitable stochastic process is therefore included.

The thesis is organized as follows. Section 2 presents a literature review, highlighting research that quantifies the value of lead time, as well as literature on supplier selection and similar problems in the automotive industry. In Section 3, the industry, case company, plant and product will be presented, followed by a description of the program in Section 4. Section 5 provides an in-depth analysis of the sales - and demand data acquired from the company. This section seeks to determine the stochastic process for demand. In Section 6, the case study is conducted, followed by a discussion of the overall thesis in Section 7. Section 8 concludes.

2 Literature Review

For the purpose of this thesis, a literature review has been performed based on peer-reviewed articles. The literature review is divided into three sections. The first section focuses on quantitative tools for evaluating lead time, the second section targets similar problems in the automotive industry and the third section reviews current literature on sourcing decisions.

2.1 Literature on Quantitative Tools for the Valuation of Lead Time

For this contribution to the literature review, a search has been performed within articles that focus on the following two topics: pricing exposure to demand risk and the derivation of the demand-supply mismatch cost.

According to Porter [1985], an efficient value chain is a source of competitive advantage. Caputo et al. [2005] underpin this observation by showing that competition among firms has recently shifted towards competition between supply chains. With increased complexity and risk in supply chains, companies seek to adopt new ways to manage supply chain risk. Cucchiella and Gastaldi [2006] present real options analysis as a framework to hedge a variety of supply chain risk. The framework describes multiple sources of uncertainty and suggests different real option types to hedge these risks. By using simulation software, Cucchiella and Gastaldi [2006] prove that when a company faces uncertain demand they it reduce risk by using an option to outsource. This option enables the company to change the production level according to demand.

By showing that supply chain risk can be hedged, Cucchiella and Gastaldi [2006] have implicitly argued that real options can be used to evaluate different opportunities that reduce supply chain risk. Further, different sources of uncertainty are considered and the effect of reducing this risk by applying real options is evaluated. One of the major sources of uncertainty in a supply chain is demand. This uncertainty generates demand risk, which can be reduced by improving lead time [De Treville et al., 2004].

De Treville et al. [2012] use the assumption that as lead time increases, more uncertainty is incorporated into the procurement process, and therefore more risk. Reducing lead time consequently reduces risk, which further generates value. De Treville et al. [2012] have developed a real options model that allows for optimization of production and sourcing choices under demand risk. The model uses the famous Newsvendor model to calculate optimal order quantity. They assume that lead time is an endogenous decision variable where demand risk increases with lead time. This enables them to derive the lowest percent unit-cost reduction needed to compensate for an increase in lead time. By combining results for different lead times, assuming demand follows a stochastic process, they are able to generate what they refer to as the cost differential frontier (CD Frontier). The CD Frontier shows the increase in unit cost a firm is willing to bear for a reduction in lead time.

Their article derives the CD Frontier for three different models of demand structure; geometric Brownian motion, Heston model, and heavy tailed distribution. They show that constant demand volatility makes incremental lead time reductions less valuable than when assuming stochastic demand volatility. When the demand has a heavy right tail, the value of reductions depends on the incorporation of extreme values in the forecasting. De Treville et al. [2012] also state that the cost of capital, i.e. the discount rate, is irrelevant to the CD Frontier when assuming constant volatility. The cost of capital in the program refers the monetary cost originating from the lag between paying for the components and selling the finished clutch servo.

De Treville et al. [2013a] build further on the work done by De Treville et al. [2012], addressing the case where information arrives at discrete points in time. The article looks at a tender structure, where information arrives at sudden events and can change the demand drastically. The tender structure is modelled by incorporating a Poisson process to a constant volatility geometric Brownian motion demand structure. This is referred to as a jump-diffusion model. De Treville et al. [2013a] conclude that the value of lead time reduction increases when jumps are present in the demand, and that demand following a jump-diffusion process with a positive jump will always lead to higher mismatch cost than when demand follows a GBM.

In the article "Valuing Lead Time," De Treville et al. [2013b] respond to the challenge put out by Joseph Blackburn in Blackburn [2012]. Blackburn demonstrated that the marginal cost of time is low for many product demand structures, but at the same time challenged researchers to identify factors that make short lead time valuable. By focusing on selected elements that affect demand-risk exposure, De Treville et al. [2013b] implement the model of De Treville et al. [2012] in various industry cases to quantify the benefits of reducing lead time. De Treville et al. [2013b] reveal factors that can increase the marginal value of time, hence make lead time reduction valuable to the firms. They show that under the assumption of constant demand volatility, a reduction in salvage value increases the marginal cost of time. In addition, they demonstrate that the value of lead time reduction increases when the possibility of demand falling to zero is present, as in the case of a tender structure. The article furthermore establishes that the marginal cost of time is highly increased when information arrives in clusters, under the assumption that demand is stochastic. Finally, service levels exceeding the profit-maximizing level from the Newsvendor model will further increase the marginal cost of time. The required cost differential can increase drastically when firms decide to set high service level requirements.

While the articles De Treville et al. [2012], De Treville et al. [2013b] and De Treville et al. [2013a]) all use the Newsvendor model as the basis for their results, none of them explicitly report whether the cost in the model incorporates supplier specific costs. Supplier specific costs include costs related to supplier selection, such as transportation cost, capital cost and storage cost. For most cases, as well as for this case study, supplier selection is a crucial undertaking when evaluating lead time. This thesis therefore seeks to extend the conducted work in the previous articles by extracting supplier specific costs from the cost in the Newsvendor model.

2.2 Literature Dealing with Similar Problems in the Automotive Industry

Clark and Fujimoto [1989] investigate the determinants of lead time performance in the automotive industry. The article explains the lead time advantage of the Japanese companies over their European and American competitors. The authors conclude that shorter lead time is preferable because of the industry's intense global competition and volatile market demands. For the case of KA, discussions with the managers lead to the conclusion that though the competition is tough, shorter lead time is not always preferable. The managers emphasize that longer lead time might be better when demand is stable, as they believe is the case for KA's clutch servos. Clark and Fujimoto [1989] seek to determine the need for efficient product development in order to keep up with rapid technological advances and changing customer demand. Further, the article points out the need for tight supplier relationships in the industry, concluding that supplier selection is essential for obtaining a competitive advantage. Fessl et al. [2010] depict the integrated networks that occur in the automotive industry in order to fulfill the requests of the OEMs. They suggest that suppliers should focus on core competences and enter into tight relationships with OEMs in order to position themselves in the industry. Design collaboration with suppliers is an important part of KA Corporation's strategy, and the tight relationships with its suppliers enable KA Corporation to provide the OEMs with customized products.

Just In Time-production (JIT) is frequently discussed in the literature dealing with the automotive industry. The ultimate goal of JIT is to eliminate waste, which can be achieved through actions such as lead time reductions, reducing set-up costs or improving quality. Ben-Daya and Hariga [2003] show the benefits of lead time reduction through Toyota's production method, which is a classical example of JIT-production. They present lead time reduction as a way to gain a competitive advantage through quick response to customer demand. In Ouyang and Chang [2002], lead time reduction is claimed to lower the level of safety stock, reduce the loss caused by stockouts, as well as increase the service level to the customer. The article considers the costs related to lead time reduction, which the authors claim to depend both on the magnitude of the lead time that is reduced and the order quantity. Ouyang and Chang [2002] assume that demand follows a normal distribution, however they do not mention their motivation for this assumption. Their objective is to simultaneously optimize the decision variables in the model; lot size, reorder point, set-up cost and lead time. The KA managers have requested that the production facility at Hvittingfoss should be treated as a black box, hence set-up cost and reorder point are not relevant for this thesis.

Explicit lead time considerations in the literature dealing with the automotive industry mainly discuss the value of reducing lead time, typically through implementation of JIT-production. However, though lead time extension is not as frequently discussed, it often appears as an effect of the globalization of value chains. Globalization of the automotive industry emerged in the 1990s, due to market saturations and trade liberalization [Sturgeon and Florida, 2000], resulting in complex value chains across the globe - and consequently longer lead time. This thesis will investigate the value and cost of lead time, both reduction and extension, on the total cost throughout the value chain for specific components. This approach has been worked out in cooperation with the managers at KA. In order to stay competitive, KA has to obtain a service level of minimum 96%. Thus, the KA managers have emphasized that lead time extension might be appropriate only if it does not have a negative effect on the service level.

2.3 Literature on Sourcing Decisions

Many articles in the literature of operations research deal with sourcing decisions. The literature can be be divided into two strands: research about the decision to produce in-house or outsource, and literature about selecting suppliers when outsourcing has been chosen. A lot of this literature is primarily optimization problems, where the challenge is to select the correct input variables in order to optimize a function, given a set of constraints. The optimization literature consists of both general models (see e.g. Talluri and Narasimhan [2004], Serel et al. [2001], Demirtas and Üstün [2008], Yu et al. [2009]) and case studies (see e.g. Gencer and Gürpinar [2007], Önüt et al. [2009], Smytka and Clemens [1993]). In the following, it will be focused on literature dealing with supplier selection, especially articles that deal with demand uncertainty and lead time.

Sislian and Satir [2000] present a framework for stratetic sourcing. When deciding whether to make internally or buy externally, they suggest that two factors should form the basis of the decision: competitive advantage and demand flexibility. For the purpose of this case study, only demand flexibility is relevant. Sislian and Satir [2000] measure demand flexibility in two ways - the time of receival of orders in relation to the delivery date, and the accuracy of the demand forecasts. Demand flexibility is highest for the case of make to order, where completely accurate orders are received before production is initiated. Make to stock represents lower demand flexibility, where the lowest possible demand flexibility occurs when demand forecasts are uncertain, and production must be initiated before actual orders are received. The time a firm must commit to production depends on the lead time, where shorter lead time allows the firm to start producing closer to delivery date. Outsourcing is concluded to be favorable when both demand flexibility is low, and the product's contribution to the firm's competitive advantage is low. While Sislian and Satir [2000] rate demand flexibility from low to high, this thesis seeks to evaluate demand flexibility by quantifying the value of lead time reduction and extension. In KA's case, Scania is able to update its orders up until the delivery date, hence KA's challenge is to be agile to deal with demand changes, as well as keep the correct amount of safety stock. The choice of a supplier highly affects KA's demand flexibility, because the supplier's lead time influences KA's ability to cope with demand uncertainty.

De Treville et al. [2004] investigate the role of lead time reduction when improving demand chain performance. The article focuses on adjusting production to fit actual demand as it materializes, known as market mediation. The article uses two factors that affect the market mediation of a relationship between a supplier and a customer: the demand information transfer and the lead time. The usefulness of the demand information depends on both the point of information transfer and the accuracy of the information. If demand information, for instance results from early sales, is made available to the supplier after its production has started, the information is not helpful. On the other hand, if demand information arrives before the production is initiated, it is highly useful. The accuracy of the information ranges from full demand information, where the supplier knows the actual demand as soon as it is available, to no demand information, where the only demand information received is the actual order. The article states that good information transfer requires tight relationships between supplier and customer, while lead time reduction can be done without involving the customer. De Treville et al. [2004] conclude that lead time reduction is a less risky undertaking than demand information transfer improvements, hence firms should always begin with lead time reduction when attempting to improve the demand chain performance. In compliance with this conclusion, this thesis will investigate KA's lead time as the supplier of the clutch servo to its customer Scania. However, the case study performed will examine the value of extending the lead time, in addition to examining the value of reducing it.

When the decision of outsourcing is made, the process of selecting a supplier becomes apparent. While De Treville et al. [2004] focus on the importance of information sharing when choosing a supplier, Verma and Pullman [1998] focus on which factors managers actually base their supplier selection on. In their article, the actual factors are compared to the managers' stated rating of the perceived importance of different supplier attributes. The article concludes that there are differences between what managers say are the most important attributes of a supplier and what they actually base their decision on. Verma and Pullman [1998] assess five factors in their analysis; cost, quality, lead-time, on-time delivery and flexibility. The result of the article shows that while managers perceive quality as the most important supplier attribute, more weight is assigned to cost and on-time delivery when the sourcing decision is made. Lead time is neither perceived important or used as the main basis for the examined decisions. Taking into account the effects lead time has on both cost and delivery performance, this thesis will treat lead time as a highly important factor when making sourcing decisions. Consequently, the case study seeks to express to KA the importance of taking lead time into account when assessing different sourcing decisions.

3 Kongsberg Automotive

The automotive industry has been chosen for the purpose of this case study, and the company to be analyzed is Kongsberg Automotive and its production facility at Hvittingfoss, KA.

In this section, the general automotive industry is briefly described, with focus on the car part manufacturers. Thereafter, KA Corporation is considered briefly, before the plant at Hvittingfoss is assessed. Finally, the product for the case study is described, as well as the specific components that are selected for the analysis.

3.1 Industry Description

Since 1998, the automotive industry has, with a few exceptions, experienced a yearly growth in production of vehicles [International Organization of Motor Vehicle Manufacturers]. According to Sturgeon et al. [2008], the characteristics of the industry's value chain have changed a lot during that period. Outsourcing boomed in the 1990s, generating a complex network of vertical business relationships across the industry. In addition, consolidation of suppliers and horizontal integration in different parts of the value chain have led to formation of giant firms. However, local presence has remained important, due to concepts such as Just In Time-production and design collaboration. Thus, the car makers, i.e. the OEMs, might prefer suppliers that are geographically close [Sturgeon et al., 2008]. The automotive industry nowadays therefore has a distinctive character, with demand for both local and global relationships. Consequently, trade-offs between costs and lead time must be made and sourcing decisions are of great importance in this industry.

After the previous financial crisis, the characteristics of the industry have changed further. According to the Plant Manager at KA Hvittingfoss, Martin Jonsson, car makers now prefer to order single components rather than systems of multiple components, hence their suppliers are forced to make less specialized products. This reduction in product complexity increases the opportunity of dual sourcing, since it is easier for car makers to switch between suppliers. Dual sourcing is the concept of using two suppliers for sourcing a single component. Dual sourcing, or even multiple sourcing, is beneficial when lead time and demand is uncertain, and customers can reduce the risk of stockout by spreading the total order of one product on many suppliers [Yu et al., 2009]. Consequently, competition has become more intense for car part manufacturers. Another important effect of dual sourcing is the possibility of lost sales for suppliers. When only one supplier is used, underproduction would force the supplier to deliver more on the next delivery to compensate for the underproduction. With dual sourcing, this could instead mean that the other supplier has to deliver more, resulting in lost sales for the underproducing supplier.

The managers at KA state that the contracts between the car part manufacturers and the car makers are usually long term agreements. Maximum production quantity is often stated in the agreement, while a minimum level of production is rarely defined. Car part manufacturers therefore face uncertainty in demand, with order quantity of zero as the worst case scenario. Usually, the daily demand has large fluctuations while the accumulated long term level tends to be stable. Car makers evaluate the car part manufacturers on every delivery, measured on quantity and time, where both factors have a binary outcome: success or failure. Delivery precision is then the average value of all deliveries. At termination, the contracts are completely renegotiated. Precision of delivery, also known as service level, can thereby be used to rank the car part manufacturers, and hence represents an important contribution to customer satisfaction. In addition, technological improvements play an important role during contract renegotiations. Suppliers risk losing contract renegotiations if they do not develop their products in accordance to new technology.

The conditions of the automotive industry make it extremely important for companies like KA to make sourcing decisions that secure a satisfying delivery precision at a tolerable cost level.

3.2 Company Description

The KA Corporation is a buy-out of the automotive parts division of Kongsberg Defence Company. The company consists of two main business areas - Automotive and Commercial Vehicles. The Automotive business is further divided into interior and driveline, and the Commercial Vehicles business is divided into fluid transfers and driver control systems. KA Corporation provides products to the global vehicle industry. It supplies OEMs, as well as first and second tier suppliers, with products from its diverse portfolio [Kongsberg Automotive Website]. Figure 1 illustrates the position of KA Corporation in the general value chain of the automotive industry. The number of supplier-levels varies across the industry, and business can even occur between suppliers at the same tier. The value chain, however, usually has three layers upstream of the OEMs: Third tier suppliers provide second tier suppliers with raw materials. The second tier suppliers make basic automotive components for the first tier suppliers, and lastly the OEMs receive components from the first tier suppliers. In Figure 1, first and second tier suppliers are presented together as Car Part Manufacturers.

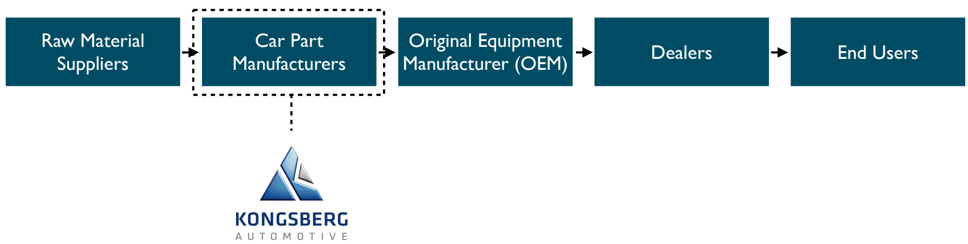


Figure 1: Kongsberg Automotive's position in the automotive industry value chain.

3.3 Plant Description

KA has 129 employees and its operation is within the Driver Control Systems (DCS) business. The production at the plant is divided into two lines: one line for gear- and clutch actuation components, and one line for chassis and components. The former generates the majority of the revenue. Figure 2 illustrates the position of the plant in KA Corporation's organizational structure.

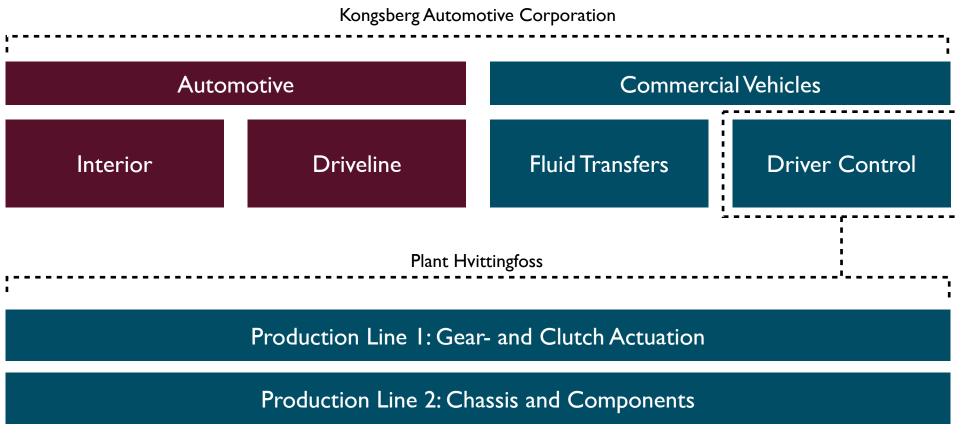


Figure 2: KA Corporation's organizational structure. The plant at Hvittingfoss operates within the driver control business. Its production is divided into two production lines.

Hvittingsfoss is one of KA Corporation's largest plants in the DCS business area. The plant had a total turnover of EUR 44,5 million, with an EBIT of 12,6%, in 2012. In addition to customer deliveries, the plant has a very attractive aftermarket business that contributes positively to the revenues. Being geographically close to the headquarters, the plant at Hvittingfoss has established a close collaboration with the R&D department at Kongsberg, and thereby has the advantage of quick access to new technology. The plant has successfully utilized advanced production technology to increase productivity and compensate for the increasing labor costs in Norway, as well as to attract new business. As a result, the facility at Hvittingfoss serves as a global center of excellence for Clutch Actuation System production, and provides other plants within KA Corporation with support.

The plant at Hvittingfoss, however, also faces some challenges. Skilled automotive workforce is a scarce resource in Norway, and recruitment is increasingly difficult. In addition, labor costs in Norway are expected to continue to increase far above the rest of Europe, and the assembly at the factory is labor intensive. The plant has a large number of different products, customers, incoming parts from suppliers, number of suppliers, as well as production processes. Consequently, conducting correct sourcing decisions is an essential undertaking for the plant in order to remain competitive.

3.4 Product Description

The case study presented in this thesis will consider different sourcing scenarios for some of the components of KA's 125mm clutch servo for Scania. This section features a description of the 125mm clutch servo.

The main principle for how a clutch servo works is the same for all producers, however the design may differ across the industry. Scania uses the same clutch servo design for all its vehicles, but the size of the servo varies. Five different sizes are offered, with the range from the small 63mm piston to the large 125mm piston. The clutch servo system is shown in Figure 3.

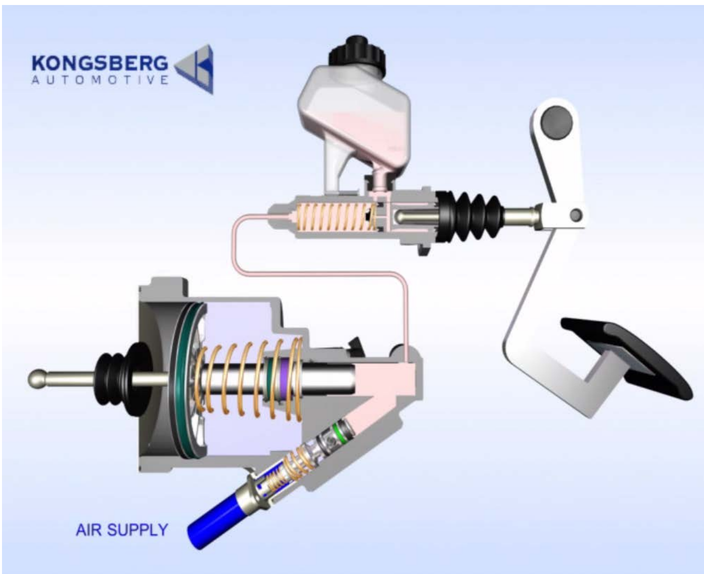


Figure 3: The clutch system for Scania trucks. The clutch servo supplies compressed air to the piston when the driver steps on the clutch pedal, hence reducing the required pressure force needed from the driver in order to actuate the clutch.

The clutch servo consists of 46 components, all of which are outsourced. Today, KA procures these components from about 20 different suppliers. All the components are ready for assembly upon arrival at KA's factory, except for the aluminum casting which needs to be machined first. Due to confidentiality concerns, this thesis uses approximations of the costs and prices that KA actually experiences. The managers at KA have estimated the total procurement cost of the components for the clutch servo to be NOK 200 and the sales price of the finished product to be NOK 550. Deliveries to customers are made twice a week, on Tuesdays and Fridays, but may occur more often when backlog is present.

As mentioned above, the clutch servo consists of 46 sourced components - potentially yielding 46 different sourcing decisions. However, for the purpose of this case study only certain components will be considered. The managers at KA are familiar with the computer program developed by Moltu et al. [2013], and when presented with the outlook of the computer program in this thesis, they handpicked three components to be of special interest. These components are the aluminum casting, the piston and the piston rod. Together, these components constitute 50% of the total procurement cost of the clutch servo. The three components are designed by KA, in cooperation with its suppliers. Hence, KA formally owns the design rights, and the components are customized for the clutch servo. Due to design creation and manufacturing adjustments, the process of changing a supplier of a customized component takes approximately one year.

The purpose of the study is to analyze potential sourcing decisions for these components. This is done by using the developed computer program. The computer program is capable of considering both lead time reductions and extensions. As of today, KA procures the aluminum casting from Serbia, the piston from South Korea and the piston rod from France. The case study will evaluate these locations against potential new sourcing locations.

4 Program Description

Accompanying this thesis is a computer program that enables firms to evaluate different sourcing alternatives. This section continues the work done in Moltu et al. [2013], with the aim of making the program more applicable for real world scenarios and as realistic as possible for the case of KA. Firstly, the underlying theory and mathematics behind the program are presented. Then, a description of the Excel-program follows, where both the general model from Moltu et al. [2013] and the customization of the model are addressed.

4.1 The Underlying Mathematics and Theory

In this section, the foundation of the model is laid with the derivations of the mismatch cost function. Firstly, the Newsvendor model is described, which serves as the basic principle for deriving the optimal order strategy. Then, the general mismatch cost function for an arbitrary demand structure is introduced. Mismatch cost is the cost that arises from the mismatch between demand and order quantity. The general mismatch cost function is derived from the Newsvendor model and can be used to evaluate lead time reduction [De Treville et al., 2013a]. In practice, the majority of applications of the standard Newsvendor model assume that demand is normally distributed. The presented model, however, assumes an arbitrary distribution, which enables flexibility of use and ability to better match a company's risks arising from demand uncertainty. Lastly, the concept of stochastic processes is introduced. This is the key concept that will enable the transition between understanding how the demand evolves and which probability distribution that describes the demand. In this subsection, the specific mismatch cost is derived assuming that demand follows (1) an MRP and (2) a GBM.

4.1.1 The Newsvendor Model

The basic principle used for the derivations of the mismatch cost function is the Newsvendor model (see e.g. Cachon and Terwiesch [2013c]). The Newsvendor model models a one-time irreversible business decision. A newsvendor has to determine how many newspapers to order for the day. If the newsvendor chooses too few newspapers, the vendor will experience lost sales. Too many newspapers will result in a stack of newspapers that the vendor will either have to sell at a discounted price back to the publisher or throw away [Hill, 2011].

The concept of the Newsvendor model is applicable beyond the simple case of newspapers. Many firms have to decide on how much to order before they are able to observe the actual demand at a later point in time. Once the demand is known, the firm will observe if the order quantity was too high - the order quantity exceeding the demand, or too low - the demand exceeding the order quantity. The firm will not be able to sell all the products when the order quantity is too high, and therefore faces costs related to this, such as inventory holding cost and cost of obsolescence. In some businesses, firms have the possibility to sell the excess inventory back to the suppliers or in a different market. In that case, the price is often less than the original price of the product, and is referred to as the salvage value [Cachon and Terwiesch, 2013b]. A more thorough assessment of salvage value is given in Section 6.2.3. Although the firm will be able to sell all its products with a too low order quantity, there are also costs related to this, such as cost of lost sales and cost of lost goodwill.

