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Causes and Effects of Poor Demand Forecast Accuracy

A Case Study in the Swedish Automotive Industry

Master's Thesis in the Master's Programmes
Management and Economics of Innovation & Supply Chain Management

TEODOR MARTINSSON
EDVIN SJÖQVIST

Department of Technology Management and Economics
Division of Supply and Operations Management
CHALMERS UNIVERSITY OF TECHNOLOGY
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TEODOR MARTINSSON
EDVIN SJÖQVIST

Tutor, Chalmers: Patrik Jonsson
Tutor, company: Johan Bystedt

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Department of Technology Management and Economics
Division of Supply and Operations Management
Chalmers University of Technology

SE-412 96 Gothenburg, Sweden
Telephone: + 46 (0)31-772 1000

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Abstract

This study is a part of a FFI (Fordonsstrategisk Forskning och Innovation) project "Future of sharing schedule information in automotive industry supply chains using advanced data analytics". The study is aimed at describing the current situation in terms of accuracy of demand forecasts sent from OEM companies to their suppliers within the Swedish automotive industry, identifying root causes for inaccuracies in demand forecasts and their effect on the suppliers. This study also aims to provide some guidance to future actions and initiatives for improvement of demand forecast accuracy.

An extensive database of delivery schedules was used to identify current patterns in forecasting accuracy, utilising FAI (Forecast Accuracy Index) to analyse forecasting performance. The study employed a case methodology, studying three customers with a single supplier as the focal point as a basis to find root causes and effects of poor forecasting accuracy.

The study found that current demand forecast accuracy was poor. Causes for poor performance were found both in sales forecasts, that were used to generate the MPS and subsequently component demand, and in the MRP systems of the customers. Inaccuracies in demand forecasts were found to mainly be dealt with through buffers of materials and finished components at the supplier. Improved forecasting accuracy is expected to allow suppliers to lower their inventory levels, resulting in cost savings across the entire supply chain. This study proposes evaluation of and changes to current MRP practices, closer integration of complementary data in the sales forecasting process and employment of machine learning algorithms in forecasting as promising areas for improving the accuracy of demand forecasts.

Keywords: Supply planning, automotive industry, demand forecasts, forecasting accuracy, delivery schedule, FAI, MRP

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Furthermore, we would like to thank the supplier studied for giving us access to the database of delivery schedules used as the primary quantitative data for this thesis. We also recognise the contribution of the persons at the supplier and their customers who allowed us insight into their forecasting and planning processes and extend our gratitude to them, this thesis would not have been possible without them.

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Teodor Martinsson & Edvin Sjöqvist

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1. Introduction

1.1 Introduction

Information flow between manufacturers and their suppliers plays an important role in reducing uncertainties in the supply chain, which in turn can lead to operational and financial benefits (e.g. Gavirneni et al., 1999; Ryu et al., 2009; and Singh, 1996). It is therefore in the interest of all parties within the supply chain to ensure smooth and accurate flow of relevant information. One way of making this information transfer is *electronic data interchange*, EDI, which refers to the transmission of structured business data (UNECE, 2019). The message format used to transmit demand forecasts is called DELFOR. In 2012 Odette (Organisation for Data Exchange by Tele-Transmission in Europe) published a recommendation to track and improve quality of information regarding future demand. Two new metrics, FAI (Forecast Accuracy Index), and a WTS (Weighted Tracking Signal) were developed to help suppliers in assessing the quality of forecasts. (See appendix 1 for definitions of FAI and WTS). FAI measures the accuracy of the forecasts, and WTS tracks systematic bias in misestimates. Suppliers within the Swedish automotive industry have indicated that FAI scores are relatively low, with significant inaccuracies in demand forecasts resulting in uncertainties that make accurate planning of capacity and production more difficult. Lack of confidence in given demand forecasts is highlighted as one of the reasons suppliers build slack into their operations through temporal capacity or material buffers (Christopher & Lee, 2004). Building on this reasoning: If quality of demand forecasts improve confidence should follow, ultimately resulting in perceived need of costly slack and buffers being lower. While forecasting does nothing to reduce actual variations in end customer demand, accurate forecasting allows for companies to plan ahead, dealing with variations in a more reliable and cost-effective way.