The profit function of the Newsvendor model depends on the sales price of the product, p, the ordering cost, c, the salvage value, s, the actual demand at the delivery date, D, and the order quantity, Q. The profit function can be written as

$$\pi(D,Q) = pE[min(D,Q)] - cQ + sE[max(Q-D,0)] \tag{1}$$

$$= (p-c)E[D] - \underbrace{(c-s)E[max(Q-D,0)] - (p-s)E[max(D-Q,0)]}_{Cost(Q)}. \tag{2}$$

The goal is to maximize the profit function with respect to Q. This is equal to minimizing the cost of supply and demand mismatch, denoted $Cost(Q)$ in Equation (2). The cost of supply and demand mismatch of the Newsvendor model depends on the level of actual demand. If the ordered quantity exceeds actual demand, the firm experiences a cost of overage, C_o, per unit of excess order. When actual demand exceeds the ordered quantity, the firm faces the cost of underage, C_u, for each unit short of order. Thus, C_o is defined as the difference between cost and salvage value, while C_u is the difference between price and cost. The expected supply and demand mismatch cost function is therefore equal to

$$E[Cost(Q)] = C_o \int_0^Q (Q - D) f(D) dD + C_u \int_Q^\infty (D - Q) f(D) dD, \tag{3}$$

$$\text{where } C_o = c - s,$$
$$C_u = p - c,$$

$f(D)$ is the demand density function, and D is the demand at delivery date. In the deterministic case, i.e. when lead time is zero and demand is known, $Cost(Q)$ is equal to zero. Solving the integrals in Equation (3) and taking the first derivative of $E[Cost(Q)]$ with respect to order quantity Q and setting it equal to zero yields

$$\frac{dE[Cost(Q)]}{dQ} = C_o F(Q) - C_u(1 - F(Q)) = 0$$
$$\Rightarrow F(Q) = \frac{C_u}{C_u + C_o},$$

where $F(\cdot)$ is the cumulative probability distribution function [Hill, 2011]. Consequently, $F(Q)$ is equal to

$$F(Q) = \frac{C_u}{C_u + C_o} = \frac{p - c}{(p - c) + (c - s)} = \frac{p - c}{p - s}. \tag{4}$$

The optimal order quantity, Q^*, is the inverse of $F(Q)$. It is the order quantity that minimizes the expected supply and demand mismatch cost function and is equal to

$$Q^* = F^{-1}\left(\frac{p - c}{p - s}\right). \tag{5}$$

The optimal order quantity is therefore dependent on the choice of demand distribution and the relationship between the cost of under- and overproduction.

4.1.2 The Expected Demand-Supply Mismatch Cost Function

In this subsection, the foundation of the computer program is laid through the derivation of the expected demand-supply mismatch cost function. The function originates from the concept of expected demand-supply mismatch cost (see e.g. Cachon and Terwiesch [2013a]), hereafter referred to as mismatch cost, and is closely related to the profit function of the Newsvendor model shown in Equation 1. Costs related to demand-supply mismatch appear when a firm has to commit to its suppliers or the production quantity before it can observe actual demand. Consequently, mismatch cost considers overproduction and underproduction. The former represents the tangible cost of leftover inventory, while the latter estimates the intangible cost of not meeting the demand. According to the Newsvendor model, as previously discussed, the mismatch cost function is equal to

$$MC(Q) = (p-c)E[max(D_T - Q, 0)] + (c-s)E[max(Q - D_T, 0)], \tag{6}$$

where D_T is the realized demand at the delivery date T. The expression is twofold, where the first term considers the expected cost of lost sales due to underproduction, and the second states the expected cost of overproduction. The function will be described in detail later in this section.

Mismatch cost depends on the operation mode. Make to order and make to stock generate the two extreme values of mismatch between supply and demand, where the latter represents the highest mismatch cost. For the case of make to order, production starts after customer orders have been received, hence the production level is based on realized demand and not on estimates. Consequently, the mismatch cost is zero for make to order.

Factors that drive the mismatch cost are the critical ratio, i.e. $\frac{C_u}{(C_o+C_u)}$, whether the process is stationary or not, and the parameters of the process, i.e. measurements of mean level and volatility. As the critical ratio decreases, excess inventory becomes costly relative to lost sales, and the mismatch cost increases. In addition, as the volatility increases, demand is harder to predict, hence the mismatch cost increases. Non-stationarity further contributes to an increase in the mismatch cost.

The mismatch cost function is derived as the difference between maximum expected possible profit, i.e. the case of make to order, and the expected profit, considering that demand follows a probability distribution $g(D_{T_i})$. Therefore, it is the difference between the expected net present value of the profit when lead time is zero, and the expected net present value of the profit when lead time is equal to $\tau = T - T_i$. T_i is the point where you have to commit to an order in order to be ready to deliver at delivery time, T. Rearranging Equation (6), the mismatch cost function can be stated as

$$MC_g(Q) = \underbrace{(p-c)e^{-r\tau}E[D_T]}_{\text{Profit with zero lead time}} - \underbrace{V_{T_i}(Q),}_{\text{Profit with lead time } \tau} \tag{7}$$

$$\begin{aligned}\text{where } V_{T_i}(Q) &= e^{-r\tau}\Bigg(\underbrace{pE[min(D_T,Q)]}_{\downarrow} - cQ + sE[max(Q-D_T,0)]\Bigg)\\ &= e^{-r\tau}\Bigg(\overbrace{-pE[max(Q-D_T,0)] + pQ} - cQ + sE[max(Q-D_T,0)]\Bigg)\\ &= e^{-r\tau}\Bigg((p-c)Q - (p-s)E[max(Q-D_T,0)]\Bigg). \end{aligned} \tag{8}$$

The profit with lead time τ, denoted by $V_{T_i}(Q)$, assuming a lead time $\tau > 0$, is a function of revenues from sales, cost of actual production, and the salvage value of overproduction if produced quantity exceeds actual demand.

Deriving and simplifying (see Moltu et al. [2013] for further explanations), the mismatch cost function is equal to

$$MC_g(Q) = e^{-r\tau}\Bigg((p-s)\int_Q^{\infty}(D_T - Q)g(D_T)dD_T + (c-s)(Q - E(D_T))\Bigg). \tag{9}$$

As for the optimal order quantity, the mismatch cost function requires an assumption about the demand probability distribution. This will be discussed in the next section.

4.1.3 Stochastic Processes

In order to calculate the mismatch cost for different lead times, the corresponding probability distribution of the demand at each lead time needs to be determined. This can be seen as the process of predicting the demand distribution for different lead times, given the current situation. In practice, firms tend to make lead time decisions implicitly assuming that demand follows a normal distribution. Firms do not always have a clear opinion about their demand distribution or how their demand evolves, and this assumption is sometimes even made unknowingly. In many cases, however, firms face demand structures that are far from being stationary and normally distributed. In this thesis, the demand evolution and probability distribution is determined by utilizing the concept of stochastic processes. A stochastic process is a family of time indexed random variables $Z(\omega, t)$, where ω belongs to a sample space and t belongs to an index set, i.e. different points in time (see Wei [2006]). By holding t constant, $Z(\omega, t)$ becomes a random variable, and by holding ω constant, the function is called a sample function. A time series is a sample function from a certain stochastic process (Wei [2006]).

Different stochastic processes are related to different probability distributions, meaning that a variable following one particular stochastic process will have a distinct probability distribution at every point in time. The prediction of the demand variable's distribution at different lead times will be related to the current situation. This probability distribution depends on the parameters of the process. Another important issue related stochastic processes is stationarity. A stationary process is a process where statistical properties remain constant over time. A non-stationary process will experience changes in either the mean, the variance or both (Wei [2006]). Accordingly, the choice of stochastic process will have large impact on the mismatch cost.

The computer program will be fitted with the option of using two different stochastic processes: a mean reverting Ornstein Uhlenbeck process and a geometric Brownian motion. In the following sections the derivations and results for the mismatch cost function, assuming that demand is following each of these processes, are shown. Additionally, a rationale for why these processes have been chosen is presented.

Stationary Process: Mean Reverting Ornstein Uhlenbeck Process

To capture the characteristics of a stationary stochastic process, the mismatch cost function is derived assuming that demand follows an MRP. In this thesis, we focus on the so-called Ornstein Uhlenbeck process, which is a particular MRP defined as

$$dD_t = \alpha(\mu - D_t)dt + \sigma dZ_t, \tag{10}$$

where α is the mean reversion rate, μ is the long run equilibrium price and σ is the volatility. A large mean reversion rate results in a quick reversion to the mean. Z_t denotes a Wiener process. The Wiener process is normally distributed with mean zero and a variance growing linearly with extensions of the time horizon, $Z_t \sim N(0,t)$.[1] The increment of a Wiener process is then represented as dZ_t, where $dZ_t \sim N(0, dt)$. It is important to note that the expected change in D_t depends on the difference between μ and D_t. Though it satisfies the Markov property, meaning that the probability distribution of demand at a later point in time is only dependent on its current value, the presented process does not have independent increments. A variable that follows an MRP is normally distributed, $D_T \sim N\left(\mu+(D_t-\mu)e^{-\alpha\tau}, (1-e^{-2\alpha\tau})\frac{\sigma^2}{2\alpha}\right)$.

The MRP has characteristics that enable it to capture the dynamics of markets where supply and demand forces are strong. In such markets, prices tend to revert towards an equilibrium level [Weron, 2000]. The reason is that when prices are high, suppliers will find it more profitable to produce and fewer consumers would want buy. A higher level of supply, along with a lower level of demand, will consequently lead to a price fall. If prices are initially low, more consumers will want to buy and fewer suppliers will find it profitable to produce. This will lead to high demand and low supply, hence prices will rise. The MRP is particularly well suited to model such markets as it allows for reversion towards an equilibrium level. Dynamics of price sensitive demand is characteristic for many markets. Examples are airline travel

[1]The notation $X \sim N(\mu, \sigma^2)$ means that the random variable X is normally distributed with mean and variance equal to μ and σ^2, respectively.

[Pindyck and Rubinfeld, 2001] and soft drinks [Brownell et al., 2009].

Moltu et al. [2013] show that the expected mismatch cost when demand is assumed to follow an MRP is equal to

$$MC_g(Q) = \underbrace{(p-c)e^{-r\tau}(\mu + (D_{T_i} - \mu)e^{-\alpha\tau})}_{(p-c)e^{-r\tau}E[D_T]} - \underbrace{\Big((p-s)(\Lambda - \hat{\Theta}) - (c-s)Q\Big)e^{-r\tau}}_{V_t(D_t,\tau,Q_t)}, \tag{11}$$

where

$$\Lambda = Q\left(1 - \Phi\left(\frac{(Q-M)}{\sqrt{V}}\right)\right) \tag{12}$$

and

$$\hat{\Theta} = \frac{\sqrt{V}}{\sqrt{2\pi}}e^{-\frac{(Q-M)^2}{2V}} - M\Phi\left(\frac{(Q-M)}{\sqrt{V}}\right). \tag{13}$$

The mean and variance of D_T is, for simplicity, represented as M and V in Equation (12) and (13), such that $D_T \sim N(M, V)$. As mentioned above, when demand follows an Ornstein-Uhlenbeck process, it holds that the demand variable is normally distributed, i.e. $D_T \sim N\left(\mu + (D_t - \mu)e^{-\alpha\tau}, (1 - e^{-2\alpha\tau})\frac{\sigma^2}{2\alpha}\right)$.

Non-Stationary Process: Geometric Brownian Motion

The dynamics of a non-stationary stochastic process is captured by deriving the mismatch cost function for demand that is assumed to follow a GBM. The GBM is given by

$$dD_t = \mu D_t dt + \sigma D_t dZ_t, \tag{14}$$

where μ is the drift rate, σ is the volatility and $Z(t)$ denotes a Wiener process.

The rationale for representing the demand as a variable following a GBM is based on the fact that there are some fundamental similarities between the properties of this stochastic process and a demand time series. Dixit and Pindyck [1994] explain three properties of the Wiener process, also known as Brownian motion. Firstly, the Brownian motion is a Markov process. When modelling stock prices, this property is very useful because it implies that only current information determines the forecasts of the stock price. Thus, the past pattern of the price is of no value to the forecast. However, when forecasting demand, trends are often valuable. Seasonality, e.g. ice cream sells better during the summer, and the demand for snow mobiles is greater during periods with snow, represents valuable trends. Seasonality effects are not captured by the GBM. However, Hausman [1969] shows that both theory and empirical results suggest that ratios of successive forecasts are independent lognormally distributed variables. The second property of a Wiener process is that its increments are independent, which means that the probability distribution is independent of any other time interval. This property enables conversion of the stochastic process to a continuous-time version of a random walk. The third property is that changes are normally distributed. When considering a GBM, the assumption is a lognormally distributed underlying process, thus changes in the natural logarithm of the demand are normally distributed. This is appropriate for a demand process, since it prevents the demand from going negative.

As derived in Moltu et al. [2013], the mismatch cost function assuming that demand follows a GBM is equal to

$$MC_g(Q) = e^{-r\tau}\Bigg((p-s)\Big(D_{T_i}e^{\mu\tau}\Phi(d_1) - Q\Phi(d_2)\Big) + (c-s)\Big(Q - D_{T_i}e^{\mu\tau}\Big)\Bigg) \tag{15}$$

$$= \underbrace{\Bigg(p-c\Bigg)D_{T_i}e^{-(r-\mu)\tau}}_{(p-c)e^{-r\tau}E[D_T]} - \underbrace{e^{-r\tau}\Bigg(Q\Big((p-c)-(p-s)\Phi(-d_2)\Big) + (p-s)D_{T_i}e^{\mu\tau}\Phi(-d_1)\Bigg)}_{V_t(D_{T_i},\tau,Q_{T_i})}, \tag{16}$$

where $d_1 = \frac{ln(\frac{D_{T_i}}{Q})+(\mu+\frac{\sigma^2}{2})\tau}{\sigma\sqrt{\tau}}$ and $d_2 = d_1 - \sigma\sqrt{\tau}$.[2] Note that Equation (16) is represented on the same form as equation (7).

[2] d_1 and d_2 are the same as in the famous Black Scholes Option Pricing formula [Black and Scholes, 1973].

4.2 The Build-up of the Program in Microsoft Excel

This section describes the build up of the computer program. The output generated by the program is described first. The aim is to give an understanding of what the program generates before describing how it is generated. Thus, the general mathematics behind the output is then explained. Lastly, the customization of the program, to make it more applicable to real world situations and the case of KA, is presented.

4.2.1 The Output of the Program

The program developed in Moltu et al. [2013] generates two curves as output - the CD Frontier and the cost curve. The objective of the CD Frontier is to quantify the lowest percent unit-cost reduction/increase needed to compensate for a percentage increase/reduction in lead time. The frontier accordingly represents an indifference curve, where every point on the curve is equally good.

In contrast to the CD Frontier, the cost curve shows the absolute cost level a firm would accept for each lead time. Consequently, the cost curve is also an indifference curve. The area below the cost curve represents the favorable part of the graph, while the area above the indifference curve makes up the unfavorable section. The cost curve is an alternative way of presenting the CD Frontier. Encounters with managers have shown that practitioners find the cost curve more intuitive than the CD Frontier. The argument has been that it is easier to relate to absolute cost levels rather than a relative cost differential. At the request of the managers at KA, this thesis will use the cost curve to present the results from the case study. However, the computer program generates both curves as output, but only the cost curve will be reported in the thesis. Figure 4 shows examples for both the CD Frontier and the cost curve.

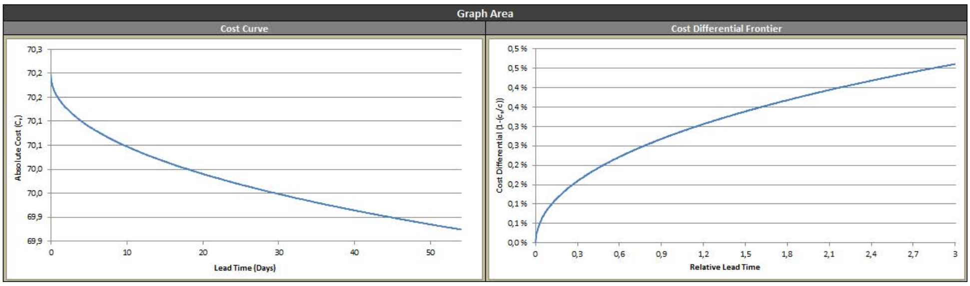


Figure 4: The graph to the left is the cost curve, where the absolute cost for each lead time, c_τ, is plotted against the respective lead time τ. The graph to the right is the cost differential frontier, and shows the cost differential, $1 - \frac{c_\tau}{\bar{c}}$, as a function of lead time τ. Both graphs are plotted for demand assumed to follow a GBM, and they have the same input parameters. The price is 192.50, cost is 70 and salvage value is 69. Drift rate and volatility for 18 days is 0% and 6.66%, respectively.

4.2.2 The General Model

The computer program is based on the work of De Treville et al. [2013a]. In the article, they define the mismatch cost function as the difference between the maximum expected net present value (NPV) of the profit when lead time is zero, and the maximum expected NPV of the profit when lead time is equal to $0 < \tau \leq 1$, where $\tau = T - T_i$. They use τ as a relative lead time. Assuming that the ordered quantity matches the optimal order quantity from the Newsvendor model, Q^*, the mismatch cost is calculated for each lead time. Orders must be placed at the commitment time T_i. However, at the commitment time the demand at delivery, D_T, is not known, unless you have a make to order operation mode. Hence, the demand at delivery is an expectation, $E[D_T]$, and depends on the distribution of the demand process. The mismatch cost is evaluated for each lead time, and both profit terms of the mismatch cost function, i.e. Equation (7), must be compared at the same reference point for each τ. Thus, the expected NPV of the mismatch function is the value at T_i.

In the case of make to order, both lead time and mismatch cost are zero. However, the value of demand at delivery depends on the commitment time. When $T_i = T$, demand at delivery is known; $D_{T_i} = D_T$. However, D_T is not known when $D_{T_i} \neq D_T$, and one must use the specific demand distribution to find the expected demand and discount it back to the commitment time. For instance, if demand is assumed to follow a GBM, the expected demand at time T_i is equal to $E[D_T] = D_{T_i} e^{-(r-\mu)\tau}$. Mismatch cost is an expected value, not a realized value, hence the first term of Equation (7) represents the expected NPV of the make to order case for an arbitrary demand distribution, discounted back to the commitment time.

The cost curve is generated by allocating a specific cost to each of the lead time cases, so that a firm will be indifferent between the alternatives on the curve. To generate the cost curve, the fact that different lead time scenarios can be compared is used. If a firm is to be indifferent between make to order and make to stock, the two operation modes should obtain the same expected NPV, hence Equation (7) has to equal zero. Generally, the cost c increases as lead time decreases. The maximum cost accepted for zero lead time therefore represents the maximum cost for all possible lead time cases, and will be denoted by $\bar{c}$ hereafter. Hence, in the program, $\bar{c}$ is constant for a given stochastic process, while the cost for each lead time τ, c_τ, varies.

Geometric Brownian Motion

Following the argument above, the cost curve for a demand assumed to follow a GBM is constructed by using that the mismatch cost is equal to

$$\begin{aligned} MC_g(Q^*) = & \underbrace{\Big(p - \bar{c}\Big) D_{T_i} e^{-(r-\mu)\tau}}_{\substack{\text{maximum expected NPV} \\ \text{of the profit when } \tau = 0}} \\ & - \underbrace{e^{-r\tau}\left(Q\Big((p-c) - (p-s)\Phi(-d_2)\Big) + (p-s) D_{T_i} e^{\mu\tau}\Phi(-d_1)\right)}_{\text{maximum expected NPV of the profit when } \tau = T - T_i} = 0 \end{aligned} \tag{17}$$

$$\Rightarrow \Big(p-\bar{c}\Big) D_{T_i} e^{-(r-\mu)\tau} = e^{-r\tau}\Bigg(Q^*\Big((p-c)-(p-s)\Phi(-d_2)\Big)+(p-s)D_{T_i}e^{\mu\tau}\Phi(-d_1)\Bigg)$$

$$\Rightarrow \bar{c} = p - \frac{Q^*\Big((p-c)-(p-s)\Phi(-d_2)\Big)+(p-s)D_{T_i}e^{\mu\tau}\Phi(-d_1)}{D_{T_i}e^{\mu\tau}}. \tag{18}$$

The cost curve is generated by performing the following steps:

Step 1:

The first step is to find the optimal order quantity, Q^*, for the current lead time. Q^* is determined by finding the maximum value of the second term in Equation (17), by using binary search. The maximum value of this term corresponds to the maximum expected NPV of the profit for the current lead time.

Step 2:

The second step is to calculate $\bar{c}$, the cost for the case of zero lead time, by inserting Q^* from the first step into Equation (18). $\bar{c}$ is kept constant in further calculations.

Step 3:

The third step is to determine the cost for each lead time scenario, c_τ. c_τ is determined by solving Equation (17), with Q^* from the first step and $\bar{c}$ from the second step:

$$\begin{aligned}(p-\bar{c})e^{-r\tau}D_{T_i}e^{\mu\tau} &= e^{-r\tau}\Bigg(Q^*\Big((p-c_\tau)-(p-s)\Phi(-d_2)\Big)+(p-s)D_{T_i}e^{\mu\tau}\Phi(-d_1)\Bigg)\\ &= e^{-r\tau}\Bigg(Q^*\Big(\alpha-\Phi(-d_2)\Big)+D_{T_i}e^{\mu\tau}\Phi(-d_1)\Bigg)(p-s)\\ &= e^{-r\tau}\Bigg(Q^*\Big(F(Q^*)-\Phi(-d_2)\Big)+D_{T_i}e^{\mu\tau}\Phi(-d_1)\Bigg)(p-s),\end{aligned}$$

where $\alpha = \frac{p-c_\tau}{p-s} = F(Q^*)$, and $F(Q^*)$ is lognormally distributed with mean $\Big[ln(D_{T_i})+(\mu-\frac{\sigma^2}{2})\tau\Big]$ and variance $\sigma\sqrt{\tau}$.

Step 4:

The last step is to derive the cost curve. Knowing c_τ for all $0 < \tau \leq 1$, the cost curve can be derived as the absolute cost c_τ, as a function of lead time τ.

Mean Reverting Process

Following the same argument as for the GBM-case, the mismatch cost function for the MRP-case from Equation (11) is equal to

$$MC_g(Q^*) = (p - \bar{c})e^{-r\tau}E[D_T] - \underbrace{\Big((p-s)(\Lambda - \hat{\Theta}) - (c-s)Q\Big)e^{-r\tau}}_{V_{T_i}(D_{T_i}, \tau, Q_{T_i})} = 0$$

$$\Rightarrow \Big(p - \bar{c}\Big)E[D_T] = \Big((p-s)(\Lambda - \hat{\Theta}) - (c-s)Q\Big), \tag{19}$$

where $\hat{\Theta}$ is given by Equation (13). The cost for the case of zero lead time, $\bar{c}$, is given by

$$\bar{c} = p - \frac{\Big((p-s)\Lambda - \hat{\Theta}) - (c-s)Q\Big)}{E[D_T]}. \tag{20}$$

The cost curve for a demand assumed to follow an MRP is constructed using the same steps as for the GBM previously discussed.

4.2.3 Customization of the Model for the Case Study of Kongsberg Automotive

In order to make the computer program match the characteristics of KA, as well as improve the program's generality, certain changes are incorporated. These changes are presented in the following paragraphs.

Incorporating Lead Time Extensions

Literature that explicitly deals with lead time mainly considers lead time reduction (e.g. De Treville et al. [2012] and Ben-Daya and Hariga [2003]). Therefore, the computer program developed by Moltu et al. [2013] only evaluates lead time reductions. However, during the collaboration with KA, the managers have explicitly requested information about the costs of extending the lead time for their clutch servo. The case study performed in this thesis thus investigates both potential lead time reductions and extensions. An important modification to the computer program is therefore the incorporation of lead time extension. This feature is implemented in a dynamic manner, so that the cost curve is extended according to the lead time of the supplier that is being investigated. The cost curve in Moltu et al. [2013] uses relative lead time to present the results, where the current situation represents relative lead time of 1. After consulting with the managers at KA, the use of absolute days for the lead time in the cost curve is chosen for this thesis. The managers stated that it is easier to relate to actual days, rather than a relative lead time.

Incorporating Supplier Specific Costs

The program developed in Moltu et al. [2013] assumed that all supplier specific costs were fixed, regardless of lead time. Recall, from the literature review, that supplier specific costs are costs that change with supplier selection, such as transportation cost, capital cost and storage cost. Hence, the cost reported in the program only referred to the per unit procurement cost. This assumption made the program unable to account for changes in supplier specific costs. However, supplier specific costs are rarely fixed for different lead times. For example, as mentioned in the literature review, Ouyang and Chang [2002] report the correlation between safety stock and lead time. Thus, supplier selection has impact on storage costs. Further, changing a supplier often yield changes in transportation cost as distance and delivery frequency may change.

When presented with the program of Moltu et al. [2013], the managers at KA and other practitioners all agreed that the program would give more realistic results if it was able to account for changes in supplier specific costs. As there are multiple costs that can affect a sourcing decision, varying from case to case, this thesis has tried to incorporate the most common ones. Based on feedback, transportation cost, storage cost and capital cost have been chosen. In addition, a field for other costs has been added. This enables users to include costs specific to their particular case. Incorporating these supplier specific costs makes the program, in addition to accounting for exposure to demand risk, able to assess changes in supplier specific costs.

To incorporate the supplier specific costs, the code had to be modified. Four input fields were added as optional fields to the input panel. This is shown in Figure 6. Since all the fields are optional, the user can still use the program to evaluate only exposure to demand risk by setting the fields to zero. The same fields were also added to the two sourcing scenario panels. To ensure that a user does not compare a scenario that accounts for supplier specific costs to a scenario that does not, a poka-yoke function was built in. The function prevents the user from comparing two scenarios with a different number of inputs.

In the code, the supplier specific costs are incorporated by simply adding the sum of the new variables to the cost of the component. This increases the cost of overproduction, c-s, but decreases the cost of underproduction, p-c. However, for the case of KA, it will only have an effect on the cost of underproduction, as KA's salvage value is proportional to the obtained procurement cost. Hence, c-s is constant, making the cost of overproduction constant. See Section 6.2.3 for details regarding these calculations.

Adding supplier specific costs has an affect on both the level and curvature of the cost curve. This is shown in Figure 5. The increased level is a result of the cost being higher after the additional costs are added. The difference in curvature is caused by changes in the cost of not meeting demand. The left part of the figure shows the effects when it is decreased. In this case underproduction is favored since the cost of underproducing is lower than the cost of overproducing. As a result the program will advise underproduction over overproduction. Since the cost of underproducing decreases after supplier specific costs are added, the cost of not meeting demand is therefore reduced. From this it follows that it will be relatively less valuable to reduce lead time and the curve becomes less steep. While it may be hard to see from the graph, the numbers show the difference clearly - NOK 4.79 at lead time 50 against NOK 4.31 at lead time 0. Thus the new graph is less steep than the old. For the right case, overproduction is favored. In contrast to the left case this graph experiences an increase in the cost of not meeting demand - the new cost of overproducing is higher than the old. Hence, it follows that it will be increasingly valuable to reduce lead time and the graph becomes more steep - NOK 4.54 at lead time 54 against NOK 4.64 at lead time 0. An important observation is that the demand risk is equal in both graphs - it is only the cost associated with it that changes.

However, this example simplifies how the cost curve is actually generated. In reality, the program does not simply favor either over or underproduction, and use the cost associated with this to generate the cost curve. Recall from Section 4.1.1 and Section 4.2.2, that the cost curve is generated by optimizing the profit function with respect to the critical fractile. Hence, if the cost of overproduction is higher than underproduction, overproduction will be favored and the cost associated with it more prominent. However, this does not mean that the cost of underproduction disappears, it is just less likely to occur - hence, it has less impact on the curvature.

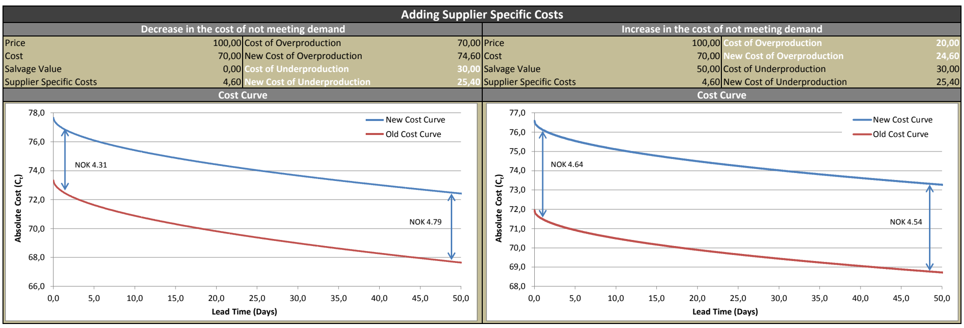


Figure 5: The effects on the cost curve of including supplier specific costs. GBM is used as the underlying process. The blue graphs are the cost curves when supplier specific costs are added. The red graphs represent the old cost curves. The input parameters not shown in the figure are: current lead time is 18 days, volatility is 10%, yearly risk-free rate is 3% and drift rate is 0%

Commercializing the Computer Program

Though the computer program developed in Moltu et al. [2013] includes many of the attributes desired for the final program, it has potential for improvement in its intuition and ease of use. The initial program was developed as a part of an academic report, and its applications were mainly intended for the academic reader. The program in this thesis, however, is customized for practitioners, represented by the case of KA's clutch servo. Discussions with the managers at KA have revealed that some aspects of the program are not sufficiently intuitive. They have suggested certain changes in order to generalize the program for applications beyond the extent of this case study. Therefore, it is within the scope of this thesis to create a program that is both useful and understandable to the managers at KA.

The managers at KA pointed out parts of the input panel in the program as a source of confusion. Certain parameters are neither relevant, nor intuitive, for practitioners, and are excluded from the input panel in the updated version. The number of steps is removed from the panel. It is just an input that affects the smoothness of the plots and does not affect the results of the case, hence it is unnecessary as an input parameter. The number of steps is set to 1000. The long term equilibrium level and initial demand are also removed as input. The reason is that changing a supplier usually has long term effects on a firm. Therefore, it is fair to assume that the long term equilibrium level is more important for the supplier selection than the current demand level. Hence, initial demand is set equal to the long term equilibrium level in the model, and both parameters are kept constant. Lastly, in order to make the panel more intuitive, the updated version categorizes the input parameters. Figure 6 shows the input panels of both versions of the program.

Inputs		
Variable	Value	Description
Current Lead Time	9	Days
Price	55	Unit Price
Salvage Value	19,81	Unit SV
Cost at Lead-Time L	20	Unit Cost
Long term equilibrium level	1	Demand at t=9
Mean reversion rate	105,15 %	For 9 Days
Volatility	41,37 %	For 9 Days
Risk Free	0,82 %	For 9 Days
Number of Steps	1000	LT Quantiles
Initial Demand	1	At time 0

INPUT		
Product Parameters		
Current Lead Time	9	Days
Price	55,00	Unit Price
Salvage Value	19,81	Unit SV
Cost	20,00	Unit Cost
Demand Process Parameters		
Volatility	41,37 %	For 7 Days
Yearly Risk-Free Rate	5,00 %	For 365 Days
Mean Reversion Rate	105,15 %	For 7 Days
Optional Parameters		
Storage Cost	0,47	Per Unit
Capital Cost	0,06	Per Unit
Transportation Cost	1,20	Per Unit
Other Costs	0,00	Per Unit

Figure 6: The input panels of the initial program to the left and the updated program to the right. The long term equilibrium level, number of steps and initial demand are removed in the new input panel. In addition, the updated version aggregates the risk-free rate on a yearly basis and the mean reversion rate and volatility on a weekly basis, rather than on the basis of the entire lead time period as done in the old program. The updated version also includes four optional parameters - storage cost, capital cost, transportation cost and other costs.

To further simplify the program, the updated version hides the underlying data for the plots by default. The main results of the program are the indifference curves of the cost curve and the cost differential frontier. The managers at KA liked the simplicity obtained by hiding the data. However, the data can be displayed by pushing the button ”show underlying data for plots”.

Further discussion with the managers revealed that the empirical input parameters, i.e. the mean reversion rate and the volatility, could be difficult to extract from empirical data. In general, the managers appreciated the output of the program, but found the required input rather comprehensive and difficult to retrieve. Ideally, the managers wanted a program where they could insert sales data and the current sourcing situation for a product, and get the indifference curves plotted right away. In other words, KA wanted the program to first do the empirical analysis of the data set and then create the indifference curve plots. This is a feature that would enhance the generality of the program. The implementation of this functionality is not within the scope of this thesis, however it would definitely add value to the program, and will be discussed in Section 8.1.

5 Empirical Data and Analysis

In order to determine which stochastic process and the corresponding parameters that may fit KA's demand structure best, KA's demand is assessed. This section will start by describing the data set used for the analysis. Then, the underlying theory for the analysis is briefly described and the analysis is performed. The results of the empirical data assessment is presented and the most suitable stochastic process is determined. In addition, a different approach of connecting the demand data to the computer program is proposed. The two approaches, i.e. the use of a stochastic process and the use of distribution forecasting of the ARMA model, are compared through a simple example. Lastly, the validity of the analysis is checked by using the available actual demand data.

5.1 Description of the Data Set

The data set used to assess the demand distribution for KA's clutch servos is actual sales data. The data is gathered from KA's SAP system during the time period from July 2009 until February 2014, resulting in 590 data points. Each data point represents an order from Scania that is delivered at the specific date.

Accompanying the actual sales is the respective service level for each delivery. The service level is calculated based on quantity and delivery date. To receive a service level of 100%, both the quantity and the date must be correct. If only one of the parameters is met, KA receives a service level of 50%. By not meeting any of the delivery terms, a service level of 0% is obtained. The most common reason for not receiving a 100% service level is by delivering less than the actual order quantity. This results in a backlog for KA. KA seeks to fulfill the backlog on one of the next deliveries, which automatically leads to an incorrect quantity for this delivery as well. However, if Scania requires delivery as fast as possible, and KA is able to produce the quantity before the next shipment, the order can be sent as an express delivery. This would result in an incorrect date as well. Hence, KA could be penalized twice for not fulfilling the order according to the specifications on delivery quantity and date.

KA also has access to real demand data. Scania places its orders for one year ahead using an EDI-system (Electronic Data Interchange), where order quantity can be updated by Scania daily up to the day of each delivery. KA thus has a good forecast for the actual demand. However, KA has not stored this demand data until now. Since this data is not stored automatically, it is impossible to retrieve historical data on how the real demand changes up until delivery. After being presented with the value this data can yield KA was advised to store the demand data every week. If this demand data is stored, KA will have a unique system that enables them to track actual demand changes directly from their customers. This will make the assessment of risk much more accurate, since KA will have multiple time series with the evolution of demand for the same product. Ultimately, KA will have a large empirical foundation from which it can make even more justified assumptions about its demand process. Few companies have access to such information. For this thesis, however, the historical sales data will be the main data set for the analysis. The real demand data will be considered as a supplement to this analysis, as it consists of few data points.

5.2 Representation of KA's Demand

Before starting the analysis of the sales data, the most suitable representation of the data set must be determined. The goal is to find a way to represent the actual demand data using the sales data provided by KA during the period from July 2009 to February 2014. The sales data is the quantity invoiced by KA to Scania for each delivery. As each delivery is invoiced on the same day as it is delivered, each data point in the sales data represents the actual quantity delivered on that day. The number may therefore deviate from the actual order quantity from Scania, and thus also from the actual demand. This is the case when KA is unable to fulfill an order, or when KA needs to fulfill its backlog. The latter will have an impact either on one of the next orders, or adding another delivery between the originally scheduled deliveries. Accompanying the sales data is the corresponding service level for each order/sale, from which conclusions about which of the data points that represent the actual demand can be drawn.

5.2.1 Daily Sales Data

The daily data is presented in Figure 7, and represents every sale to Scania during the period. Thus, each day without a sale is removed. The daily data provides a good insight to the variation in the orders from Scania.

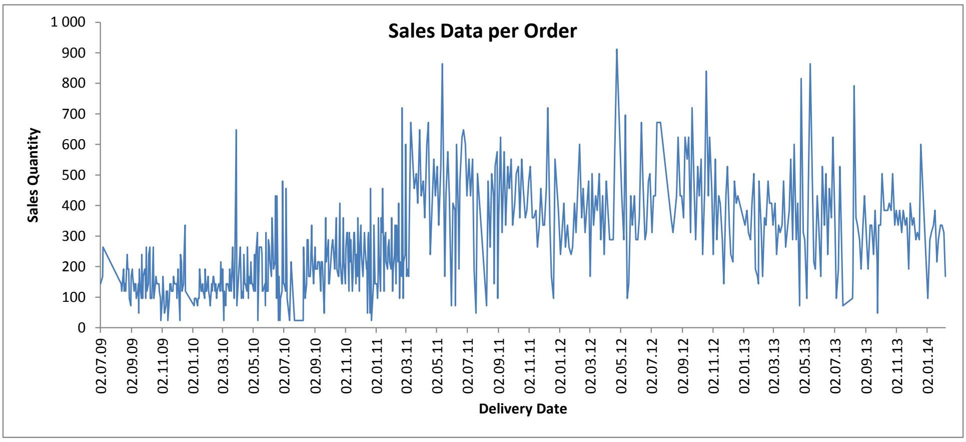


Figure 7: Every completed sale from KA to Scania in the period from 2009 to 2014. It is a time series that contains the sales quantity for the given date. Dates without sales are removed from the time series.

There are some issues related to using this data set directly. The first problem encountered in this data set is the consistency in the series. There is a shift in the average order delivery around March 2011. This shift in the time series is caused by a new ordering sequence from Scania. Up until this point in time the ordering occurred on Mondays, Tuesdays, Thursdays and Fridays. After this point the orders came, with some exceptions, just two days per week, on Tuesdays and Fridays. This had implications for the daily ordering quantity, thus causing a shift in the time series.

Further implications of choosing this data representation is that the demand does not have evenly spaced time intervals between the orders. Since the goal is to determine a stochastic process that fits well with the data, it is convenient to have evenly spaced intervals.

Additionally, this data set does not consider the fact that some of these data points have a non-perfect service level. The variations in the data set could therefore be caused by KA not fulfilling an order, which, as explained above, inflicts two data points; the actual order that KA fails to complete, and one of the later orders at which the remaining backlog is added.

The first problem can be mitigated by dividing the time series into two different sections, before and after the shift in number of deliveries per week. Then, both demand time series can be analyzed, and the parameters can be calculated as a weighted average of the two sections. A possible way of managing the problem of non-even spacing is to assume that each order is evenly spaced, and use the average time between deliveries as the interval length. Still, the problem with non-perfect service level will be apparent. Therefore, the sales that do not have a 100% service level is removed from the time series.

5.2.2 Daily Data Containing Only 100% Service Level Orders

As KA is able to report the service level for each sale, one can extract the deliveries that were correct according to both date and quantity from the original data set. This results in a data set containing only the sales that are completed with a 100% service level. The remaining data points are shown in Figure 8 and represent the actual demand KA experienced from Scania in the period from 2009-2014.

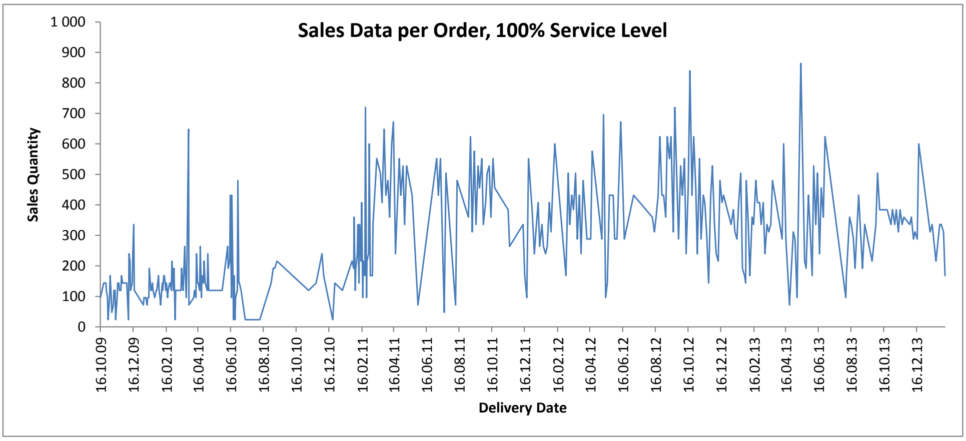


Figure 8: Sales data from 2009-2014, without sales that had less than a 100% service level. This time series therefore represents the actual demand KA experienced for clutch servos in the period.

Still, there are some problems within the data set that need mitigation. Firstly, the shift in the ordering strategy from Scania around March 2011 is still apparent. The data set also has the problem of not having evenly spaced time intervals. These problems can be mitigated by applying the same actions as mentioned in the previous section, i.e. generating two sections and assuming that the orders are evenly spaced with the average time between deliveries as a proxy. A representation of the 100% service level sales after the shift in March 2011 is shown in Figure 9.

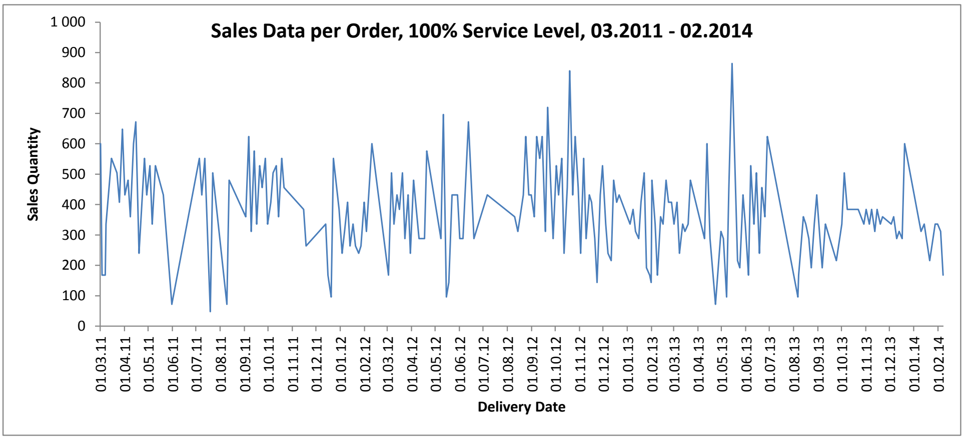


Figure 9: Sales data from March 2011 to February 2014, without sales that had less than a 100% service level. This time series therefore represents the actual demand KA experienced for clutch servos in this time period. Thus, this time series manages the problem of the shift in ordering strategy from Scania.

The major problem with this data series is that many data points have been removed. Thus, this data series lacks a lot of the information about the actual demand for clutch servos. A method to handle this problem is to use the intervals that are complete within the data set. This will, however, result in very small samples, which will make the estimates less powerful.

5.2.3 Weekly Data

Another way of representing the data set is to aggregate the sales within one week, as shown in Figure 10. The sales for a given week is summed up so that the time series show the total weekly sales quantity for every week from 2011 to 2014.

The reason for using weekly data is to manage the problem of unevenly spaced time intervals between daily orders, Scania's change in ordering frequency, and to represent the actual demand without removing too much information from the data set. The first two problems are managed through the aggregation. For the demand issue, weekly data does not account for the service level directly. However, as KA is fulfilling the actual order from Scania as quickly as possible, aggregating the different orders within each week should capture the total orders during a week. Thus, it provides a close estimation of the actual demand under the assumption that the backlog is fulfilled within the same week of the actual order. Therefore, using weekly data yields a complete weekly time series, which can be analyzed. The problem with this time series is the "outliers" we see during vacations. These interruptions may be difficult to model without including a Jump-process.

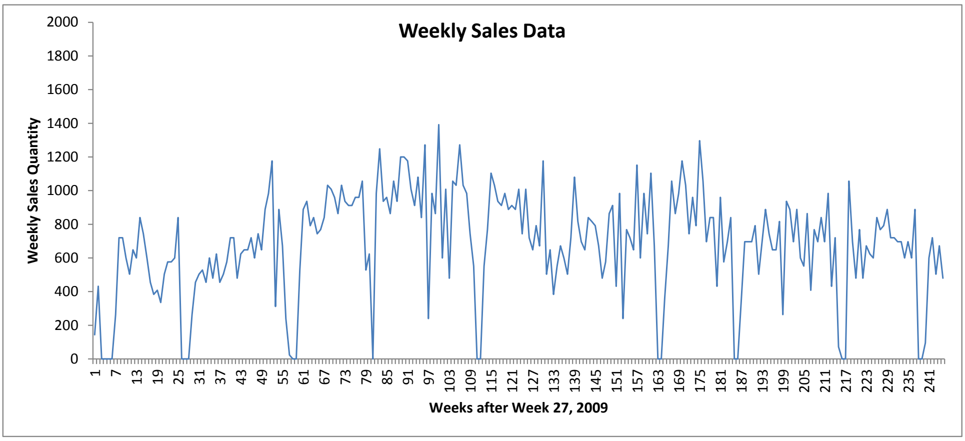


Figure 10: The weekly sales data for the clutch servo. The deliveries within each week are aggregated to give an estimate of the actual demand KA experienced in the period from 2011 to 2014.

To represent the data without the outliers, the vacation months are removed, as seen in Figure 11. Vacation weeks are defined as week 29-32 (summer vacation), week 52, 53 and 1 (Christmas) and Easter, which varies between week 14 and week 17 for different years. By removing these vacations, the time series represents how the demand evolved during regular business periods. This should be a good proxy for capturing the desired information in order to determine the stochastic process for the demand time series. However, during the time period of the data set, minor orders did occur during some vacations. This signals that some information may be lost by this alteration of the data set.

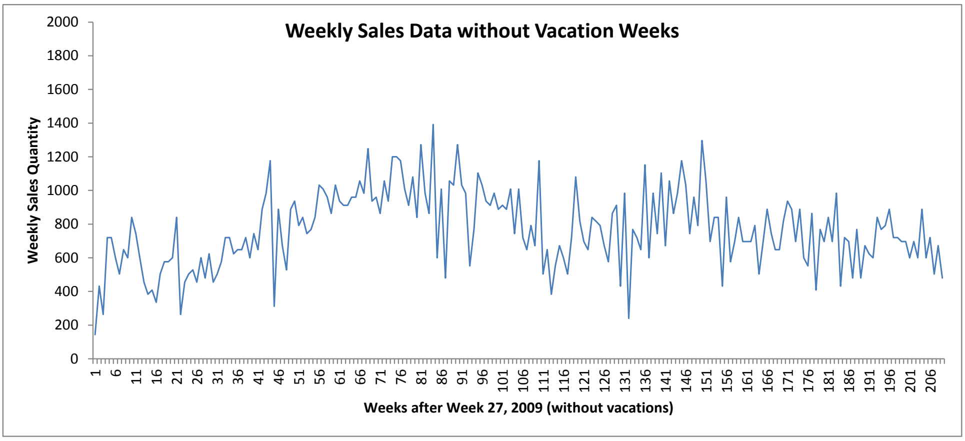


Figure 11: The weekly sales data for the clutch servo, adjusted by removing vacation weeks. The deliveries within each week are aggregated to give an estimate of the actual demand KA experienced.

5.2.4 Semi-weekly Data

To try to capture more of the order specific fluctuation, the data is altered to show semi-weekly data, given in Figure 12. This data series consists of the sales on weekdays Monday through Wednesday on one order, while Thursday and Friday are added to the second order for each week. Thus, the time series captures the order frequency KA experienced from Scania. However, this approach will not capture the demand that is not met on one delivery but is fulfilled on the next scheduled delivery. An example of this is if the demand for an order on Tuesday is not met, and the demand is fulfilled on the next scheduled delivery (Thursday) the same week. This time series will therefore experience problems with demand being added on the wrong order.

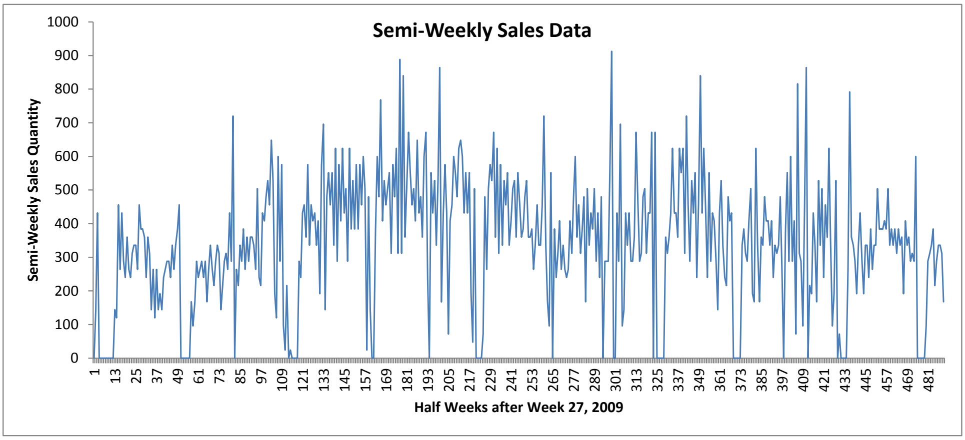


Figure 12: The semi-weekly sales quantity at different dates. The semi-weekly sales quantity is calculated by summing up weekday orders Monday through Wednesday on one order, while Thursday and Friday are aggregated for the second order. This is done to capture the order specific fluctuation in the demand for clutch servos.

5.2.5 Choosing the Data Representation

After evaluating the different data representations, it is difficult to choose one solution that mitigates all the problems regarding the data. The most favorable solutions to represent KA's demand are the weekly sales data with or without vacations. These representations are complete time series that aggregate the sales with evenly spaced time intervals between the data points. The reason for the decision lies within the enablement of a thorough time series analysis of the data, and the fact that these data represent the actual demand in a good way, without removing too much of the order fluctuation. Since the outliers originating from the vacations are recurring events and will have significant impact on the analysis, the time series without vacations is chosen as the most suitable data set for the model identification.

5.3 Model Identification of the Chosen Representation

This section will focus on determining which model represents KA's demand in the best way. In order to determine this, the concept of time series analysis is utilized. The calculations and statistical analysis are performed in R, and the code for the calculations is given in Appendix B. The results will be used to determine which of the stochastic processes mentioned in Section 4.1.3 may fit the time series best.

5.3.1 Overview of the Model Identification Process

The model fitting process used in this section is based on the process described in Wei [2006] and consists of various statistical concepts that will be presented together with the process. For a more thorough description of the time series analysis and statistical concepts, see e.g. Wei [2006].