This study will explore forecasting accuracy across different time horizons, focusing on finding root causes of poor forecasting accuracy. These variations can have a number of different reasons, for example MRP ‘nervousness’ and bullwhip effects among others. Blackburn et al. (1985) argue that due to shifting demand from downstream processes, material requirements in the MRP system needs to be rescheduled. This creates nervousness in the system which can trigger upcoming orders to be sent upstreams. Variations given with short notice can prove problematic for suppliers as they cannot be fully compensated for and mitigated in planning. These variations require other measures, such as safety stocks to ensure high delivery precision to the customer. As significant safety stocks will prove expensive in the long run, it is of interest to investigate measures that the supplier can take to mitigate short term variations. Mackelprang & Malhotra (2015) found that suppliers that are able to utilise both production coordination with customers along with inventory and capacity buffers to mitigate the bullwhip effect experience a positive effect on their return on assets. This implies not only that suppliers to a significant extent are able to mitigate the bullwhip effect, but also that they could potentially gain a competitive edge by doing so.

To better be able to manage these variations, suppliers view it as important to understand where and why inaccuracies in communicated demand forecasts appear, and how specifically they impact the organisation. Finding ways to improve FAI scores on the customer end and developing a more sophisticated way of dealing with inaccuraccies on the supplier end would provide to add value to the supply chain by reducing costs from slack and buffers.

1.2 Aim

The aim of this study is to perform an in-depth case analysis of FAI data at a Tier 1 supplier within the Swedish automotive industry. Based on findings a cause and effect analysis will be performed to assess how the supplier is affected by the quality of forecasts and provide suggestions on ways to mitigate or reduce variation and inaccuracies in delivery schedules from the OEMs.

1.3 Limitations

To facilitate an in-depth investigation while keeping the workload manageable, the study is focused on the communication and demand forecast data between the supplier and three of their most important OEM customers (by revenue share). Furthermore, this study will not discuss aspects related to the design or relationships of the supply chain as a whole, but rather examine events occurring within the relationship of two business, or inside the organisational boundaries of these two entities operating within a larger supply chain.

1.4 Specification of issue under investigation

Considering the context and limitations of the study, three main research questions were formulated:

1. What is the current level of forecasting accuracy in DELFOR messages? What patterns can be seen in FAI and WTS scores?

2. Why do inaccuracies in demand forecasts in DELFOR messages appear, and what actions could organisations take to improve their forecasting accuracy?

3. What are the effect on suppliers stemming from inaccurate forecasts in DELFOR messages?

The study will be divided into two phases, the first phase will be quantitatively focused and seeks to answer the first research question. The second phase will seek to explain and provide suggestions based on the results of the first phase, answering the second and third research questions.

2. Methodology

The methodology will cover our chosen approach to the subject matter and how each of the stages of the study was approached.

2.1 Research approach

This study employed a mixed approach, utilising both quantitative and qualitative methods during different phases of the project. Quantitative analysis was used to analyse and find patterns and inconsistencies in the Forecast Accuracy Index (FAI) and Weighted Tracking Signal (WTS) data. Based on the results of the quantitative analysis cause and effect correlations were explored using a qualitative approach. The purpose of the second phase study was to generate suggestions for improvement in regards to the issues identified. This study seeks to explore a specific instance of the issue and does not seek to establish general findings that are universally representative. According to the reasoning of Davies & Hughes (2014), a qualitative approach is then suitable. It was decided that as the study sought to find in-depth insights, and that access to people within the organisations were given to the researchers, semi-structured interviews would be the main source of qualitative data.

Apart from initial informal interviews and discussions aimed at building a basic understanding of the organisations involved, interviews were conducted in two main rounds. One primary round based on findings in the quantitative analysis, and a secondary round based on findings of the combined analysis of quantitative data and the first round of interviews. The second round of interviews was used to further explore key findings from the first round of interviews and to address any discrepancies between the quantitative and qualitative data.