The first step in the procedure is to carefully examine the chosen time series plot from Section 5.2.5 in order to look for indications of trends, seasonality, outliers, non-constant variances, non-normality and non-stationarity. This examination may indicate a need for transformations of the data, e.g. through differencing and/or power-transforms.

The second step consists of examining the autocorrelations (ACF) plot and the partial autocorrelations (PACF) plot to further investigate whether any differencing and transformations are needed. In this step, unit root tests for stationarity, such as Augmented Dickey-Fuller test and Phillips-Perron test, are performed as well.

Thereafter, the third step is to determine the orders of p and q in the ARMA(p,q) model for the properly transformed time series. Here, p and q are the highest orders of the autoregressive polynomial and the moving average polynomial, respectively. ACF and PACF plots are used to define a tentative ARMA(p,q) model. Neighboring models, i.e. different p and q values, are assessed to determine which of the models that fits the data best. To determine the best fit, the Akaike information criterion (AIC) is used as a proxy. Additionally, the assumption that the residuals are white noise is checked. The white noise assumption is checked by a Box-Ljung test, and the distribution of the white noise is investigated.

5.3.2 Identifying the Model for KA's Demand

Following the procedure above, the first action in the identification of the model for KA's demand is to examine the time series plot of the demand. Figure 13 shows the weekly aggregated sales quantity from the summer of 2009 until February 2014. The plot shows no consistent trend or seasonality, and seems to be stationary over time. However, from summer 2009 to 2011 there was an increase in demand. According to the managers at KA, this can be related to recovery from the Financial Crisis. In Section 5.2, the time series was manipulated by removing vacations. Any outliers seem to have been successfully removed by extracting the vacation weeks from the time series. Additionally, the variance in the data set does not appear to change with time or with regards to the current level of demand. Consequently, the plot suggests that no transformation or differencing is needed.

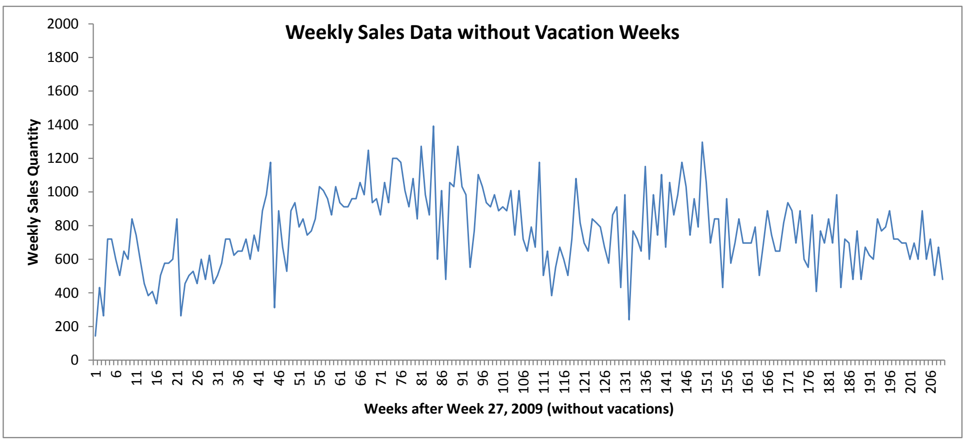


Figure 13: The weekly sales quantity without vacation data at different dates. There is no consistent trend or seasonality in the time series other than the recovery from the Financial Crisis, and it looks stationary over time.

To further check for stationarity and necessity of additional transformation of the data, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test is performed in R. The results of the tests are presented in Table 1. Additionally, the ACF and PACF plots are examined.

Both ADF and PP are statistical hypothesis tests. PP tests the null hypothesis that a time series is integrated of order 1. A time series must be integrated of order 0 to be stationary. The Augmented Dickey-Fuller test checks the null hypothesis of a unit root in the time series. As the results show, the ADF test concludes that rejection of the null hypothesis is not justified. However, the PP-test rejects the null hypothesis at a 1% confidence level. Considering the plot in Figure 13, the further analysis will assume that the time series is stationary, and therefore no differencing and/or transformations are performed on the data series.

Stationarity Tests			
Augmented Dickey-Fuller Test		**Phillips-Perron Test**	
Test statistics	-2,365	Test statistics (Dickey-Fuller Z)	-168,8288
Lag order	5	Lag order	4
p-value	0,4231	p-value	< 0.01
Conclusion	Cannot reject hypotesis of non-stationarity	Conclusion	Reject hypthesis of non-stationarity

Table 1: The results of the stationarity tests, Augmented Dickey-Fuller test and Phillips-Perron test, for the weekly sales data without vacations, from 2009 to 2014, for the clutch servo. The Phillips-Perron test indicates stationarity in the data set, while the Augmented Dickey-Fuller test does not indicate stationarity.

The ACF and PACF plots are shown in Figure 14. The ACF plot tails off with a steady decay after lag 2. The PACF plot tails off after lag 2, with some irregularities at lag 5 and 6. According to the rule of thumb suggested by Wei [2006], this does not directly indicate a need for differencing the data set. Therefore, no transformation or differencing is performed on the time series. This corresponds to the intuition about the demand by the experts at KA. According to them, the demand is stable around a given level, with some deviations. It is therefore fair to assume that the sales data is stationary. To additionally check whether differencing would be appropriate, differencing was performed and ACF and PACF were investigated. This led to both the ACF and PACF becoming negative, which is a sign of over-differencing.

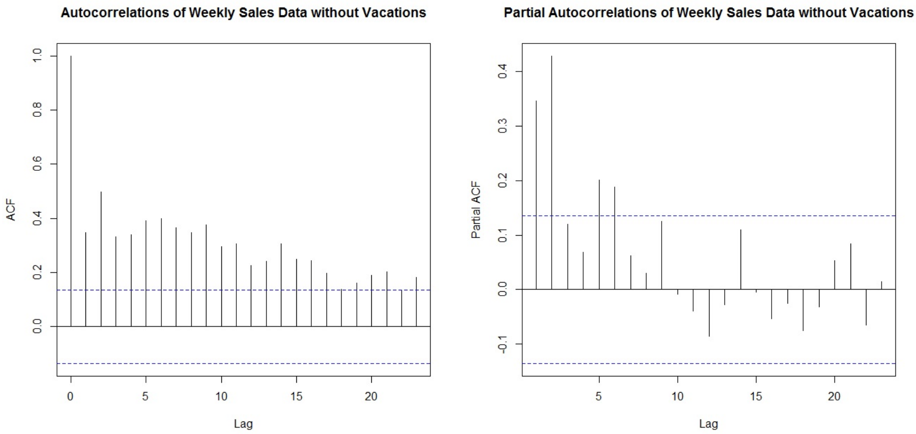


Figure 14: Left graph: ACF plot of the time series. It spikes at lag 2 and tails off with steady decay. Right graph: PACF plot of the time series. It spikes at lag 2, and cuts off quickly.

To determine the actual model specification, Wei [2006] suggests trial and error within the general ARMA(p,q) models. The ARMA(p,q) models are fitted to the data using R, and the respective Log-likelihood and AIC for each model is recorded and the model coefficients are estimated. ARMA(2,2) is chosen as a tentative model since both ACF and PACF spike at lag 2. Neighboring models, i.e. different values surrounding p=2 and q=2, are tried, fitted and registered in R.

Model coefficients, ARMA(p,q)																			
p	q	AR1		AR2		AR3		MA1		MA2		MA3		Intercept		Sigma^2	Log likelihood	AIC
		coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)			
1	2	0,9687	0,0218					-0,8979	0,0688	0,1144	0,0598			728,91	79,988	32372	-1375,68	2761,36
1	3	0,9755	0,0189					-0,8709	0,0709	0,2676	0,0863	-0,2084	0,0834	722	86,831	31446	-1372,67	2757,35
2	1	0,7727	0,0966	0,1872	0,0842			-0,7292	0,079					730,39	78,302	32165	-1375,01	2760,03
2	2	0,3681	0,188	0,5817	0,1835			-0,3255	0,2047	-0,327	0,174			727,32	81,048	31758	-1373,71	2759,41
2	3	0,7392	0,2141	0,2298	0,2067			-0,658	0,2027	0,0896	0,2037	-0,1928	0,091	722,12	86,579	31255	-1372,06	2758,12
3	1	0,8768	0,0972	0,2627	0,09	-0,1646	0,0846	-0,814	0,0643					725,09	83,721	31577	-1373,1	2758,21
3	2	0,7358	0,2983	0,3795	0,2344	-0,1449	0,1004	-0,6695	0,2942	-0,1115	0,2171			725,75	83,62	31536	-1372,98	2759,95
3	3	0,7149	0,1656	-0,2511	0,238	0,4918	0,1847	-0,6121	0,1403	0,5538	0,1864	-0,5977	0,1304	723,99	85,654	30624	-1370,03	2756,05

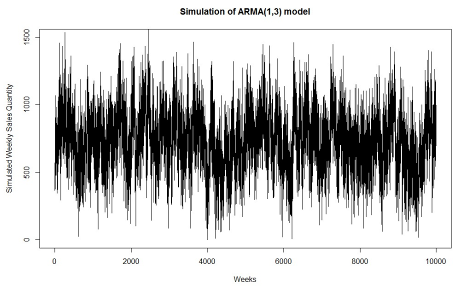
Table 2: The coefficients, log-likelihood and AIC for different ARMA(p,q) models fitted to the data set.

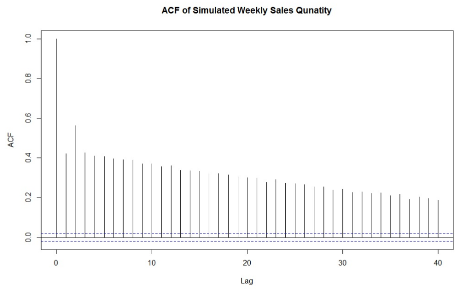
Table 2 shows the different ARMA(p,q) models and the corresponding model coefficients. According to the AIC, either ARMA(1,3) or ARMA(3,3) provides the best model fit for the data set. Since a model with fewer variables will make computations of expected values and variance in forecasts easier, the ARMA(1,3) model is chosen. For the ARIMA(1,3), all the coefficients are significantly different from zero. This can be seen by looking at the standard error (s.e.) for the coefficients in Table 2. In Table 3, a 95% confidence interval is shown for each coefficient. For the ARMA(3,3), the AR(2) coefficient is not significantly different from zero. This is a problem with over-parametrization.

Model comparison					
ARMA(1,3)	Estimate	s.e	95% Confidence Interval		Significant
AR1	0,9755	0,0189	0,938456	1,012544	yes
MA1	-0,8709	0,0709	-1,009864	-0,731936	yes
MA2	0,2676	0,0863	0,098452	0,436748	yes
MA3	-0,2084	0,0834	-0,371864	-0,044936	yes
Intercept	721,9974	86,8305	551,80962	892,18518	yes
ARMA(3,3)	Estimate	s.e	95% Confidence Interval		Significant
AR1	0,7149	0,1656	0,390324	1,039476	yes
AR2	-0,2511	0,238	-0,71758	0,21538	no
AR3	0,4918	0,1847	0,129788	0,853812	yes
MA1	-0,6121	0,1403	-0,887088	-0,337112	yes
MA2	0,5538	0,1864	0,188456	0,919144	yes
MA3	-0,5977	0,1304	-0,853284	-0,342116	yes
Intercept	723,9921	85,654	556,11026	891,87394	yes

Table 3: The coefficients for the two models, ARMA(1,3) and ARMA(3,3), with corresponding confidence intervals and significance.

To investigate whether the model fit is reasonable, a simulation with the estimated model coefficients is run i R. The simulation is done over 10000 weeks. The results of the simulation are shown in Figure 15, with a simulated time series and corresponding ACF and PACF. Both the simulated ACF and PACF have the same features as the actual ACF and PACF, with the same decreasing trend for the ACF and cut off after lag 2 for PACF. Additionally, the simulated PACF returns irregularities in lag 5 and 6, which was seen in the actual PACF, and both graphs spike at lag 2.





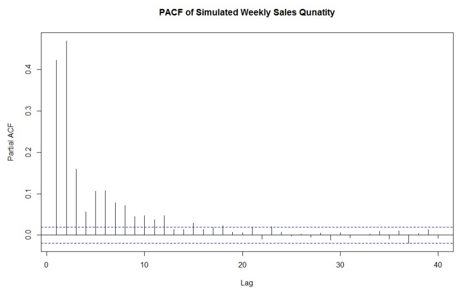


Figure 15: The results of a simulation run in R, with the coefficients for the fitted ARMA(1,3) model on the weekly sales data without vacations.

To validate the ARMA(1,3) model, the underlying assumption for the model must be verified. Figure 16 shows the properties of the residuals. The underlying assumption for the model is that the residuals are serially uncorrelated random variables with zero mean and finite variance, i.e. independent and identically distributed. From the plot in the top left figure, the residuals look random and uncorrelated. The top right figure shows the histogram of the residuals. The histogram is unimodal, has a bell shape and looks symmetric, which indicates a normal distribution. This assumption is further checked by the QQ-plot. The linearity of the points and the fact that the QQ-plot follows the QQ-line suggest a normal distribution. Lastly, in the bottom right corner of Figure 16, the ACF for the residuals are shown. None of the lags are significant. Therefore, the residuals appear to be white noise and the model assumption is verified. This conclusion is further justified by running a Box-Ljung test on the residuals in R. The test returns a X-squared = 0.188, and p-value = 0.6646. Thus, the conclusion of the test is that the null hypothesis of the autocorrelations being zero cannot be rejected. This indicates that the residuals are white noise.

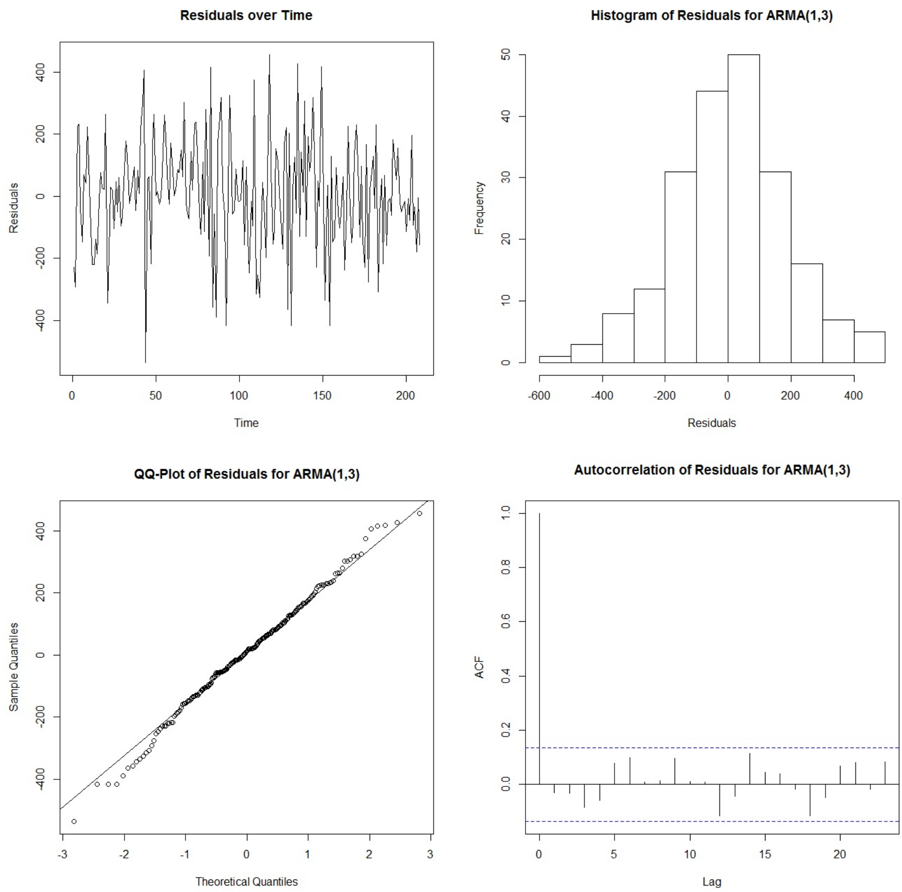


Figure 16: Top left: Residuals plotted over time, resembling white noise. Top right: Histogram of residuals. The histogram is unimodal, has a bell shape and seems to be symmetric. Bottom left: Normal quantile-quantile plot. The QQ-plot follows the QQ-line in a tightly manner. Bottom right: ACF of residuals. None of the autocorrelation lags are significant.

To sum up the model fitting procedure, the model chosen as the best fit for the data is an ARMA(1,3), which is given by the following equation:

$$D_{t+\tau} = \mu + \phi(D_{t+\tau-1} - \mu) + a_{t+\tau} + \theta_1 a_{t+\tau-1} + \theta_2 a_{t+\tau-2} + \theta_3 a_{t+\tau-3}, \tag{21}$$

where $D_{t+\tau}$ is the demand at time $t+\tau$, where τ is lead time. $a_{t+\tau} \sim N(0, \sigma^2)$ is the Gaussian white noise.

The following coefficients are found through the model fitting process and are listed in Table 3: μ is the intercept, ϕ is the AR1, θ_1 is the MA1, θ_2 is the MA2 and θ_3 is the MA3. The ARMA(1,3) model can be written as:

$$D_{t+\tau} = 722 + 0.9755(D_{t+\tau-1} - 722) + a_{t+\tau} + -0.8709a_{t+\tau-1} + 0.2676a_{t+\tau-2} + -0.2084a_{t+\tau-3}. \tag{22}$$

5.4 Incorporating the Model into the Computer Program

In Section 4, the computer program for evaluating lead time decisions was described. The goal of this section is to connect the demand data to the program in order to generate the cost curve. The program was developed on the basis that a stochastic process is assumed, and the demand specific program inputs are calibrated according to the demand data. Thus, the most suitable stochastic process must be determined. Additionally, another way to connect the demand and the cost curve is proposed by utilizing forecasting techniques of the fitted model from Section 5.3.2. This new way of incorporating the demand data into the program has been implemented in the program, making it much more flexible to different demand structures.

5.4.1 Assuming a Stochastic Process

Recalling that the program has been developed for two different stochastic processes, i.e. MRP and GBM, the results of the empirical data analysis must be compared against these. The MRP is the continuous version of the discrete AR(1) process, and is stationary. The GBM, on the other hand, is non-stationary. Assuming that the data follows a GBM, the data would therefore require appropriate differencing and transformation in order to be evaluated using the steps in Section 5.3.2. This is done by taking the natural logarithm of the differenced data set. Such alterations were not performed in Section 5.3.2 to find the best model fit. This suggests that the mean reverting Ornstein Uhlenbeck process will be the better choice of the two.

To see how well the AR(1) process fits the data, it is fitted in R. The resulting coefficients and model fit are presented in Table 4. The AR1 coefficient and the intercept are significantly different from zero for the fitted model. However, the model does not perform as well as the ARMA(1,3) with regards to log likelihood and AIC. This indicates that the AR(1) model is not the best way to describe the data set.

Model Coefficients, AR(1)					
AR(1)	Estimate	s.e	95% Confidence Interval		Significant
AR1	0,3518	0,0654	0,223616	0,479984	yes
Intercept	767,871	22,0226	724,706704	811,035296	yes
Parameters					
Sigma^2	Log likelihood		AIC		
42582	-1403,76		2813,52		

Table 4: The coefficients and parameters for the fitted AR(1) model with corresponding confidence intervals and significance.

To further analyze the AR(1) model's validity of the data, the residual diagnostics are performed. The results of the analysis are shown in Figure 17. As the top left graph shows, the residuals seem to contain certain patterns. This indicates that the residuals are not uncorrelated. The histogram and QQ-plot show that normality is a fair assumption for the distribution of the residuals. However, if the assumption that the residuals are white noise is to be correct, the residuals have to be uncorrelated. By looking at the ACF plot in the bottom right graph, it is clear that there are significant correlations between different lags of the residuals, e.g. at lag 1, 2, 5 and 6. Hence, the assumption of white noise residuals is not justified.

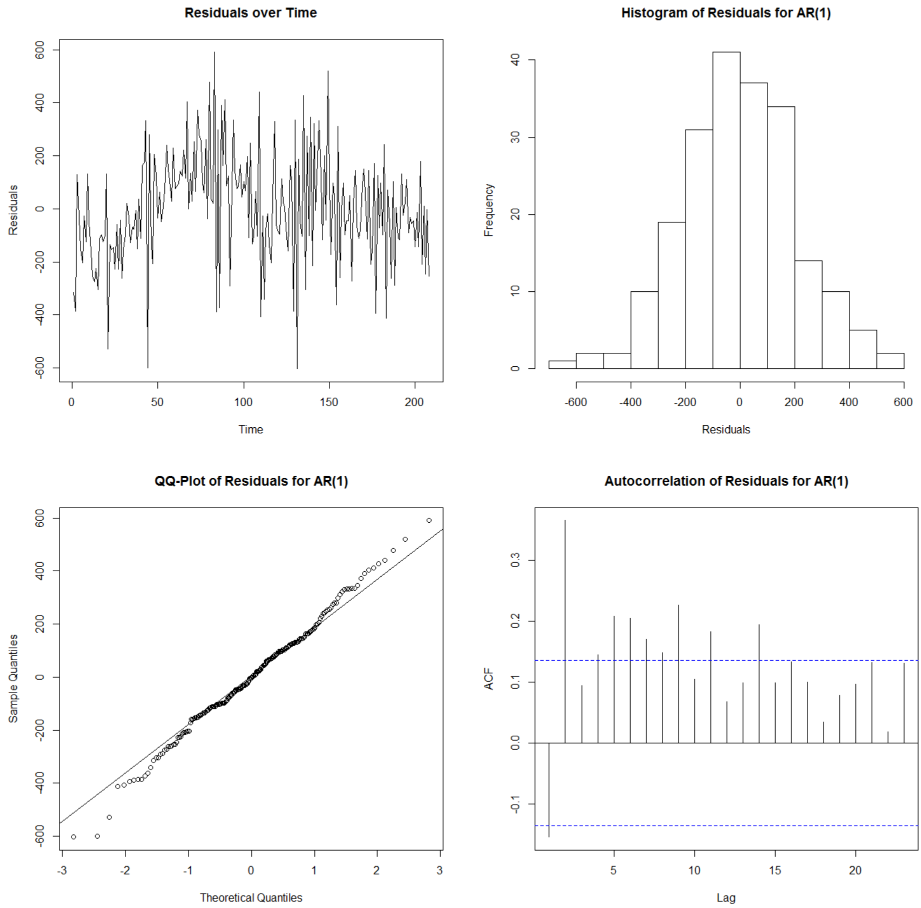


Figure 17: Top left: Residuals plotted over time. There seems to be some correlations within the residuals. Top right: Histogram of residuals. The histogram is unimodal, has a bell shape, but seems to experience some skewness and excess kurtosis. Bottom left: Normal quantile-quantile plot. The QQ-plot follows the QQ-line in a tightly manner, with slightly heavy tails, especially in the lowest quantiles. Bottom right: ACF of residuals. Multiple lags have significant autocorrelation.

The conclusion is that the AR(1) model, representing the MRP, fits the data better than the GBM, because of the stationarity of the time series and the lack of need for transformation of the data. However, the AR(1) model is not the best model fit for the data set.

Calibrating the Model Parameters for the Computer Program

Assuming that the weekly sales time series can be modeled as a stationary AR(1) process, the parameters of the process can be estimated using either an Ordinary Least Square (OLS) method or a Maximum Likelihood method. OLS estimation was performed on the weekly sales data without vacations in R. The parameters are estimated and presented on a per week basis in Table 5, as the time series have weekly increments.

Mean Reverting Ornstein Uhlenbeck Process Parameters		
Parameter	Symbol	Value
Mean reversion rate per week	α	1,05
Long term equilibrium	μ	771
Volatility per week	σ	41,37 %

Table 5: The results of the OLS calibration of the MRP parameters, based on the weekly sales data without vacations from 2009 to 2014 for the clutch servo.

It is noticeable that the mean reversion rate, α, is above 1. This means that the process reverts quickly towards the long term equilibrium, with a half life of 0.66 weeks. Additionally, the weekly volatility, σ, is relatively large, and represents 319 clutch servos per week. The implication of these findings will result in a quickly reverting cost curve. The cost curve will most likely be relatively flat after the first two weeks since the variance will stabilize at the equilibrium level at this point. Hence, reducing lead time is only expected to be valuable within the first two weeks. Consequently, the value of reducing lead time from long lead time to two weeks is expected to be low.

5.4.2 Using the Fitted ARMA Model in the Computer Program

In this section, a direct link between the best model fit and the computer program is proposed. Recall that the mismatch cost function from Section 4.1.3 is derived for a demand variable that is assumed to follow an MRP, and has a normal probability distribution. The derivation was performed on a general basis, enabling usage of any process or model that has a normal distribution. The next step is to determine the probability distribution for different lead times.

After fitting the demand data to an ARMA(p,q) model, residual analysis and forecasting techniques from time series analysis can be utilized to predict the probability distributions of the demand variable. The ARMA(1,3) model was found to be the best fit for KA's demand data. The model has normally distributed error terms, i.e. residuals. Thus, the ARMA(1,3) has a demand variable that is normally distributed. Further, the distribution for different lead times needs to be determined. This is done by calculating the mean and variance for the forecast at different steps ahead. The steps ahead will in this case represent different lead times.

The expected mean of the ARMA(1,3) model for 1, 2, 3, and τ steps ahead can be written as:

$$\begin{aligned}
E[D_{t+1}|D_t, D_{t-1}, ...] &= \mu + \phi(D_t - \mu) - \theta_1 a_t - \theta_2 a_{t-2} - \theta_1 a_{t-3}, \\
E[D_{t+2}|D_t, D_{t-1}, ...] &= \mu + \phi(E[D_{t+1}] - \mu) - \theta_2 a_t - \theta_3 a_{t-2}, \\
E[D_{t+3}|D_t, D_{t-1}, ...] &= \mu + \phi(E[D_{t+2}] - \mu) - \theta_3 a_t, \\
E[D_{t+\tau}|D_t, D_{t-1}, ...] &= \mu + \phi(E[D_{t+\tau-1}] - \mu) \qquad \forall \tau \geq 4.
\end{aligned}$$

The expected forecast error variance for the same model is given by:

$$Var(D_\tau) = \sigma^2 \sum_{i=0}^{\tau-1} \psi_i^2,$$

where

$$\begin{aligned}
\psi_0 &= 1, \\
\psi_1 &= \theta_1 + \phi, \\
\psi_2 &= \theta_2 + \phi\psi_1, \\
\psi_3 &= \theta_3 + \phi\psi_2, \\
\psi_j &= \phi\psi_{j-1} \qquad \forall j \geq 4.
\end{aligned}$$

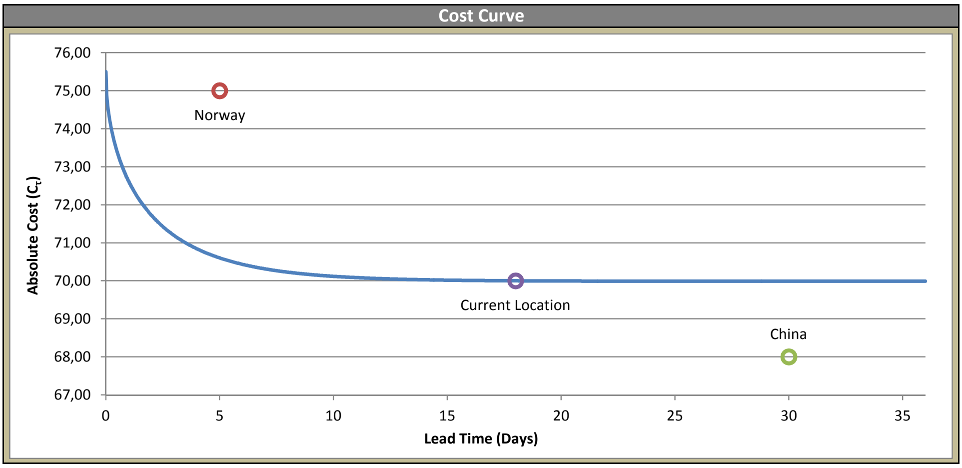
The coefficients, θ, μ, σ^2 and ϕ, are the ARMA(1,3) model coefficients from Table 2.

As a sourcing decision has great strategic impact and often has investment costs related to the change between suppliers, it is crucial that the decision is valid over a long time period. Since the ARMA(1,3), in this case, is stationary, the mean and variance will revert to a long term level. Thus, the input demand for the calculation of the expected mean demand is assumed to be the same as the long term mean in the program. Hence, the cost curve will be mostly affected by the variance of the forecast, which corresponds to the objective of the program - to estimate risk of different lead times and value this risk.

Following the proposition of using forecast techniques as a tool to predict the probability distribution for the demand variable at different lead times, it is clear that the computer program can be customized to a large variety of demand time series. For the general expected mismatch cost function, assuming a normal distribution, the corresponding expectation of mean and forecast error variance for different lead times are needed to define the distribution and to build the cost curve. Further additions, such as differencing, can be included. The general expected mismatch cost function, assuming a log-normal distribution, can be utilized if the time series needs logarithmic transformation.

5.4.3 Comparing the Approaches

To see the difference and similarities between the two approaches of connecting the demand data to the computer program, both programs are run on a simple example case. As both the MRP and the ARMA(1,3) are stationary, they should experience a mean reverting behavior. Additionally, since the graphs have the same underlying data set, the cost level should be relatively equal. The difference between the curves is likely to origin from how fast the curve stabilizes. Figure 18 shows the two cost curves generated by MRP in the left graph, and by use of ARMA(1,3) in the right graph.



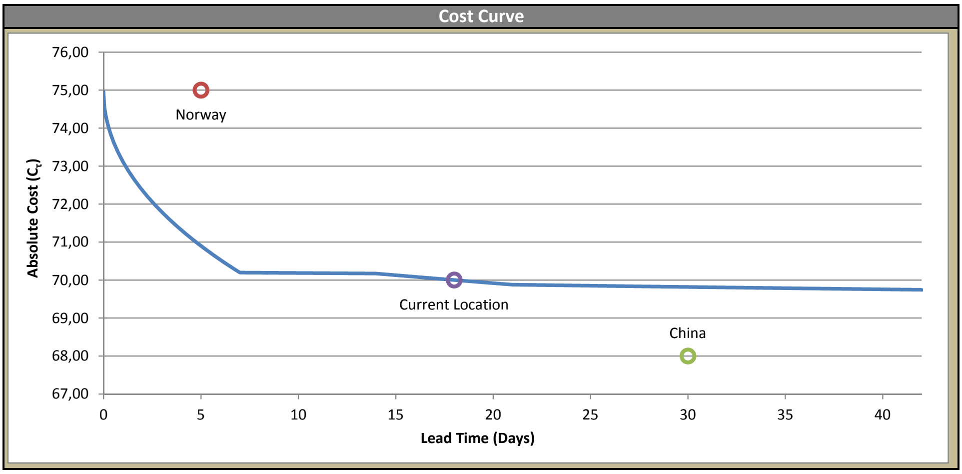


Figure 18: The results of the the computer program run with the MRP stochastic process in the top graph and the ARMA model in the bottom graph. The parameters for the MRP and the coefficients for the ARMA model are determined from KA's demand data. Program input: Current lead time is 18 days, Price is NOK 100, Salvage Value is NOK 50 and Cost is NOK 70.

As mentioned above, both curves experience mean reversion and a relatively equal cost level. However, the MRP curve stabilizes more quickly than the ARMA(1,3) curve. The cost curve of ARMA(1,3) actually continues to decrease at longer lead times. This means that although the demand is stationary, the stable level is not reached within the first 7-8 weeks. Hence, the demand risk is greater at lead times of e.g. 7 weeks compared to e.g. 2 weeks, and the cost at longer lead times should account for the increase in risk.

It is also worth noticing that the cost curve generated by using the ARMA(1,3) forecast is not smooth, unlike the MRP. The reason for the kinks in the cost curve is that the forecasts of mean and variance are made on a weekly basis, and then interpolated to generate the points between.

To sum up, the graphs produced by the different approaches are relatively equal, and will not lead to significantly different conclusions when evaluating different sourcing alternatives. For the following case study only the MRP graph will be shown.

5.5 Actual Demand Data

As mentioned in Section 5.1, KA has started gathering actual demand data for the clutch servo. The data set contains actual demand forecasts for every delivery in the coming year - provided by Scania. Due to the nature of the forecast series, the first data point is actually the experienced demand for the time the forecast series was extracted because it represents what Scania wanted at that particular time. Hence, the first data point of all the forecast series extracted in the collection period from November 2013 to February 2014 is the experienced demand at the time of extraction. This corresponds to 12 weeks of actual demand data at delivery and 12 weeks associated forecasts for these actual demands. This is directly gathered from the EDI-system. In the given period, Scania had an average order frequency of three orders per week, yielding a total of 36 data points.

Since the data set only contains a limited number of data points, it cannot be used by itself to generate a trustworthy representation of the actual development of KA's demand. However, it is fair to believe that the demand data can be used to check whether the assumptions made for the weekly sales data analysis are reasonable. This assessment is done in two ways. Firstly, the demand is assessed by investigating how the demand changes from order to order, as a time series. Then, the evolution of each order's forecast demand up until delivery is assessed.

In Figure 19, the actual demand time series for the clutch servo is shown. The left graph is the actual demand per order, while the right graph shows weekly aggregated orders. Although it is hard to conclude from such small samples, there seems to be no consistent trend in the left graph. The two time series seem to be relatively volatile, but while the left graph is stationary around the mean, the weekly aggregated data seems to have a downward trend. However, it is worth noticing that the right graph is based on only 12 data points. In addition, the variance does not seem to change over this time period in the left graph. This corresponds to the findings in Section 5.3.2.

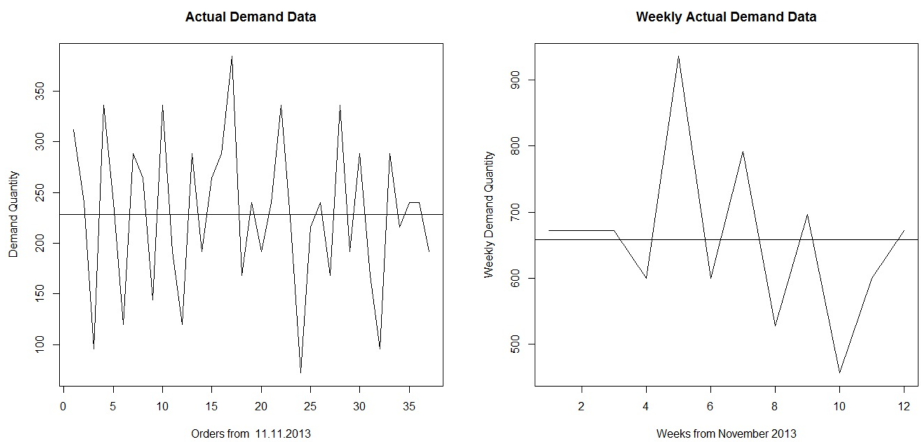


Figure 19: Actual demand for clutch servos. Left plot: The time series with all orders from 11.11.2013 to 14.02.2014, 36 data points. Right plot: The aggregated weekly demand for the same period. The mean is shown as a straight line.

To assess how the demand for each specific order evolves through time, each order and its demand forecast up until delivery is evaluated. Figure 20 shows the distribution of the forecasts at different weeks before delivery, and Figure 21 shows how the mean and standard deviation of the forecast develops over the same time period. Thus, it can be compared to the forecasting of the ARMA(1,3) model in Section 5.4.2 and the calibration of the MRP, as these estimate how the parameters (mean and standard deviation) of the demand distribution evolve at different lead times. Both processes assume a normal distribution, where the forecast of the mean approaches an equilibrium level and the forecast of the standard deviation increases initially, but stabilizes over time.

The histograms of the forecast demand with short time to delivery seem to be more normal than those where time to delivery is long. Thus, assuming a normal distribution is justified with few weeks to delivery and at delivery, but less justified for a longer time horizon. As these histograms are produced with few data points, they only provide an indication of the distribution. A large sample would yield a more trustworthy assessment of the distributions for different forecasts. However, the assumption of normality is overall fairly justified.

From Figure 21, the mean of the demand forecast is stable, but the forecasts are consistently above the actual demand at delivery. The mean at each week before delivery is always within one standard deviation from the actual demand at delivery. Thus, the assumption about a stable demand seems to be valid. The graph to the right shows that the standard deviation of the demand is lowest at delivery and is increasing for the first forecasting weeks. From week 3 to week 11 the standard deviation has some variation, but the trend stabilizes. This is similar to how the predicted standard deviation given by the ARMA(1,3) model and the Ornstein Uhlenbeck process develops. Consequently, this finding supports the chosen model of KA's demand.

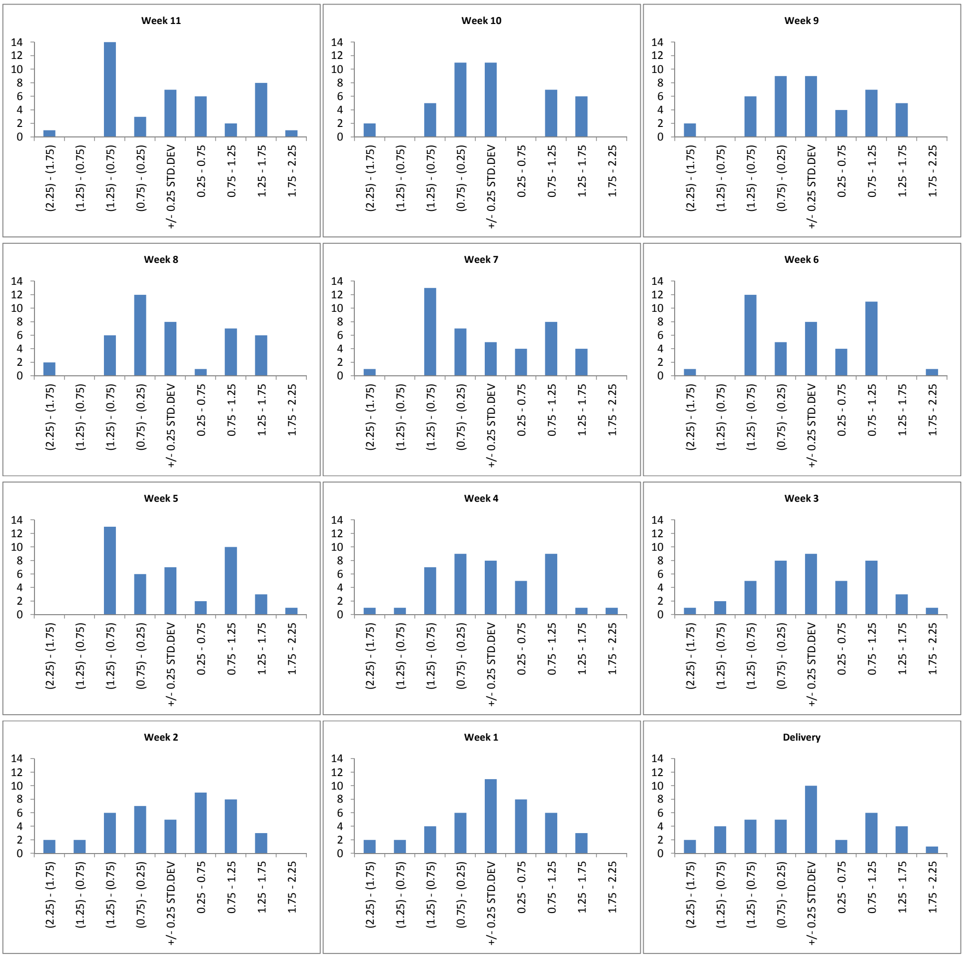


Figure 20: Histograms of actual demand forecast from 11 weeks before delivery until actual demand realized at delivery, 42 observations per histogram as there were 3 order per week in the period. The vertical axis is the frequency of observations, and the horizontal axis is how much the orders deviate from the mean, given in standard deviations. Thus, the middle bar includes the observations that are within +/- 0.5 standard deviations from the mean.

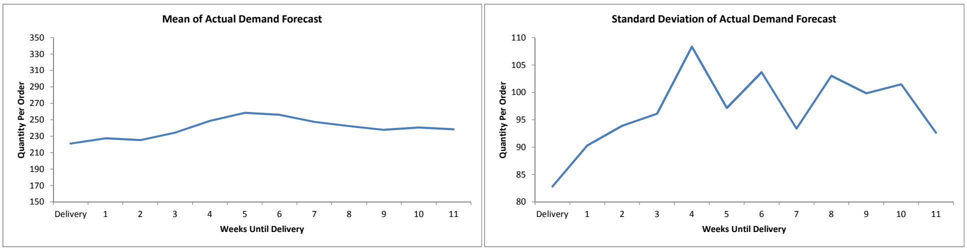


Figure 21: Based on the histograms of Figure 20, these graphs show the development of the mean and standard deviation for all orders as delivery approaches. For both graphs, the horizontal axis presents weekly intervals - starting at the actual demand at delivery and ending at the forecast demand 11 weeks before delivery. The graph to the left shows the development of the demand forecast mean, while the graph to the right shows the standard deviation of the forecast.

According to the findings by assessing the actual demand data, it seems as the assumption of using a stationary mean reverting process, without differencing or transforming the data set, is justified. Although this assessment was performed using a small data sample, the results point in the same direction as the findings in Section 5.3.2. In addition, the results are in accordance with the intuition of the managers at KA about how the demand develops.

6 Case Study and Analysis

As earlier mentioned, this case study will focus on sourcing decisions associated with three of the input components for KA's clutch servo. The motivation behind the selection of components will be discussed first, before the program input parameters is explained and derived. Thereafter, considerations specific for the case are identified and discussed. Then, three sourcing cases, one for each component, will be evaluated using the computer program. Lastly, a sensitivity analysis on the sourcing cases is performed. For each case, all the input parameters needed to replicate the results are reported in Appendix A.

6.1 Motivation

The automotive industry is a very competitive industry, where the pressure for continuous improvements is high. For KA, this means that they are constantly challenged by their customers to find quicker, cheaper and better solutions in order to remain competitive. Consequently, KA is constantly revising their current sourcing partners with hope of finding better ones. This is a time consuming activity and KA therefore needs to prioritize the components that are believed to have the highest possible gain.

Of all the 46 components that make up the clutch servo, the piston, piston rod and aluminum casting account for 50% of the total procurement cost. These components are also of high strategic importance for KA as they are crucial for the reliability and performance of the servo. As a result, the quality requirements are extra high for these components. In addition, as for all other components, the piston, piston rod and casting all need to comply with the industry ISO standards. This shows that choosing the right supplier for these components is not only important, it can also be hard as strict requirements limit the number of potential suppliers.

Further, these components are specialized for the 125mm clutch servo. This high degree of customization makes the components, and some of the production gear, worthless for the supplier if they are to lose the contract with KA. Suppliers therefore tend to require longer contracts to cope with this risk. As a result, it is important for KA to choose the correct supplier for these components the first time. The reason is that they can not simply change the supplier without incurring additional investment costs and penalties for not fulfilling the contract, if the agreement turns out to be non-optimal. The customization also makes the process of choosing a supplier more complex as KA will need to educate the supplier in how to manufacture these components.

As the nature of these three components shows, choosing the correct supplier can save KA both money and time. In addition, the high strategic importance of the components makes KA always seek to have a high service level to limit the risk of a stock out. This is because KA cannot simply buy them elsewhere if the supplier is to run out. Finding an optimal mix of quality, service level and price is therefore key when assessing different suppliers. As the piston, piston rod and casting all have strict requirements to quality and service level and represent a high possible cost reduction - the managers at KA have chosen them as the components of interest for this case study.

6.2 Input Parameters

This section will explain the reasoning for each of the parameters that are plugged into the program. The generic parameters, which are similar for all components, will be discussed first. Then, an assessment of the parameters unique to each component follows. Figure 22 shows the computer program's input panel. The mean reversion rate and volatility refer to the mean reversion rate per week and volatility per week, reported in Table 5 of Section 5.4.1. As Figure 22 shows, the risk free-rate is, in contrast to the volatility and mean reversion rate, defined yearly.

INPUT		
Product Parameters		
Current Lead Time	0	Days
Price	0,00	Unit Price
Salvage Value	0,00	Unit SV
Cost	0,00	Unit Cost
Demand Process Parameters		
Volatility	41,37 %	For 7 Days
Yearly Risk-Free Rate	5,00 %	For 365 Days
Mean Reversion Rate	105,15 %	For 7 Days
Optional Parameters		
Storage Cost	0,00	Per Unit
Capital Cost	0,00	Per Unit
Transportation Cost	0,00	Per Unit
Other Costs	0,00	Per Unit

Figure 22: The computer program's input panel.

6.2.1 Cost

In this case study, the cost in the program refers to the per unit procurement cost for each component. As mentioned in the product description, the figures reported in this case study are approximations of the real costs. These approximations were carried out by the managers at KA due to confidentiality concerns. The total procurement cost of the clutch servo is set to NOK 200. The aluminum casting is the most expensive component - with the cost of NOK 70 per unit. The piston rod has a cost of NOK 20 and the piston costs NOK 10. Together, these three components account for 50% of the total procurement cost. The costs are stated in Figure 23.

6.2.2 Sales Price

This case study considers components that go into the clutch servo, meaning that the they are not sold separately. Hence, the sales price for each component is not known. In cooperation with the managers at KA, this thesis estimates the sales prices. The estimates are based on the assumption that each component accounts for the same fraction of the clutch servo's sales price as it does for the total procurement cost.

For the aluminum casting, this means that the sales price is calculated as follows: the total procurement cost for the clutch servo is NOK 200 and the procurement cost for the casting is NOK 70. Hence, the component constitutes 35% of the total procurement cost. The sales price of the clutch servo is estimated to be NOK 550. Thus the sales price of the aluminum casting is therefore estimated to be NOK 192,50, i.e. 35% of NOK 550. Included in the sales price is a value add of NOK 30 and the obtained margin of 48,05%. The calculations for the remaining components are carried out using the same procedure and are shown in Figure 23.

Cost and sales price breakdown for the components										
Component	Standard Cost		Value Added		Total Cost		Margin	Sales Price		
Casting	kr	70,00	kr	30,00	kr	100,00	48,05 %	kr	192,50
Piston Rod	kr	20,00	kr	5,00	kr	25,00	54,55 %	kr	55,00
Piston	kr	10,00	kr	5,00	kr	15,00	45,45 %	kr	27,50
Other Components	kr	100,00	kr	60,00	kr	160,00	41,82 %	kr	275,00
Sum	kr	200,00	kr	100,00	kr	300,00	45,45 %	kr	550,00

Figure 23: Cost and sales price breakdown for the components.

6.2.3 Salvage Value

The salvage value is defined as salvage revenue less the unit salvage cost required to dispose the unsold product [Hill, 2011]. In other words, it is the estimated value an asset will realize upon its sale when production exceeds demand. At first, the whole concept of salvage value seemed not applicable to KA. The reason is that if KA overproduces, it is not forced to sell its products at a lower price. KA will instead put the excess products in storage and use them in its next delivery. This way of handling overproduction is possible because the demand for clutch servos is rather stable. However, setting the salvage value equal to the sales price poses an incorrect scenario. KA will then be encouraged to produce at maximum capacity all the time, because the profit will then depend on the production quantity and not on the actual demand. Further assessment of the problem revealed a different scenario for the treatment of salvage value. When asked why they did not produce at maximum capacity all the time, the KA managers pointed out that this would yield high storage costs and tie up unnecessary working capital in finished goods. In cooperation with the managers, the salvage value in the case study is therefore defined as the initial procurement cost minus both the incurred storage cost per unit and the capital cost of holding the component. The managers at KA's reported internal rate of return of 12% is used to calculate the capital cost. In other words, this means that KA sells its excess production in future deliveries, and therefore has to store the products meanwhile. This results in storage costs and unnecessary use of capital. Thus, the salvage value is reduced to less than the procurement cost.

As the procurement cost for each component is known, an estimate of the annual storage cost per clutch servo is needed to calculate the salvage value. These calculations were carried out in cooperation with the managers at KA and are done in four steps. The results are shown in Figure 24.

Step 1: Estimating the Total Annual Storage Cost of the Factory
As KA does not explicitly report their total storage cost, this needed to be estimated. This is done by adding together all costs associated with the operation of the storage facility. This gives the total storage cost for the whole factory.

Step 2: Extracting the Annual Storage Cost of Finished Goods
To obtain the storage cost for finished clutch servos, the storage cost for all finished goods first needs to be defined. By dividing the total capital tied up in finished goods by the total capital tied up in storage, a proxy for the percentage share of total storage cost associated with finished goods is obtained. This number is then multiplied with the total storage cost for the factory, obtained in step one, to get the annual storage cost for finished goods.

Step 3: Extracting the Annual Storage Cost for the Clutch Servos
With the annual storage cost for finished goods known, one now needs to isolate the costs associated with the clutch servo. Then dividing the total revenue for the clutch servo by the total revenue of the plant, a proxy for the clutch servos' share of the finished goods is obtained. This number is then multiplied with the annual storage cost for finished goods, calculated in step two, to obtain the annual storage

cost for the clutch servos.

Step 4: Estimating the Per Unit Storage Cost for Scania Clutch Servos
The last step estimates the total number of clutch servos that are in storage in a year and uses this to obtain the per unit storage cost. The assumption that only products that are in storage should have a storage cost is used. The total number of clutch servos in storage per year is found by multiplying the average clutch servo stock size with 52 weeks. Confirmed by the KA managers, the average clutch servo storage is 281. Further, the managers at KA assume that a clutch servo is never in storage for more than one week. As most of the servos in storage are used in the upcoming delivery, instead of new products, this is thought to be a good assumption. Dividing the yearly clutch servo storage cost by the total number of clutch servos in storage then gives the per unit storage cost.

Step 1		
Estimating the total annual storage cost of the factory		
Truck drivers	kr	3 528 000,00
Maintenance of the storage facility	kr	250 000,00
Trucks and fork lifts	kr	288 000,00
Total annual storage cost of factory	kr	4 066 000,00

Step 2		
Extracting the annual storage cost of finished goods		
Total capital tied up in storage	kr	19 000 000,00
Capital tied up in finished goods	kr	3 500 000,00
Percentage finished goods of total		18,4 %
Annual storage cost of finished goods	kr	749 000,00

Step 3		
Extracting the annual storage cost for Scania clutch servos		
Total revenue	kr	260 000 000,00
Revenue Scania clutch servo	kr	18 000 000,00
Percentage clutch servo revenue of total		6,9 %
Annual storage cost for Scania clutch servos	kr	51 853,85

Step 4		
Estimating the per unit storage cost for Scania clutch servos		
Clutch servos in storage per week		281
Total clutch servos in storage per year		14612
Annual storage cost for Scania clutch servos	kr	51 853,85
Per unit storage cost for Scania clutch servos	kr	3,55

Figure 24: Calculation of per unit storage cost for the clutch servo.