2.2 Data collection

The quantitative data used for this study was pre-existing and organised in a database, and therefore no quantitative data collection was performed as a part of this study. The data included delivery schedules sent to a supplier by all of their customers between January 2018 and January 2019. In this study, delivery schedules that refers to the demand in the calendar year 2018 is analysed. No further quantitative data were not collected and analysed. Due to this, this section is mainly focused on the qualitative data collection.

Qualitative data collection was done through semi-structured interviews. The study focused on a local supplier (henceforth “Supplier” or “the Supplier”) and three different supply chain segments they are active in. Interviews were conducted at the Supplier and three of their direct customers. Of the direct customers, one is an OEM, one is a company doing pre-assembly for an OEM and one is an aftermarket organisation. In addition to these three, employees at the OEM that one of the direct customers does pre-assembly for were interviewed. A more detailed description of each supply chain segment is provided under section 4. The different types of customer organisations and different role of the Supplier in each of the supply chain segment was expected to give a good overview of different aspects that impact the accuracy of demand forecasts. At all customer organisations people involved in order planning and monitoring were interviewed. Additionally, at the manufacturing and assembling customers, production planners were also interviewed. At the Supplier, production planners for the different component groups sold in the three supply chain segments were interviewed, along with procurement personnel. At the customer organisations interviews were focused around research question 2, gathering data on how forecasts were created and used within their respective organisations to build an understanding of the forecasting process and potential sources of inaccuracies. Interviews at the Supplier focused on gathering data on how they used the demand forecasts sent by customers and if they had experienced any negative effects connected to poor forecasting accuracy from their customers. Figure 1 shows a summary of the interviews conducted, with the company, role of the interviewee and the main topic of the interview.

Company	**Role**	**Main interview topic(s)**
Customer D	Material planner	Order process, information exchange
	Volume & program manager	Sales forecasts, Component breakdown
Customer E	Purchase planner	Freeze times
	Senior Manager Global Sourcing & Optimization	Forecasts, MRP
OEM 1	Material planner	Order process, information exchange
	Volume & program manager	Sales forecasts, Component breakdown
Customer H	Manager Customer Service and Assembly Planning	Usage of forecast data, MRP
	Manager Supply Planning/ Inbound Logistics	Effects of demand variations & forecast quality
The Supplier	Logistics Coordinator	Effects of demand variations & forecast quality
	Supply Chain Coordinator	Effects of demand variations, production planning
	Purchasing	Lead times, purchasing
	Production planner	Effects of demand variations, production planning

Figure 1. Summary of interviews conducted for the study.

In those cases questions arose after the interview session interviewees were contacted to provide complementary information. Interviewees were all from the examined organisations and selection was done using *Snowball sampling*. Snowball sampling includes asking interviewees for others who may possess valuable information (Easterby-Smith et al., 2015), and was deemed a good fit for the study as it sought to identify the effects of inaccurate demand forecasts and potential mitigating initiatives across the organisation in production, planning and purchasing. The different functions were expected to have different perspectives and views on the forecasting process, its value and its issues. Therefore, for the interviewees in customer organisations that were interviewed, an attempt was made to interview employees with similar areas of responsibility and expertise in all organisations to provide additional opportunity for comparison. The key methods and theories applied during interviews to ensure accuracy and validity in the collected data will be outlined below.

As a first measure to ensure accurate transcription of interviewee answers, interviewees were asked to agree to an audio recording of the interview being made. Since the study did not seek to confirm or deny a pre-formulated hypothesis, but rather served as an exploratory case study, it was decided to follow an interviewing strategy proposed by Steinar Kvale. Kvale (1996) suggests that the interviewer should be mostly reactive in how they ask their questions, in order to allow room for the expertise and knowledge of the interviewee. Follow-up questions should be asked based on answers to open questions to further build on interesting aspects of the answer. This allows for greater flexibility during the interview, building primarily on the knowledge and experience of the interviewee rather than the ideas and hypotheses of the interviewer. It does however place importance on the attentiveness of the interviewer to ensure that well formulated and relevant follow-up questions are asked. In this study, both researchers were present for all interviews in an attempt to encapsulate more perspectives with follow-up questions.