The calculation of each component's salvage value is given by the equations below and the results are shown in Figure 25. The salvage value (SV) is found by taking each component's procurement cost (PC) and subtracting its storage cost (SC) and capital cost (CC):

$$SV_{component} = PC_{component} - (SC_{component} + CC_{component}).$$

To find the component's storage cost, the precentage procurement cost is used as a proxy:

$$SC_{component} = SC_{unit} \frac{PC_{component}}{PC_{unit}}.$$

The monetary cost of capital per component is derived using the seven day average storage time assumption, along with KA's annual cost of capital of 12%:

$$CC_{component} = PC_{component}(e^{ln(1,12)\frac{7}{365}} - 1)e^{-ln(1,12)\frac{7}{365}}.$$

This leads to the salvage values reported in Figure 25.

Calculation of each component's salvage value							
Variable	Piston Rod		Piston		Casting		Comments
Procurement cost	kr	20,00	kr	10,00	kr	70,00	*Each component's procurement cost, reported by KA*
Percentage of total procurement cost		10 %		5 %		35 %	*Procurement cost / total procurement cost (NOK 200). Used as a proxy for calculating storage costs*
Storage cost per unit	kr	0,35	kr	0,18	kr	1,24	*Storage cost per unit * Percentage cost of total procurement cost*
Cost of capital (7 days in storage)	kr	0,04	kr	0,02	kr	0,15	*Based on the procurement cost and 7 days with 12% cost of capital*
Salvage Value	kr	19,60	kr	9,80	kr	68,61	*Per unit salvage value*

Figure 25: Calculation of each component's salvage value.

However, recall from Section 4.2.3 that adding supplier specific costs to the program yields higher procurement costs. Since the reasoning behind the calculation of KA's salvage value bases its intuition on KA selling its excess production back to itself, they will also have to pay the supplier specific costs for these products. Hence, these costs should be added to the salvage values reported in Figure 25 to yield the correct salvage value. However, since the calculation of supplier specific costs are subject to assumptions and therefore can vary, this theses has concluded to report the salvage values without including them. The supplier specific costs are simply added to the calculated salvage values, of Figure 25, in the program.

6.2.4 Estimation of Supplier Specific Costs

Storage cost, capital cost and transportation cost are all costs that highly depend on the nature of a sourcing scenario. Since this case study features several different sourcing scenarios, general models for estimating these costs have been developed. The derivation of the models, along with the underlying theory, is presented in this section. As there are no other costs reported for the case of KA, the variable "other costs" is set to zero throughout the case study.

Estimating the Per Component Storage Cost for Different Sourcing Scenarios

To find out how storage costs for different components vary with different sourcing scenarios, this thesis uses changes in stock level. KA operates with two different stock levels for their raw materials - safety stock and cycle inventory. The cycle inventory is the inventory held between two shipments from a supplier to satisfy demand. If one assumes a constant demand within this period, i.e. the inventory is decreasing at a steady rate, the average cycle inventory (ACI) can be defined as:

$$ACI = \frac{CI_{max} - CI_{min}}{2},$$

where CI_{max} is the maximum level of cycle inventory and CI_{min} is the minimum level of cycle inventory. If one then assumes that KA sells all its cycle inventory between two shipments, $CI_{min} = 0$ and CI_{max} becomes the ordering quantity (Q). Q is then defined as the expected demand between two shipments [Chopra, 2013]:

$$Q = \mu F,$$

where μ is the average demand per week, as reported in Section 5.4.1, and F is the number of weeks between deliveries. The average cycle inventory then becomes:

$$ACI = \frac{\mu F}{2}. \tag{23}$$

Since μ is constant for different suppliers, the ACI only depends on the order frequency, F, which may vary for different suppliers. The safety stock (SS) is defined as the level of extra stock that KA maintains to mitigate the risk of stockouts due to uncertainty in demand [Chopra, 2013]. According to Chopra et al. [2004], SS is defined as follows:

$$SS = F^{-1}(CSL)\sqrt{\sigma_{D,LT}^2 + \cancelto{0}{(\mu\frac{L}{7})^2 s_L^2}}, \tag{24}$$

where $F^{-1}(\cdot)$ is the normal inverse function, CSL is the customer service level, $\sigma_{D,LT}$ is the standard deviation of demand for the given lead time, $\mu\frac{L}{7}$ is average demand per week scaled according to lead time, and s_L is the standard deviation of lead time. Recall that demand is modeled as a mean reverting Ornstein Uhlenbeck process.

Thus, $\sigma_{D,LT}$ is given by the variance formula in Section 4.1.3, and the demand is normally distributed. In compliance with the managers at KA, the standard deviation of lead time is assumed to be zero. This assumption cancels the last term of Equation (24). Since desired service level and standard deviation of demand are not dependent on supplier selection, the safety stock for different scenarios only depends on lead time. This is also in accordance with the findings of Ouyang and Chang [2002] from the literature review.

With the level of both inventories known, the cost associated with each of them is found as follows:

$$SS_{cost} = TSC_{rm} \frac{PC_{component}}{C} \frac{SS}{SS + ACI}$$

and

$$ACI_{cost} = TSC_{rm} \frac{PC_{component}}{C} \frac{ACI}{SS + ACI}, \tag{25}$$

where SS_{cost} is the cost of the safety stock, ACI_{cost} is the average cost of the cycle inventory, TSC_{rm} is the annual raw material storage cost for the clutch servo and $\frac{PC_{component}}{C}$ is the component's share of the total procurement cost. This fraction is used to scale the TSC_{rm} to only capture the cost associated with that component. The TSC_{rm} is found using the same approach as in Section 6.2.3. Figure 26 shows the results.

Step 2		
Extracting the annual storage cost of raw materials		
Total capital tied up in storage	kr	19 000 000,00
Capital tied up in raw materials	kr	11 500 000,00
Percentage raw material of total		60,5 %
Total annual storage cost of factory	kr	4 066 000,00
Annual storage cost of raw materials	kr	2 461 000,00

Step 3		
Extracting annual storage cost for Scania clutch servo raw materials		
Total revenue	kr	260 000 000,00
Revenue Scania clutch servo	kr	18 000 000,00
Percentage clutch servo revenue of total		6,9 %
Annual storage cost of raw materials	kr	2 461 000,00
Scania clutch servo raw materials storage cost	kr	170 376,92

Figure 26: Calculation of annual raw material storage cost for the clutch servo. The calculations are the same as step two and three in Figure 24.

As the TSC_{rm} is the current cost, this approach can only be used to find the SS_{cost} and ACI_{cost} for the current sourcing scenario. If KA decides to choose a different supplier, the TSC_{rm} might change, yielding a different SS_{cost} and ACI_{cost}. To find the costs for a potential sourcing scenario, this thesis uses the relative increase in

SS and ACI to scale SS_{cost} and ACI_{cost} accordingly. This method is shown in the following equation:

$$SS_{cost_{new}} = SS_{cost_{old}} \frac{SS_{new}}{SS_{old}} \quad \text{and} \quad ACI_{cost_{new}} = ACI_{cost_{old}} \frac{ACI_{new}}{ACI_{old}}. \qquad (26)$$

These costs are, however, only the cost of operating the storage facility for different inventory levels, broken down on different components. To obtain the complete storage cost for each component ($SC_{component}$), one needs to add the capital cost of holding the inventory. This method is shown in the following equation:

$$SC_{component} = \underbrace{(SS_{cost} + ACI_{cost})}_{operating\ cost} + \underbrace{(SS + ACI)(e^{ln(1,12)} - 1)e^{-ln(1,12)}}_{capital\ cost}, \qquad (27)$$

where $(SS + ACI)$ is the inventory level, calculated in equation (24) and (23). Finally, to obtain the per component storage cost ($SC_{per\ component}$), the $SC_{component}$ is divided by 52μ, which is the annual number of components bought:

$$SC_{per\ component} = \frac{SC_{component}}{52\mu}.$$

Important to note is that this storage cost is not the same as the storage cost used to calculate salvage value - that was the storage cost of finished goods.

Estimating the Per Component Capital Cost for Different Sourcing Scenarios

KA experiences a lag between the date the payment of procured goods is due, and the date they receive the payment from Scania for the sold goods. It is this lag that causes a capital cost. KA is obligated to pay its suppliers 90 days after the procured goods are delivered. In legal terms, the goods are delivered when they leave the supplier's factory. At the other end of the transaction, Scania's net payment is due within 90 days after delivery, with the same delivery terms as KA has with its suppliers. Thus, KA's lag between payment of procured goods and receiving payment from Scania depends on the lead time of the supplier and KA's production time. For the purpose of this thesis, the managers at KA wanted the plant at Hvittingfoss to be treated as a black box with a production time of 7 days. The capital cost for the component ($CC_{component}$) is calculated from the component's procurement cost

($PC_{component}$) in the following equation:

$$CC_{component} = PC_{component}(e^{ln(1,12)\frac{x}{365}} - 1)e^{-ln(1,12)\frac{x}{365}},$$

where x is the sum of the supplier's lead time and KA's production time. For instance, when sourcing from a supplier with a lead time of 40 days and a procurement cost of NOK 50, KA's capital cost is:

$$CC_{component} = NOK\ 50(e^{ln(1,12)\frac{47}{365}} - 1)e^{-ln(1,12)\frac{47}{365}} = NOK\ 0.72,$$

where x = (40 + 7) days = 47 days. If KA, for example, is able to reduce this lead time to 20 days, the capital cost will decrease by 42% to NOK 0.42. Figure 27 illustrates how the lag between KA's and Scania's payment date causes a capital cost for KA.

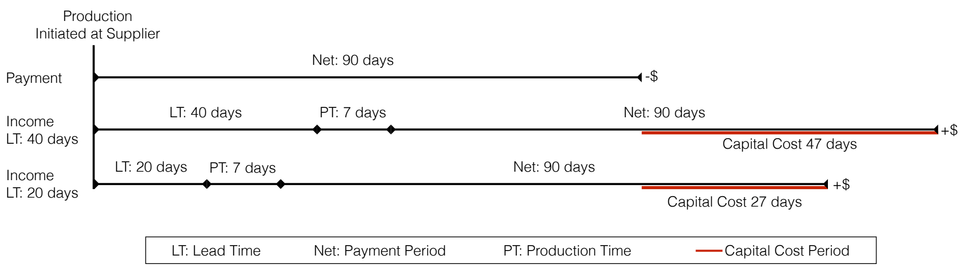


Figure 27: Illustration of the lag between the date the payment of procured goods is due, and the date KA receives the payment from Scania for its sold goods. It is this lag that causes a capital cost for KA. The upper line represents KA's payment to the supplier, while the middle line presents KA's income with a lead time of 40 days and the lower line shows the income when the lead time is 20 days.

Estimating the Per Component Transportation Cost for Different Sourcing Scenarios

Transportation cost highly depends on the distance between KA's factory and the location of the supplier. The managers at KA have provided estimates of the transportation cost for the locations evaluated in the case study, and the relative differences between the different locations are presented in Figure 28.

Transportation Costs	
Reducing Distance to Supplier	
From Asia to Europe	-25 %
From Europe to Norway	-33 %
Increasing Distance to Supplier	
From Norway to Europe	33 %
From Europe to Asia	50 %

Figure 28: The relative differences in transportation cost for the locations evaluated in the case study.

6.3 Case Specific Considerations and Assumptions

If the case study in this thesis is to give realistic results, the computer program has to be able to capture the dynamics of KA's operations. For certain parts of the analysis, the underlying theory and mathematics can represent KA's reality in a good way. However, some aspects are impossible to implement directly without weakening the validity of the program. Therefore, some assumptions and case specific considerations are made in the program. These aspects are presented in this section.

6.3.1 The Use of Service Level

As discussed in Section 3.1, the service level is highly important for the competitiveness of suppliers in all tiers of the automotive industry. However, in this thesis, the term service level has two different definitions. The definitions are not based on the same derivations, hence they are not comparable in any way. The first definition of the term is KA's minimum required delivery precision to Scania, which is 96%. This service level is described in detail in Section 5.1. The second definition of the term refers to the service level from the Newsvendor model. This service level is obtained from the critical fractile in Equation (4), and depends on the price, cost and salvage value of a product in the following ratio: $\frac{p-c}{p-s}$. The Newsvendor model finds the production quantity that optimizes the expected profit, hence the service level from the model is optimal with respect to profit maximization.

The computer program used in this thesis is based on the principles of the Newsvendor model, hence the obtained service level in the program has nothing to do with KA's suggested delivery precision.

6.3.2 Treatment of Underproduction

The model presented in Moltu et al. [2013] uses the assumption that if you produce less than demand, you will lose sales. This, however, is not the case for KA. If KA underproduces on one delivery, and consequently is unable to meet Scania's demand, it is simply forced to deliver the backlog on the next delivery. If KA underproduces over a longer period of time, it is forced to create a recovery plan to deal with the backlog. As this reveals, KA does not actually face lost sales. Instead, they are simply forced to cover up for any underproduction on future deliveries. This makes the assumption of underproduction incorrect and consequently the program less applicable. If incomplete KA-deliveries result in production stops at its customers, KA must pay major fines to compensate for the losses. If such an event should happen, KA is most likely not considered for future business. This aspect makes KA more drawn towards producing too much, rather than risking backlog.

The nature of KA's agreement with Scania forces them to always strive to produce on demand as underproduction has dramatic effects on the relationship. Consequently, the program will have to relate some cost to not meeting demand to prevent the program from systematically advising underproduction. The reason is that if there is no cost associated with underproduction, but there is a cost of overproduction, the program will favor underproduction. This obviously yields the wrong result. Taking this into account, one can look at the assumption of lost sales as a way of modeling this problem. Hence, the program assigns the cost of lost profit, $p - c$, to every lost sale. For the purpose of this case study, this assumption is therefore thought to be a valid replication of the actual case. Incorporation of underproduction will simply prevent the program from favoring underproduction by default. When presented with this assumption, the managers at KA agreed that this was a good way to replicate their situation.

KA is currently the only supplier of the clutch servo for Scania. However, this situation might change, as Scania has implied that dual sourcing might be taken into use in the near future. If dual sourcing is introduced by Scania, KA will actually face the risk of losing sales. This will therefore increase their demand uncertainty, because Scania can choose which supplier to use for every order. The current contract with Scania does not define a minimum order quantity. In addition, Scania's demand for clutch servos will not change if dual sourcing is implemented, thus KA's maximum possible demand is unchanged. In other words, KA risks a drop in demand if dual sourcing is implemented and lost sales may occur. Consequently, KA's delivery precision will be more important than before, and it can distinguish them from the competitors - for better or for worse. The computer program already assumes that lost sales occur when demand exceeds the produced quantity, hence the program is directly applicable if dual sourcing becomes a reality.

6.4 Piston

6.4.1 Product Specifics

The piston is the component within the clutch servo cylinder that compresses air by reducing the cylinder's volume. This creates pressure, which is then used to release the clutch. In its simplest form, it is basically an aluminum disc. The piston is a customized component made solely for the 125mm Scania clutch servo. It is ready for assembly upon arrival at plant Hvittingfoss, and is simply stored until it is mounted onto a clutch servo. There are two pistons per clutch servo, one small and one large. The component of interest here is the larger one.

6.4.2 Case Specifics

The piston is currently sourced from South Korea with a lead time of 47 days. As this lead time is relatively long, KA is not looking to extend this further. This is based on the fact that they believe the piston is currently sourced from the cheapest alternative, relative to lead time. Extending the lead time further will give increased storage cost and capital cost and may lower the service level, without any procurement cost reduction.

Internally, KA has a policy of sourcing expensive products from nearby suppliers to reduce storage cost, capital cost and improve the service level. Based on this, KA wants to look at the alternative of sourcing the piston from a supplier with a shorter lead time. Of the potential suppliers, a producer in France has been proposed as a suitable alternative. The supplier offers a procurement cost of NOK 13, representing a 30% increase from South Korea. However, they can offer a lead time of only 7 days, 40 days shorter than South Korea. In addition, as shown in Figure 28, the transportation cost of the French supplier entails a 25% reduction from the South Korean level. The storage cost and cost of capital are reduced as well when choosing the French producer. KA is currently evaluating this alternative, but keeps finding the increase in procurement cost too high to justify the lead time reduction. They are therefore wondering if the outcome would change if they also take exposure to demand risk into account. The question is therefore whether the increased costs associated with sourcing from France will justify the decrease in demand risk.

6.4.3 Results

Figure 29 shows the result obtained from the computer program. As the figure shows, the producer in France has a cost that is way above the indifference curve. Recall from Section 4.2 that the indifference curve shows the cost at which you are indifferent between different lead times. Hence, sourcing from France is not favorable. The indifference cost for a seven day lead time is only marginally higher than the cost in South Korea. To be favorable, the producer in France will therefore need to drastically decrease its procurement cost, supplier specific costs or further reduce its lead time. However, there are other factors associated with reducing the lead time by 40 days that will affect the sourcing decision. Aspects such as service level, communication issues, currency risk and quality are not accounted for here and may very well influence the result. However, these factors are not believed to be sufficient enough to alter the conclusion. A more thorough assessment of such additional costs and risks is presented in Section 7.

While it may be hard to see from the graph, due to scaling purposes, the cost curve has a relatively steep curvature when the lead time approaches zero. This basically means that KA only obtains value if they manage to reduce their lead time drastically and close to zero. This is equivalent to saying that the demand risk increases quickly short term, but stabilizes at the long term level within one to two weeks. The question for KA is therefore not whether they should have a moderate lead time or a long lead time. The question is whether they should have a really short lead time, eliminating most risk, or a long lead time - incorporating almost all the demand risk. Further assessment of the cost curve will be given in Section 7.

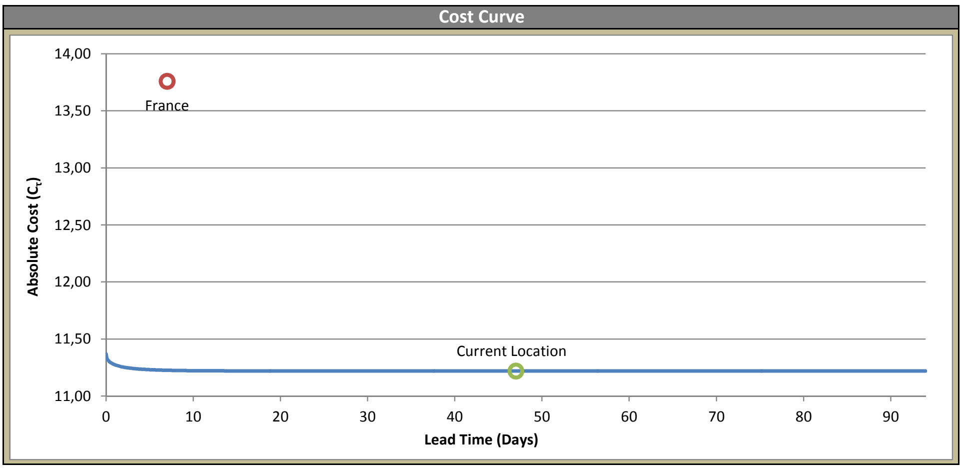


Figure 29: Cost curve for the piston. Input parameters are: Price is NOK 27.50, cost is NOK 10, salvage value is NOK 9.80 and the current lead time is 47 days. Storage cost is NOK 0.28, capital cost is NOK 0.14 and transportation cost is NOK 0.80, quoted per unit. The reduction scenario lead time is 7 days and the cost is NOK 13. The per unit cost of storage, capital and transportation is NOK 0.08, NOK 0.02 and NOK 0.60, respectively, for the reduction scenario.

6.5 Aluminum Casting

6.5.1 Product Specifics

The aluminum casting is the actual body of the clutch servo, which all the other components are mounted onto. In its simplest form, the casting is a solid piece of aluminum that has been processed into the desired shape. It is one of the most crucial components of the clutch servo in terms of quality and availability. Availability is especially important as the casting is the only component in the clutch servo that needs to be further processed at Hvittingfoss before it can go into production. This means that if there is a stock out, KA will first have to process the incoming castings before the rest of the production can start. This can potentially cause a longer down period in the clutch servo production. There is only one casting per servo.

6.5.2 Case Specifics

Because of its high strategic value, the sourcing of the casting is constantly revised. It is currently sourced from Serbia with a lead time of 18 days. The procurement cost is NOK 70. KA is very comfortable with the current situation, but lately an alternative in South Korea has emerged. The alternative features a 150% increase in lead time and a 5% decrease in procurement cost. Since there are few potential suppliers of the casting, due to its high degree of customization, KA would like to evaluate the alternative. As mentioned before, KA has an internal policy of sourcing expensive products from nearby locations to reduce capital cost and storage cost, as well as to improve the service level. Increasing the lead time for the casting would directly contradict this policy. However, the cost decrease can have a large impact on KA's profits. Regardless of their internal policy, the managers at KA want to evaluate if the small decrease in cost can justify the high increase in lead time, and thus potentially an increase in exposure to demand risk.

6.5.3 Results

Figure 30 shows the result obtained from the computer program. As for the piston case, the cost curve for the casting is very steep as lead time approaches zero. The reason is that these components have the same demand structure, because they both go into the same product. The small differences in the observed shapes are only a result of different scaling of the graph. However, in contrast to the piston, this case shows that KA should choose to source differently. As the graph shows, South Korea's cost is lower than the accepted cost at the given lead time. This further strengthens the argument that KA should not consider whether to have a moderate lead time or a long lead time. Rather, the consideration should be whether they should have a really short lead time or a long lead time. If a really short lead time is impossible to obtain at a fair price, KA might as well source from a supplier with a long lead time. The reason is, as for the piston case, that decrease in demand risk only occurs within the last weeks prior to delivery, while the long term demand risk is stable. Hence, if the lead time exceeds one week, KA is already exposed to all the risk in the demand structure. However, sourcing from South Korea will most likely increase KA's exposure to factors such as cultural differences, political instability and nature disasters. These aspects arise on the supply side of KA's operations, and are not accounted for in this analysis. Hence, South Korea might become less favorable, even unfavorable, when these aspects are considered. In addition, the increased lead time can potentially reduce KA's service level. It is therefore important for KA to evaluate these aspects before deciding to source from South Korea. A more extensive discussion on such risks is featured in Section 7.

Lastly, the storage cost for the two alternatives are exactly the same in the program. The average cycle inventory, ACI, is the same because both suppliers offer delivery once a week (the ACI only depends on the order frequency, F, as shown in Equation (23)). The safety stock is equal for both alternatives, because the lead time of South Korea roughly presents the same demand risk as the case of Serbia, as discussed in the previous paragraph. Recall from Equation (24) that safety stock depends on the demand uncertainty. Low storage cost is usually expected when choosing a supplier that is geographically close, thus the obtained storage cost in this supplier selection is surprising. KA should therefore evaluate these costs in more detail before making a final decision. In fact, only changing the ordering frequency from once a week to once every two weeks is just enough to raise South Korea over the indifference curve. However, changing the ordering frequency will most likely reduce the transportation cost. Therefore, finding the optimal combination of ordering frequency, storage level and transportation cost is important for KA when making the sourcing decision.

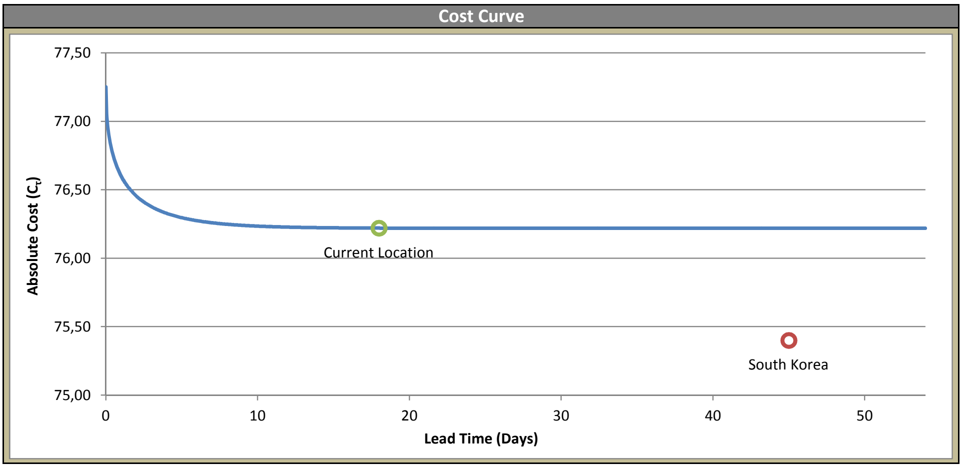


Figure 30: Cost curve for the aluminum casting. Input parameters are: Price is NOK 192.50, cost is NOK 70, salvage value is NOK 68.61 and current lead time is 18 days. Storage cost is NOK 1.63, capital cost is NOK 0.39 and transportation cost is NOK 4.20, quoted per unit. The extension scenario lead time is 45 days and the cost is NOK 66,50. The per component cost of storage, capital and transportation is NOK 1.63, NOK 0.97 and NOK 6.30, respectively, for the extension scenario.

6.6 Piston Rod

6.6.1 Product Specifics

The piston rod is the component within the clutch servo that connects the larger air chamber to the smaller hydraulic chamber. The piston rod transfers power from the hydraulics to the air cylinder, which again presses on the piston. In its simplest form, the piston rod is basically an aluminum shaft. There are two piston rods in a clutch servo, one small for the hydraulic chamber and one larger for the connection between the two chambers. The piston rod of interest here is the larger one. There is no need for further processing of the piston rod upon arrival at plant Hvittingfoss.

6.6.2 Case Specifics

The piston rod is currently sourced from France with a lead time of 9 days. This is a relatively short lead time compared to the other components that go into the clutch servo, and could therefore be beneficial to extend. However, KA has not been able to find any potential suppliers in low cost countries. The suppliers they have found all entail a reduction in lead time and an increase in cost. In light of KA's internal policy of sourcing expensive products nearby, these alternatives should however be evaluated. The problem for KA today is that the increase in procurement cost is significant for these small reductions in lead time, while the effects on storage cost, transportation cost and capital cost are marginal in monetary terms. However, the relative impact is greater - sourcing from Norway entails a 33% reduction in each of these costs. As a result, most alternatives with a minimal lead time reduction are today discarded. KA is therefore eager to find other ways of assessing such alternatives, as they believe that it may be beneficial to further reduce the lead time in many cases. Currently, they are evaluating a specific alternative in Norway, with a lead time of 6 days and a cost of NOK 24. The question is whether the increase in cost Norway poses will justify the small decrease in lead time.

6.6.3 Results

Figure 31 shows the result obtained from the computer program. As one can see from the figure, the cost at which KA will be indifferent for a lead time of 6 days is just above NOK 21.50. The cost of sourcing from the Norwegian supplier, however, is above NOK 25. Hence, sourcing from Norway is not favorable. Based on the results, it is clear that for a shorter lead time to be favorable, the supplier can only have a marginal cost increase. A fair assumption is that the supplier's distance from the factory is closely correlated to the supplier's lead time. As KA's plant is situated in a high cost country, and as most countries within a close proximity also present a fairly high cost level, it is found unlikely that KA will obtain a nearby supplier that will be favorable. Therefore, it may be beneficial for them to look for a supplier with a longer lead time, instead of one with a shorter lead time.

However, choosing to source from a domestic supplier may bring major benefits to KA that could justify the cost increase. When a company chooses an international supplier, it automatically exposes itself to various types of risk. Min [1994] states that choosing the correct international supplier is a complicated process, due to factors such as currency exchange rates, cultural differences, ethical standards, political situations, communication barriers and quality standards. When choosing to supply domestically, KA will mitigate these risks, which obviously has a value. This value is not accounted for in the result of the previous paragraph and may very well tilt the result in the opposite direction. Further, as mentioned in Section 6.1, the piston rod is custom-made for KA. This means that KA will need to educate the supplier in how to produce the component, yielding a more complex communication than for a standardized product. When choosing an international supplier, this increased need for communication may represent additional risk. Hence, the value of sourcing domestically may be greater for the piston rod than for a standardized product.

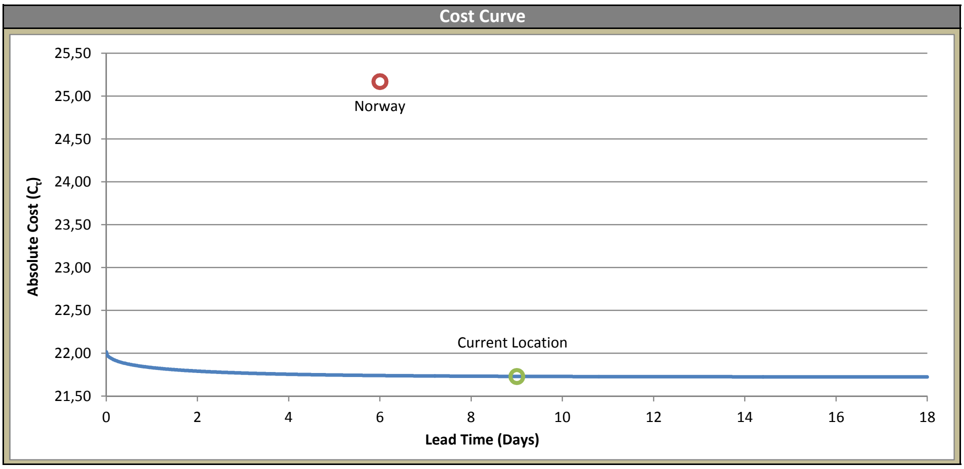


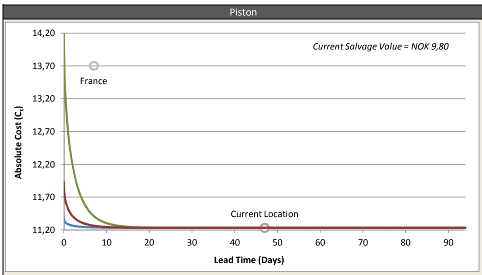
Figure 31: Cost curve for the piston rod. Input parameters are: Price is NOK 55, cost is NOK 20, salvage value is NOK 19.60 and current lead time is 9 days. Storage cost is NOK 0.47, capital cost is NOK 0.06 and transportation cost is NOK 1.20, quoted per component. The reduction scenario lead time is 6 days and the cost is NOK 24. The per unit cost of storage, capital and transportation is NOK 0.33, NOK 0.04 and NOK 0.80, respectively, for the reduction scenario.

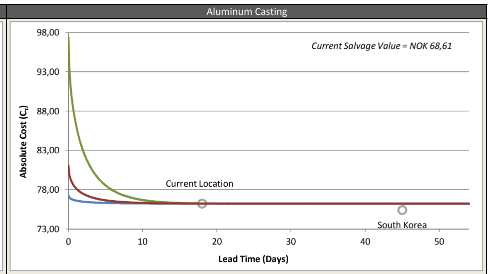
6.7 Sensitivity Analysis

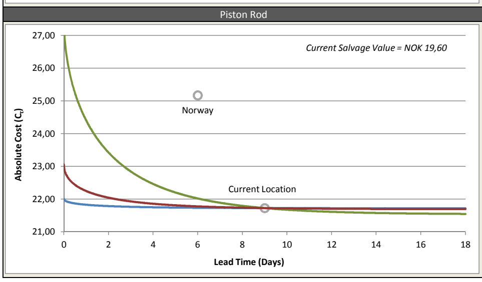
The results obtained in the case study are based on parameters extracted from sales data for the last five years and from analyses of KA's operations. Thus, the results assess the sourcing decisions of the case study assuming that KA's future will resemble its past. Due to KA's stable demand in the data set, and the fact that the automotive industry is well established, this appears to be a plausible assumption. However, the features of the industry might change, consequently affecting the input parameters used in the case study. Therefore, a sensitivity analysis is performed in this section, investigating how a change in certain input parameters will influence the results of the case study. Three parameters are considered to be interesting for the sensitivity analysis: salvage value (SV), volatility (Vol) and mean reversion rate (MRR).

6.7.1 Sensitivity to Salvage Value

As mentioned in Section 6.2.3, the salvage value of the clutch servo is difficult to estimate. The calculation is based on various assumptions, thus the obtained value used for the different components in this case study includes uncertainty. However, all the assumptions have been verified by the managers at KA. For instance, an assumption is that clutch servos never become obsolete in storage. This might be incorrect if the storage time increases drastically, if demand suddenly drops or if rapid technological advances change the demanded features of the product. Another assumption is that KA does not face the risk of losing contracts, and thereby being stuck with useless clutch servos in storage. Both these risks are assumed to be absent. If either of the assumptions turn out to be incorrect the salvage value should be reduced. Therefore, the sensitivity analysis investigates the case of a 10% reduction in the salvage value. Lastly, the sensitivity analysis also evaluates the effect of the salvage value being zero, which is the case when the excess products for a delivery are considered to be worthless. Though this penalizes overproduction very hard, the assumption highlights the fact that the clutch servo is customized for Scania and is useless to other OEMs. Figure 32 shows the cost curves for different salvage values for the three components.







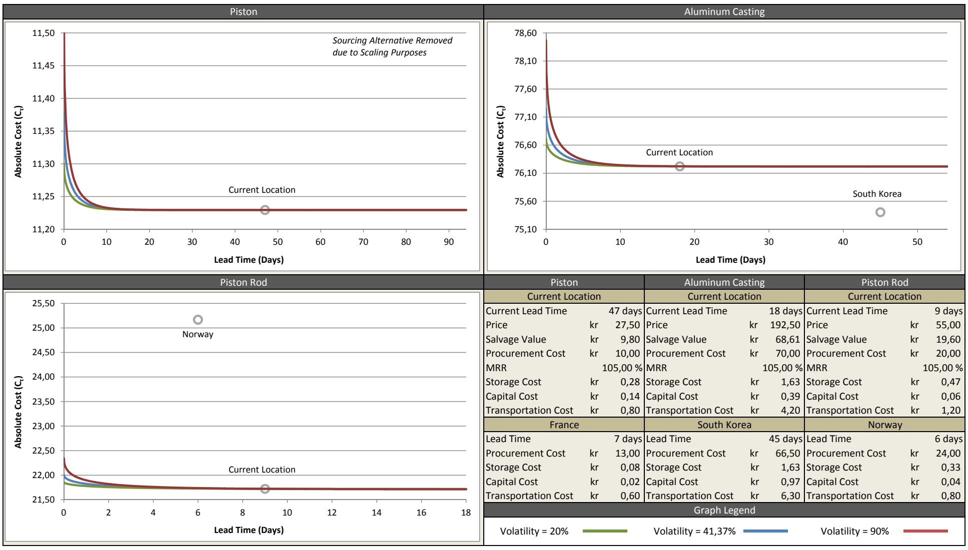
Piston			Aluminum Casting			Piston Rod		
Current Location			Current Location			Current Location		
Current Lead Time		47 days	Current Lead Time		18 days	Current Lead Time		9 days
Price	kr	27,50	Price	kr	192,50	Price	kr	55,00
Procurement Cost	kr	10,00	Procurement Cost	kr	70,00	Procurement Cost	kr	20,00
Volatility		41,37 %	Volatility		41,37 %	Volatility		41,37 %
MRR		105,00 %	MRR		105,00 %	MRR		105,00 %
Storage Cost	kr	0,28	Storage Cost	kr	1,63	Storage Cost	kr	0,47
Capital Cost	kr	0,14	Capital Cost	kr	0,39	Capital Cost	kr	0,06
Transportation Cost	kr	0,80	Transportation Cost	kr	4,20	Transportation Cost	kr	1,20
France			South Korea			Norway		
Lead Time		7 days	Lead Time		45 days	Lead Time		6 days
Procurement Cost	kr	13,00	Procurement Cost	kr	66,50	Procurement Cost	kr	24,00
Storage Cost	kr	0,08	Storage Cost	kr	1,63	Storage Cost	kr	0,33
Capital Cost	kr	0,02	Capital Cost	kr	0,97	Capital Cost	kr	0,04
Transportation Cost	kr	0,60	Transportation Cost	kr	6,30	Transportation Cost	kr	0,80
Graph Legend								
Current Salvage Value			10% Decrease in Salvage Value			Salvage Value set Equal to 0		

Figure 32: The cost curves for the three components are plotted for varying salvage value. The salvage value is different for each component (without supplier specific costs): the piston's SV is NOK 9.80, the aluminum casting's SV is NOK 68.61 and the piston rod's SV is NOK 19.60. Recall from Section 6.2.3 that to obtain the salvage value used in the program the supplier specific need to be added. The relative salvage value used in each of the plots is the current salvage value, a 10% decrease in salvage value and a salvage value of zero. The upper left graph shows the results for the piston, the upper right graph the aluminum casting and the lower left graph the piston rod. The panel in the lower right corner shows the input parameters for all three graphs.

Figure 32 shows that the results of the case study are valid for all the salvage values tested in the sensitivity analysis. Even a salvage value of zero yields the same sourcing decision - hence, the results are robust in terms of salvage value. When salvage value is reduced, the cost of overproduction increases, thus the mismatch cost increases. The mismatch cost can be reduced by better meeting the demand, which can be achieved by reducing the lead time. Consequently, it can be seen in Figure 32 that shorter lead times become more favorable as the salvage value decreases. From the piston rod graph it can also be seen that longer lead times become less favorable when the salvage value is reduced - explicitly seen by the green graph. This is actually the same for all components, but can only be seen in the piston rod example due to different scaling of the other graphs. This result originates from the same argument as above. When the salvage value is decreased the mismatch cost increases. Since a longer lead time incorporate more risk, which yields a higher mismatch cost, these lead times become less favorable - making the graph decline further. The same risk is also present when the salvage value is high, but since the cost of not meeting demand is marginal, due to low overage cost, it does not have a significant effect on the cost curve. Recall from the literature review that De Treville et al. [2013b] found the marginal cost of time to increase as salvage value decreases for constant volatility demand structures. This finding coincide with their results.

6.7.2 Sensitivity to Volatility

The demand for clutch servos has proved to be rather stationary, with large fluctuations around the mean level. If the current conditions continue, the demand uncertainty will most likely remain close to its present level. However, as mentioned in Section 6.3.2, Scania might introduce dual sourcing which will increase KA's demand uncertainty. In addition, the demand for car parts is correlated to macro trends in the general automotive industry. Thus, the clutch servo may experience more uncertainty when the market in general is more volatile. In addition, the production of heavy trucks has declined over the last two years [International Organization of Motor Vehicle Manufacturers]. If this development continues, KA might experience reduced demand but may also encounter higher volatility due to increased competition. Aspects such as dual sourcing and production decline make it interesting to analyze the effects of increasing volatility on the case study. On the other hand, KA's contracts with Scania define a maximum order size, but they do not specify a minimum quantity. If the contracts were to include a minimum order quantity, KA's demand uncertainty would decrease. Hence, the sensitivity analysis investigates the effect of reduced volatility as well. Figure 33 shows the cost curves for different volatility for the three components.



Piston			Aluminum Casting			Piston Rod		
Current Location			Current Location			Current Location		
Current Lead Time		47 days	Current Lead Time		18 days	Current Lead Time		9 days
Price	kr	27,50	Price	kr	192,50	Price	kr	55,00
Salvage Value	kr	9,80	Salvage Value	kr	68,61	Salvage Value	kr	19,60
Procurement Cost	kr	10,00	Procurement Cost	kr	70,00	Procurement Cost	kr	20,00
MRR		105,00 %	MRR		105,00 %	MRR		105,00 %
Storage Cost	kr	0,28	Storage Cost	kr	1,63	Storage Cost	kr	0,47
Capital Cost	kr	0,14	Capital Cost	kr	0,39	Capital Cost	kr	0,06
Transportation Cost	kr	0,80	Transportation Cost	kr	4,20	Transportation Cost	kr	1,20
France			South Korea			Norway		
Lead Time		7 days	Lead Time		45 days	Lead Time		6 days
Procurement Cost	kr	13,00	Procurement Cost	kr	66,50	Procurement Cost	kr	24,00
Storage Cost	kr	0,08	Storage Cost	kr	1,63	Storage Cost	kr	0,33
Capital Cost	kr	0,02	Capital Cost	kr	0,97	Capital Cost	kr	0,04
Transportation Cost	kr	0,60	Transportation Cost	kr	6,30	Transportation Cost	kr	0,80
Graph Legend								
Volatility = 20%			Volatility = 41,37%			Volatility = 90%		

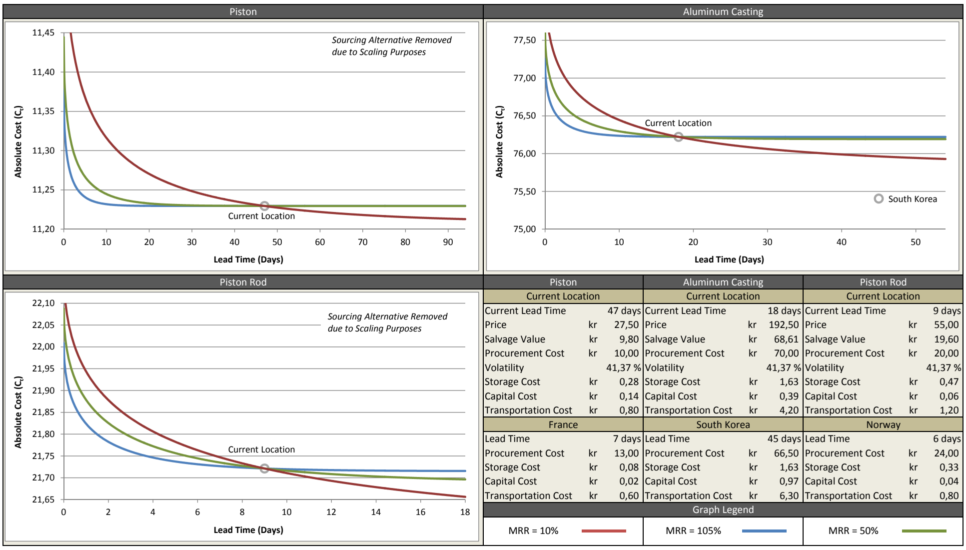
Figure 33: The cost curves for the three components are plotted for varying volatility. The volatility used in the plots are 20%, 41,37% (the current volatility) and 90%. The upper left graph is for the piston, the upper right graph is for the aluminum casting and the lower left graph is for the piston rod. The panel in the lower right corner shows the input parameters for all three graphs.

Figure 33 shows that the cost curves of the case study are not strongly affected by a change in volatility. Even more than a doubling of the volatility from the case study yields the same results with regards to sourcing decisions. Hence, the results are robust in terms of volatility. As seen in the different plots of Figure 33, volatility may only affect the sourcing decision when a really short lead time is evaluated. This is true because KA's demand is quite stable, and it reverts quickly back to the mean when demand spikes occur. Hence, the additional risk of longer lead time decreases as the lead time increases. However, the major contributor to the small effects is the high salvage value. Even though a higher volatility obviously yields a higher risk, this risk has little value since the cost of overage is so low. Hence, if the salvage value is to be decreased along with the MRR, an increase in volatility will have substantially larger effect. For instance - if the salvage value is decreased by 10% and the MRR to 30%, a volatility of 90% will make South Korea unfavorable for the aluminum casting.

Figure 33 also show that the curvature of the different cost curves, to some extent, differ from component to component. While some of this can be explained by various scaling of the graphs, the differences in overage and underage cost are also large contributors. These differences yield different values of risk which further make the curvature of the graphs deviate from each other.

6.7.3 Sensitivity to Mean Reversion Rate

The analysis of KA's sales data revealed that the demand for clutch servos has a very high MRR. This implies that when an order deviates from the mean, the demand reverts quickly back to the equilibrium level in the subsequent orders. Since KA's MRR is already high, it seems most unlikely that it will become any higher. This is because an even higher MRR would imply that the demand is almost constant - eliminating most of the demand risk. It is therefore assumed to be more likely that the MRR would decrease. A potential reason for a decrease in MRR could be seasonality. For the current demand structure, seasonality is low. However, it might increase if KA, for instance, initiates a cooperation with a tractor producer, as the demand for tractors depends on a season's crop. Increased seasonality and uncertainty within the seasons lead to a reduced MRR as the demand will first revert back to its mean when the season is over. The MRR can further be reduced if dual sourcing becomes a reality. Thus, the demand may not be as stable as for the current situation. Therefore, only the effect of reducing the MRR is analyzed in the sensitivity analysis. Figure 34 show the results for all three components.



Piston			Aluminum Casting			Piston Rod		
Current Location			Current Location			Current Location		
Current Lead Time		47 days	Current Lead Time		18 days	Current Lead Time		9 days
Price	kr	27,50	Price	kr	192,50	Price	kr	55,00
Salvage Value	kr	9,80	Salvage Value	kr	68,61	Salvage Value	kr	19,60
Procurement Cost	kr	10,00	Procurement Cost	kr	70,00	Procurement Cost	kr	20,00
Volatility		41,37 %	Volatility		41,37 %	Volatility		41,37 %
Storage Cost	kr	0,28	Storage Cost	kr	1,63	Storage Cost	kr	0,47
Capital Cost	kr	0,14	Capital Cost	kr	0,39	Capital Cost	kr	0,06
Transportation Cost	kr	0,80	Transportation Cost	kr	4,20	Transportation Cost	kr	1,20
France			South Korea			Norway		
Lead Time		7 days	Lead Time		45 days	Lead Time		6 days
Procurement Cost	kr	13,00	Procurement Cost	kr	66,50	Procurement Cost	kr	24,00
Storage Cost	kr	0,08	Storage Cost	kr	1,63	Storage Cost	kr	0,33
Capital Cost	kr	0,02	Capital Cost	kr	0,97	Capital Cost	kr	0,04
Transportation Cost	kr	0,60	Transportation Cost	kr	6,30	Transportation Cost	kr	0,80
Graph Legend								
MRR = 10%			MRR = 105%			MRR = 50%		

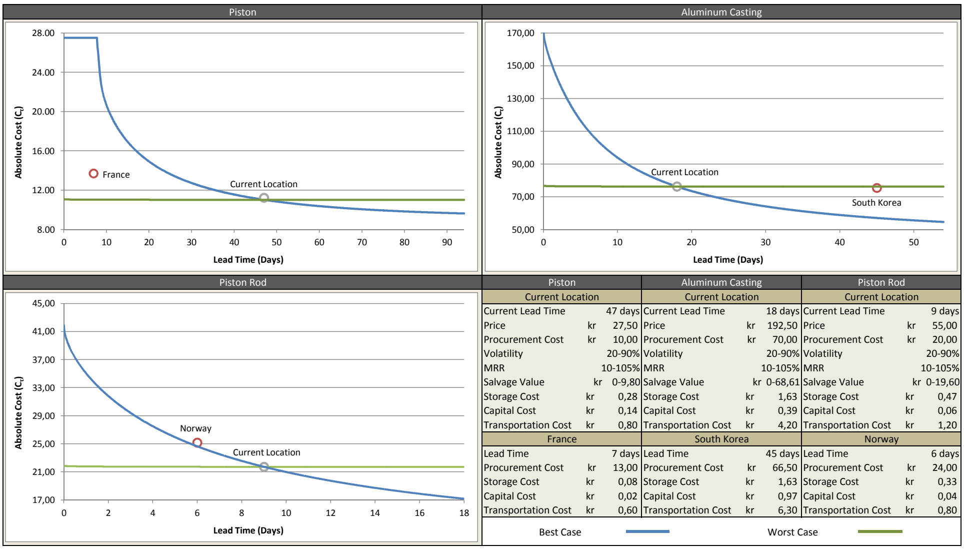
Figure 34: The cost curves for the three components are plotted for varying MRR. The MRR used in the plots are 105% (the current MRR), 50% and 10%. The upper left graph is for the piston, the upper right graph is for the aluminum casting and the lower left graph is for the piston rod. The panel in the lower right corner shows the input parameters for all three graphs.

In line with the results of the two previously discussed input parameters, Figure 34 shows that varying the MRR does not change the outcome of the different sourcing decisions. In other words, the results are robust in terms of MRR. However, the plots show that varying the MRR yields noticeable changes to the cost curve. Regardless of component, the plots show that lead time reduction becomes more favorable when the MRR decreases. When the MRR is low the demand becomes less stable, yielding a higher risk. This higher risk has a value, which makes it worth eliminating - hence, reducing lead time becomes more favorable. On the other hand, a high MRR indicates a stable demand - hence reducing lead time becomes less favorable. Figure 34 also show that varying MRR has, to some extent, different effect on the different components. For example, the graph for the piston rod looks to be much steeper than for the other components. Once again, some of these differences can be explained by different scaling of the graphs. However, another reason is, as for the volatility, that the different components have different costs of overage and underage.

6.7.4 Changing Multiple Parameters

As discussed above, the cost curves for the different components are robust in terms of changes in single parameters. However, the discussion shows that the results are highly dependent on how the different variables interact. Hence, changing only one parameter at a time only leads to minor changes in the cost curve. Therefore, the results when more than one parameter is altered should be investigated. For instance, if both the risk of the demand and the cost of overproducing increase, the cost curve would experience large shifts. Thus, the resulting cost curves are dependent on the link between the parameters.

To show how the links between the parameters affect the cost curve, the most extreme cases from the previous sensitivity analysis are combined to generate a sample space. This is the space between the blue and the green graphs in Figure 35. The blue graph corresponds to the most stable demand and lowest cost of overage, while the green graph represents the opposite case of high volatility, low MRR and no salvage value. KA is not believed to encounter more extreme cases than shown in the graphs. Clearly, these graphs show that changes to multiple parameters have large impacts on the cost curve and the associated sourcing decisions. Both France and South Korea are located between the two extreme borders. This makes it likely that if changes to KA's demand structure and cost of overproduction become a reality, France might become favorable, while South Korea does not. Norway, however, is just outside this region. Hence, it is very unlikely that Norway would become favorable.



Piston			Aluminum Casting			Piston Rod		
Current Location			Current Location			Current Location		
Current Lead Time		47 days	Current Lead Time		18 days	Current Lead Time		9 days
Price	kr	27,50	Price	kr	192,50	Price	kr	55,00
Procurement Cost	kr	10,00	Procurement Cost	kr	70,00	Procurement Cost	kr	20,00
Volatility		20-90%	Volatility		20-90%	Volatility		20-90%
MRR		10-105%	MRR		10-105%	MRR		10-105%
Salvage Value	kr	0-9,80	Salvage Value	kr	0-68,61	Salvage Value	kr	0-19,60
Storage Cost	kr	0,28	Storage Cost	kr	1,63	Storage Cost	kr	0,47
Capital Cost	kr	0,14	Capital Cost	kr	0,39	Capital Cost	kr	0,06
Transportation Cost	kr	0,80	Transportation Cost	kr	4,20	Transportation Cost	kr	1,20
France			South Korea			Norway		
Lead Time		7 days	Lead Time		45 days	Lead Time		6 days
Procurement Cost	kr	13,00	Procurement Cost	kr	66,50	Procurement Cost	kr	24,00
Storage Cost	kr	0,08	Storage Cost	kr	1,63	Storage Cost	kr	0,33
Capital Cost	kr	0,02	Capital Cost	kr	0,97	Capital Cost	kr	0,04
Transportation Cost	kr	0,60	Transportation Cost	kr	6,30	Transportation Cost	kr	0,80

Figure 35: The cost curves for the three components are plotted for the extreme values of Salvage Value (Calculated - 0), Volatility (20% - 90%) and MRR (105% - 10%). The upper left graph is for the piston, the upper right graph is for the aluminum casting and the lower left graph is for the piston rod. The panel in the lower right corner shows the input parameters for all graphs.

It is worth noticing that for the piston, the blue graph cuts of at a 8 day lead time. This happens because the cost equals the price at this point, and KA would not in any case be willing to pay more than the sales price for the piston. Hence, for this extreme case of demand risk, KA will be indifferent between not earning any profit at a lead time of 8 days and the current situation. Consequently, the current situation does not appear to be favorable either - given the demand structure and related costs of over- and underproduction. This gives rise to a whole new conclusion for the supplier selection of the piston. In addition to not sourcing the component from France, KA should actually reevaluate their current supplier. For instance, the results from this case can be used to negotiate a lower price for the current supplier.

7 Discussion

In this section, a discussion of the main challenges in the thesis will be presented. Firstly, considerations of the empirical study and the computer program are discussed. Then, an assessment of the case study follows, focusing on the applications of the results and the implications of the assumptions in the model.

7.1 Empirical Analysis and Program Considerations

With the presented framework, determining the best model fit for the demand data is a crucial aspect of evaluating lead time. As shown in previous case studies by De Treville et al. [2013a], different demand evolution yields large variations in the level and curvature of the CD Frontier, and thus also the cost curve. Considerations about demand's stationarity vs. non-stationarity and the distribution determinations, e.g. normality, log-normality, heavy tails and jumps, will have large effects on the indifference costs at different lead times. Hence, the empirical data analysis and the choice of stochastic process construct an important foundation for further lead time analysis. Three main issues have been at the core of the empirical data analysis in this thesis; finding a representation of the actual demand data, determining the best model fit, and incorporating the findings about the demand structure into the program.

Most companies do not have access to actual demand data and must represent their demand through historical sales data. This may cause misinterpretation, as these data points do not necessarily represent what the customer actually ordered. This is especially apparent within businesses that do not operate with backlog and thus experience lost sales. In cases where lost sales are not reported and orders exceed the on-hand stock, the sales data is merely a representation of the on-hand stock at the time of delivery. Thus, order data should be kept to build knowledge about the demand evolution, as this may prove beneficial for either stock control, forecasting of production, or for sourcing and lead time decisions. For businesses that are allowed to deliver backlog, data can be aggregated to identify the demand, under the assumption that the backlog is delivered within the period of aggregation. A potential problem is the loss of order specific fluctuation. Additionally, if the assumption of delivering backlog within the aggregation period does not hold, the data set can experience false spikes and drops, which will adversely affect the analysis. Hence, if the company has access to real demand data, or records ordering data, the data analysis would represent the demand in a better way and the results would become more trustworthy.

How one decides to represent the demand for a product will greatly affect the program's determination of the magnitude and evolution of demand risk at different lead times. For instance, if demand is assumed to be stationary with a normal demand distribution, a mean reverting Ornstein-Uhlenbeck process can be used to represent the demand. However, if the demand is believed to be non-stationary with a log normal demand distribution, the GBM process will be appropriate. The cost curve of the two processes can be highly different, depending on the MRR in the MRP and volatility, where the indifference curve for the GBM-case will yield a higher increase in demand risk for longer lead times. Consequently, choosing the best process for demand is crucial for the results. Therefore, time series analysis should be performed in order to find the best model fit and stochastic process. However, the use of time series analysis and ARMA model fitting require some background knowledge. For practitioners, much information can be drawn from visually investigating the time series of demand. By using intuition about stationarity and whether the distribution of demand is skewed in any way, they can help decide on a certain process for demand. The results and assumptions of the data analysis should always be validated by industry experts to bridge the quantitative analysis to the real world, as assumptions made along the way may interrupt the final result.

This thesis has proposed and implemented an additional way of connecting the demand data to the computer program. The original approach assumes a stochastic process and then calibrates the parameters according to the data. This has been developed for a GBM and an MRP in the program. The new approach finds the best discrete ARMA model fit for the data and uses forecasting techniques directly in the program. Thus, the program is now able to capture a larger variety of demand structures, and not only those that fall into either the MRP or the GBM category. The program has been fitted with the possibility to use all ARMA(p,q) models, where p = (0,1) and q = (0,1,2,3). However, additional models can be easily be added to the framework. A drawback with the new approach is the smoothness of the curve. As the ARMA(p,q) model is discrete, the smoothness of the curve is directly related to the frequency of the demand data. If the demand is reported in weeks, the ARMA(p,q) will have weekly increments. Consequently, the program will produce weekly predictions of the demand risk evolution and the curve will experience weekly kinks. This is not the case for the stochastic process approach, as this will produce continuous predictions of the demand risk and a smooth cost curve. The stochastic process approach will provide a more accurate result when the demand is recorded infrequently, e.g. when sales data has to be aggregated on a weekly or a monthly basis. In situations where the curves yield only marginally differences with regards to demand evolution, the continuous versions are preferred.

7.2 Applications and Interpretation of the Case Study Results

The results of the case study are obtained from the accompanying computer program and seek to advise KA in three different sourcing decisions. A lot of aspects become evident when a firm is to decide between different suppliers, and this thesis accounts for the demand uncertainty and supplier specific costs in such a decision. Consequently, the results in the case study are not meant to solely guide KA in a sourcing decision. In this subsection, the applications and interpretation of the results of the case study are presented.

7.2.1 The Threat of Dual Sourcing

As mentioned in Section 6.3.2, KA might lose its exclusivity of the clutch servo, as Scania has implied that dual sourcing might be implemented. If dual sourcing is introduced, the risk of lost sales will occur and the demand uncertainty will increase due to Scania's ability to choose the supplier for every delivery. Thus, a different stochastic process representation of the demand may be appropriate. Consequently, dual sourcing will intensify the competition and the service level will be an important source of competitive advantage. Ouyang and Chang [2002] claim that the service level can be increased by reducing the lead time. In addition, Ben-Daya and Hariga [2003] present lead time reduction as an effective tool to cope with demand fluctuations. Thus, if dual sourcing is to be realized, lead time reduction might become more favorable for KA than it currently is.

As discussed in the results for each component in the case study, the majority of demand risk occurs the last week prior to delivery, and little risk is added at longer lead time. However, the introduction of dual sourcing might alter the preferred lead time, and ultimately affect the choice of supplier. Though the product and supplier specific input parameters will not change, the demand specific parameters may change, consequently changing the cost curve. Additionally, the importance of delivery precision will increase. Hence, lead time reduction might become more favorable in order to secure a high service level and mitigate the alteration in the demand uncertainty. For instance, in the case of dual sourcing, the favorable supplier of the piston in Section 6.4 might change. In line with the arguments of the previous paragraph, it is fair to assume that sourcing from the French supplier will reduce KA's risk of lost sales and ensure a high delivery precision. Therefore, KA might be willing to bear a higher cost than suggested by the cost curve in Figure 29. Consequently, the introduction of dual sourcing can make the cases of lead time reductions more interesting.

7.2.2 Other Sources of Risk

The cost curve in this thesis considers exposure to demand risk, as well as supplier specific costs. However, KA is also exposed to risk that originates from the supply side of its operations. First of all, KA is exposed to a lot of risk in the process of changing a supplier. In the early stage of a cooperation, uncertainty arises from the specific terms of the agreement - for instance, a functional relationship must be established, product specifications must be decided, delivery terms must be agreed upon and the duration of the cooperation must be clarified. KA must evaluate the potential suppliers based on all these risk aspects. However, the reliability of a supplier is difficult to fully fathom, hence a supplier selection will always entail risk exposure. The cost curves of Section 6, however, do not account for the risk that arises from the process of changing a supplier, hence they do not give a complete overview of the sourcing decision.

Supply risk is often correlated with lead time - if KA decides to source components from suppliers located in distant countries, it is more exposed to supply risk. The increase in supply risk mainly comes from a longer period of risk exposure. According to Zsidisin [2003], supply risk generally arises from individual supplier failures. In his case study, the majority of the investigated firms list delivery, quality, price and relationships as issues originated from individual supplier failures. For the piston from Section 6.4, the following assessment can be made on the potential elements of supply risk.

Firstly, transportation of components from South Korea is subject to more risk than the corresponding transportation from France - the shipment is more likely to experience delays due to poor weather and equipment malfunctions on its long way from South Korea. A lot of these risks can be mitigated, for instance, by using quality shipments rather than low cost offers. However, some risks are more or less unavoidable - such as earthquakes and terrorist attacks. Secondly, the incentive for choosing South Korea is mainly low cost, however low cost can be related to low quality. KA faces the risk of procuring components that do not fulfill the internal quality requirements at Hvittingfoss when choosing a supplier based solely on cost. Lastly, Hofstede [1983] presents a framework for identifying differences in people's work-related values among multiple countries. One of the dimensions in his model is power distance. South Korea has a large power distance, meaning that employees are reluctant to speak their mind to coworkers higher up in the firm. For KA, large power distance at the potential supplier can result in improper products due to poor communication at the supplier. A way of mitigating such risk can be to source from, for instance, Norway. Norway has a rather small power distance, and employees are generally given responsibility and the ability to make own decisions [Hofstede, 1983]. Consequently, employees get a feeling of mastery that enhances the wish to do a good job, which ultimately will improve the quality of the products.

The generated cost curve might incorrectly favor suppliers with long lead time, because the computer program does not account for supply risk. If supply risk were to be included in the analysis, the choice of supplier of the piston in Figure 29 might not be as obvious as it now seems - the South Korean supplier might be related to more supply risk than the French alternative, consequently making the French supplier a more attractive supplier than currently shown in the figure.

7.2.3 Applications of the Program and the Results

In this section, the effect of implementing supplier specific costs in the program is discussed. Supplier specific costs refer to storage cost, capital cost and transportation cost. Thereafter, an assessment of the applications of the program follows, where the influence of circumstantial conditions is considered.

As mentioned in Section 4.2.2, the computer program developed in Moltu et al. [2013] is based on the work of De Treville et al. [2013a]. The program is further developed in this thesis, and the implemented changes are addressed in Section 4.2.3. An important addition to the program is the incorporation of storage cost, capital cost, transportation cost and other variable costs. These supplier specific costs have been added at the request from KA. The consequences of the addition can be twofold: On one hand, the addition makes the program more qualified to make a sourcing decision, as it presents a more holistic assessment of the situation. Hence, the incorporation of the supplier specific costs increases the application area of the program, by allowing it to better capture the dynamics of a sourcing decision. On the other hand, the program is already based on assumptions and simplifications of the real world. By including more variables in the program, the uncertainty of the results might increase. Thus, the supplier specific costs might dilute the results of the program. The supplier specific costs' effect on the results of the program is difficult to evaluate, as it depends on the specific situation. However, the addition is completely optional and the user can choose to insert zeros for all the supplier specific costs, and still run the program. Therefore, the addition is believed to be a positive contribution to the computer program. Also, it is worth mentioning that if a component has variable costs, these have to be implemented in the Newsvendor model to yield a correct result. Failing to do so will make the costs of under and overproduction wrong - giving a non-optimal critical fractile. Since the Newsvendor model and its critical fractile is so crucial for the calculation of the mismatch cost function it is believed to be better to include the costs than omit them. Therefore, this thesis advises to always include supplier specific costs when possible.

The computer program seeks to be as general as possible, but some aspects are rather dependent on the specific situation. Firstly, the program requires a salvage value as input. Encounters with practitioners have revealed that this term is hard to grasp, and that the salvage value depends on the specifics of the product and the sales situation. For the case of KA, the salvage value was estimated by making various assumptions, hence the obtained value is uncertain (see Section 6.2.3 for the calculations). The salvage value highly affects the results of the program, where a reduction in salvage value causes a higher cost of overproduction. The less applicable the concept of salvage value is, the less accurate the results will be. Secondly, if the user decides to insert the supplier specific costs in the program, the effect highly depends on the accuracy of the parameters. For instance, KA's per component storage cost for the different sourcing alternatives were hard to retrieve, and simplifications were made (see calculations in Section 6.2.4). As for the salvage value, if these estimates are questionable, the results obtained from the program will be less applicable. In general, the program will yield reasonable results when the required input parameters are simple to obtain, however its applicability is reduced when the input parameters are adjusted beyond recognition in order to fit the program.

The program evaluates each component separately. Consequently, the result from the program presents an isolated solution for the investigated component, and does not take the specifications of other components and factors into account. For instance, if KA were to source 45 of the 46 components of the clutch servo from Norway, sourcing the aluminum casting from South Korea to obtain a low cost might be sub-optimal, even if the program suggests it. All the components depend on the aluminum casting (see Section 6.5.1), and by choosing a long lead time the clutch servo will be exposed to a lot of demand risk even though 98% (45/46) of the components are sourced domestically. Thus, the sourcing decision for a component should be treated in context with other factors that might affect KA's ability to finalize the clutch servo, and potential synergy effects and pitfalls should be identified in advance. In addition to lead time considerations, KA's profit and delivery performance of the clutch servo also depend on the balance between transportation cost and order frequency for each component, and the interaction between every component that go into the final clutch servo. Consequently, the program guides KA in autonomous sourcing decisions, but KA's overall performance relies on the combination of the features of each component.

8 Conclusion

The purpose of the performed case study was to evaluate the sourcing decisions associated with three of the components in KA's clutch servo. The computer program developed in the thesis uses the cost curve of Section 4.2 to present the results. The cost curve is based on the expected demand-supply mismatch cost function derived from the the Newsvendor model of Section 4. The cost curve represents an indifference curve, made up by the accepted procurement cost for each lead time scenario. In contrast to earlier research, the program presented in this thesis also incorporates the ability of increasing lead time.

Sales data for the last 5 years have been analyzed in order to choose the best model for KA's demand. The analysis revealed that their demand is rather stationary, with large short term fluctuations between orders. The best model fit was concluded to be the discrete ARMA(1,3) model due to its low AIC compared to other models and absence of over-parameterization. However, when implementing the model to the computer program a drawback with the approach was revealed. Since the ARMA(p,q) model is discrete, the smoothness of the curve is directly correlated to the frequency of the demand data. As KA's demand data is best reported weekly, the ARMA(1,3) model consequently yielded weekly increments giving a piecewise linear curve. Due to the similarities between the ARMA(1,3) model and the mean reverting Ornstein Uhlenbeck process, the latter was therefore chosen because of its continuous nature. The process's mean reversion rate was found to be high along with a relatively high demand volatility. Thus, KA's demand risk increases with high pace short term and stabilizes long term.

As a result of the demand data analysis, one of the main findings from the case study was that KA should either strive to have a really short lead time or a long lead time for the clutch servo. The conclusion arises from the fact that the majority of KA's demand risk develops close to delivery, while it stabilizes for long time horizons - yielding that little risk is added for longer lead times. Therefore, KA should either acquire a short lead time to mitigate the uncertainty, or choose a long lead time to benefit from the low obtained procurement cost. This can, for instance, be shown in the aluminum casting case where South Korea turned out favorable even though it represented a 150% increase in lead time. The results of the case study coincide with the characteristics of the commercial automotive industry, where intense competition make suppliers in all tiers tend to choose either low cost or high responsiveness, i.e. long lead time or short lead time. In addition, the obtained results are in line with the intuition of the managers at KA. This further strengthens the validity of the performed case study.

While the relatively small values of changing lead time was an interesting finding itself, the reasoning behind the results is important to note. Assessing the different input variables of the program revealed that the shape of the cost curve is highly dependent on the interaction between the mean reversion rate, salvage value and volatility. First of all, the high salvage value obtained yields that little cost is assigned to overproduction. This entails that the mismatch cost is reduced and less value is obtained when reducing risk. This explains the relatively small increase in the curve obtained when lead time approaches zero. Secondly, the high mean reversion rate makes the risk stabilize as lead time increases. This yields that less risk is added for longer lead times and the cost curve consequently flattens out for longer lead times. This does however not mean that there is no risk associated with a longer lead time, but since the added risk is so small, the low mismatch cost makes the effects marginal. Lastly, the relatively high volatility was believed to yield larger values of reducing risk. However, since the MRR is so high, the risk quickly reverts and stabilizes yielding only short term effects. As this shows, the relatively small values of changing lead time is a product of several factors. To investigate this further, a sensitivity analysis with respect to these variables was performed in Section 6.7. The analysis showed that even though the cost curves are highly dependent these parameters, the conclusions are still robust. Hence, KA is advised to source the piston and aluminum casting from South Korea, and the piston rod from France. However, as discussed in Section 7, there are aspects and risks that might affect the situation, such as dual sourcing and supply risk, that are not considered in the case study. The inclusion of these may ultimately alter the outcome of the sourcing decision.

Further, this thesis proposes an addition to the literature by adding more focus to supplier specific costs - transportation cost, capital cost, storage cost and other variable costs. By adding such costs, the level of the cost curve is increased and the curvature of the graph is shifted according to the way the cost of over- and underproduction is affected. It is therefore highly advised to account for these costs when performing a sourcing decision as they provide a more holistic description of the situation. Following the first finding, it is also interesting to note that if KA is to evaluate two sourcing alternatives with long lead times, the procurement cost and supplier specific costs is most likely the only variables that will influence the decision. This is because the cost curve flattens out for long lead times. Hence, failing to add supplier specific costs may result in the wrong conclusion.

Lastly, the program and the underlying concepts have been presented to practitioners within other businesses than the automotive industry. The responses have been entirely positive, and both PwC and Jernia has expressed interest in testing the program for a retail case.

8.1 Further Research

As mentioned in the commercialization paragraph of Section 4.2.3, the managers at KA really appreciate the output of the program developed in this thesis. However, they find some of the required input parameters difficult to retrieve, and they worry that the program might be tedious to use. Encounters with practitioners within retail revealed similar concerns. In general, the empirical analysis needed to run the program has been pointed out as the biggest obstacle for the program to become applicable for practitioners. Therefore, the KA managers suggested that the empirical analysis should be integrated in the program. The user would then simply be asked to paste sales/demand data into a predefined template, then enter the product parameters, and optional parameters if desired, from Figure 22 and finally hit the "Run Program"-button. The implementation of this functionality would obviously improve the convenience of the program, and highly increase its generality. However, the analysis required to decide the appropriate stochastic process for the demand is comprehensive. Due to constrained time, this is not within the scope of this thesis. However, including this functionality would add a lot of value to the program, ultimately making it a complete tool for the assessment of demand risk uncertainty in sourcing decisions.

The program has been fitted with the possibility to use all ARMA(p,q) models, where p = (0,1) and q = (0,1,2,3). Further improvements of the program can be made by including additional models. These models can be connected directly to the empirical analysis, so that the program automatically chooses a model based on the demand data, and runs the program accordingly.

A The Parameters Used in the Case Study

Figure A.1 presents all the parameters that are used in the case study.

Parameters	Description	Piston	Aluminum Casting	Piston Rod
Generic Product Parameters				
Price	Per unit sales price	kr 27,50	kr 192,50	kr 55,00
Salvage Value	Per unit salvage value	kr 9,80	kr 68,61	kr 19,60
Demand Process Parameters				
Volatility	For 7 days	41,37 %	41,37 %	41,37 %
MRR	For 7 days	105,00 %	105,00 %	105,00 %
Yearly Risk-free Rate	For 365 days	5,00 %	5,00 %	5,00 %
Current Sourcing Location				
Location	Country	South Korea	Serbia	France
Current Lead Time	Days	47 days	18 days	9 days
Procurement Cost	Per unit	kr 10,00	kr 70,00	kr 20,00
Storage Cost	Per unit	kr 0,28	kr 1,63	kr 0,47
Capital Cost	Per unit	kr 0,14	kr 0,39	kr 0,06
Transportation Cost	Per unit	kr 0,80	kr 4,20	kr 1,20
Other Costs	Per unit	kr -	kr -	kr -
Order Frequency	Weeks between deliveries	6	1	1
Potential Sourcing Location				
Location	Country	France	South Korea	Norway
Current Lead Time	Days	7 days	45 days	6 days
Procurement Cost	Per unit	kr 13,00	kr 66,50	kr 24,00
Storage Cost	Per unit	kr 0,08	kr 1,63	kr 0,33
Capital Cost	Per unit	kr 0,02	kr 0,97	kr 0,04
Transportation Cost	Per unit	kr 0,60	kr 6,30	kr 0,80
Other Costs	Per unit	kr -	kr -	kr -
Order Frequency	Weeks between deliveries	1	1	0,5

Figure A.1: The parameters used in the case study.

B R-Code for Empirical Analysis

```
-- ## Loading the packages: fBasics, tseries, VarianceGamma,
stats4, MASS, SMFI5, stats, nortest, forecast, TSA ## -
library(fBasics);
library(tseries);
library(VarianceGamma);
library(stats4);
library(MASS);
library(SMFI5);
library(stats);
library(nortest);
library(forecast);
library(TSA);

-- ## Model Identification Based on the Chosen Data Representation ## --
## Plotting the time series of the data ##
ts.plot(data, main = "Weekly Sales Data Without Vacations Time Series",
xlab = "Weeks from Summer 2009", ylab = "Sales Quantity")

## Checking for stationarity using ADF and PP tests ##
# Augmented Dickey-Fuller Test #
adf.test(data)

# Phillips-Perron Unit Root Test #
pp.test(data)

## Checking the auto correlations and partial auto correlations in
the time series ##
```

```
acf(data, main = "Autocorrelations of Weekly Sales Data without Vacations")
pacf(data, main = "Partial Autocorrelations of Weekly Sales Data
without Vacations")

## Fitting different ARMA(p,q) models to the data set ##
fit10 = arima(data, c(1,0,0))
fit01 = arima(data, c(0,0,1))
fit11 = arima(data, c(1,0,1))
fit21 = arima(data, c(2,0,1))
fit31 = arima(data, c(3,0,1))
fit12 = arima(data, c(1,0,2))
fit22 = arima(data, c(2,0,2))
fit32 = arima(data, c(3,0,2))
fit13 = arima(data, c(1,0,3))
fit23 = arima(data, c(2,0,3))
fit33 = arima(data, c(3,0,3))

## Simulating a process based on the fitted parameters for a ARMA(1,3)
model and checking the model specifications (ACF, PACF) ##
interc = 721.9974
stddev = sqrt(31446)

arma.sim = interc + arima.sim(model = list(ar = c(0.9755),
ma = c(-0.8709,0.2676,-0.2084)), n = 10000)*stddev

ts.plot(arma.sim, main = "Simulation of ARMA(1,3) model",
ylab = "Simulated Weekly Sales Quantity", xlab = "Weeks", ylim = c(0,1500))
```

```
acf(arma.sim, main = "ACF of Simulated Weekly Sales Qunatity")
pacf(arma.sim, main = "PACF of Simulated Weekly Sales Qunatity")

## Checking the assumptions of no correlation and normality in the
residuals for ARMA(1,3) ##
res13 = resid(fit13)

# Finding the moments for the residuals #
mean(res13)
sd(res13)
skewness(res13)
kurtosis(res13)

# Plotting residuals diagonstics #
plot(res13, main = "Residuals over Time", ylab = "Residuals")
hist(res13, main = "Histogram of Residuals for ARMA(1,3)", xlab = "Residuals")
qqnorm(res13, main = "QQ-Plot of Residuals for ARMA(1,3)")
qqline(res13)
acf(res13, main = "Autocorrelation of Residuals for ARMA(1,3)")

# White noise test for Residuals ARMA(1,3) #
Box.test(res13, type = "Ljung")

-- ## Connecting the Model and the Computer Program ## --
## Checking the white noise assumption of the fitted AR(1) model
and residual diagnostics##
res10 = resid(fit10)
```

```
plot(res10, main = "Residuals over Time", ylab = "Residuals")
hist(res10, main = "Histogram of Residuals for AR(1)", xlab = "Residuals")
qqnorm(res10, main = "QQ-Plot of Residuals for AR(1)")
qqline(res10)
acf(res, main = "Autocorrelation of Residuals for AR(1)")

# White noise test for Residuals AR(1) #
Box.test(res, type = "Ljung")

## Estimating MRP (Ornstein Uhlenbeck) parameters ##
# MLE #
N = length(data);
x = as.matrix(cbind(int=1, as.vector(data[1:N-1])));
y = as.vector(data[2:N]);
xy = t(x)%*%y;
xxi = solve(t(x)%*%x);
ols = xxi%*%xy;
resid = y-x%*%ols;

c = ols[1];
b = ols[2];
delta = sd(resid);

dt = 1

alpha = -log(b)/dt;
theta = c/(1-b);
sigma = delta/sqrt((b^2-1)*dt/(2*log(b)));
```

```
halflife = log(2)/alpha

# Least Squares #
S = data;
end = length(S)-1;
delta = 1

Sx  = sum( S[1:end-1] );
Sy  = sum( S[2:end] );
Sxx = sum( S[1:end-1]^2 );
Sxy = sum( S[1:end-1]*S[2:end] );
Syy = sum( S[2:end]^2 );

a  = ( n*Sxy - Sx*Sy ) / ( n*Sxx -Sx^2 );
b  = ( Sy - a*Sx ) / n;
sd = sqrt( (n*Syy - Sy^2 - a*(n*Sxy - Sx*Sy) )/n/(n-2) );

lambda = -log(a)/delta;
mu     = b/(1-a);
sigma  =  sd * sqrt( -2*log(a)/delta/(1-a^2) );

## Prediction of ARMA(1,3) mean and standard deviation ##
pred13 = predict(fit13, n.ahead = 100)

ts.plot(pred13$pred)
ts.plot(pred13$se)
```

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