While having more than one interviewer is of marginal value in a structured interview, Bechhofer, Elliott & McCrone (1984) argue that it could be useful in a more unstructured interview format, providing several benefits. Utilising multiple interviewers allows for one of the interviewers to focus more on note-taking and observation of the direction of the interview and topics yet to be cover. Additionally, the more passive interviewer could also step in should the main interviewer get stuck and become unable to continue a line of questioning or switch to a new one. It was therefore decided that for this study, both researchers would be present to improve fluidity of the discussion, provide additional input, and allow for more detailed notes and recollection of the interview. The authors also highlight that if done correctly, the interview can be made to feel more like a discussion, helping the interviewee to relax.

The study sought to employ the technique of *laddering up* to connect general perceptions to specific occurrences and underlying reasoning. Laddering up is described as a technique where the interviewer, often by asking ‘why’ questions, tries to build a deeper understanding of the value base of the interviewee (Easterby-Smith et al., 2015). This was deemed appropriate to the study, as suggestions for changes provided would need to be anchored to the needs and wants of different parts of the organisation to provide a positive effect. If there is no understanding of the underlying values and perception of the employees, any change would risk being misguided or miscommunicated resulting in the value would not being understood or realised.

2.3 Analysis

The approach of the data analysis can be described as an iterative process, where collection and analysis of data takes place simultaneously. By analysing the collected data early in the research process, the results imply the direction of the next steps of the data collection process. (Bryman & Bell, 2011)

As mentioned in earlier section, the process of the study was divided into two phases. The first phase aimed to provide answer to the first research question and the process is of quantitative nature. The second phase aimed to provide answer to the second and third research question and the process is of qualitative nature.

In the first phase, the database of information regarding delivery schedules were analysed by using performance measures and figures created in Qlik Sense. The database contained all delivery schedules the Supplier received from their customers. In order to analyse the data, certain choices were made based on different criterias. The first criteria is related to the components produced at the Supplier. Depending on which component type produced by the Supplier, components were aggregated in different groups. When the analysis of the component groups were completed, customers of the Supplier that purchase roughly more than 10 % of the total volume for each component group were identified. Delivery schedules of these customers were then analysed in order to find irregular patterns. When irregular patterns were identified, these were saved for further analysis in the following phase. Depending on the amount and type of identified patterns, it guided the further work. During the analysis, irregular patterns were identified in three different supply chains, which implied for further investigation. Each supply chain starts with the Supplier providing their customers with components. In two of the examined chains, the customer is in direct contact with the Supplier. In the third chain, one party is located between the Supplier and customer, performing pre-assembly for the customer.

The analysis in the second phase was based on the results from the analysis performed in the first phase. To be able to find the causes and effects of the irregular patterns identified, the data was further analysed by conducting interviews with the parties involved in the examined supply chains. The data collected from the interviews were sorted and organised in a suitable way. Different codes and labels of relevant subtopics were used to facilitate the analysis depending of its relevance to the research. According to Easterby-Smith et al., (2015) it is of great importance to prepare the data in a way that support the future analysis process and achieve a rewarding analysis. Relevant parts from the collected data should be filed systematically and categorised in a consistent way. Bryman & Bell (2011) state that it is common that qualitative research generate high amounts of data, in forms of documents, transcripts and field notes and argue that coding of data facilitates understanding of the data and support the possibilities to manage high amounts of gathered data.

2.4 Validity

According to Bryman & Bell (2011) reliability can be described as a question whether the same results of a study could have been achieved if the study was carried out with the same approach and methodology. Reliability can be divided into two subsections; external and internal reliability. External reliability refers to the possibility that a study can be replicated, and whether the findings can be applied across a general context. The approach used in this study can lead to difficulties to recreate the same social context in a future state, due to fact that the study is limited to only a few specific supply chains. Bryman & Bell (2011) argue that this is one of the main issues in qualitative research related to reliability, since it is almost impossible to achieve the exact same social context as used in previous studies. To achieve higher reliability, the internal reliability, which is concerned with whether the observations made by the researchers match the theoretical ideas developed (Bryman & Bell, 2011) , was considered in the study. Bryman & Bell (2011) state that the members of the research team can interpret observations in different ways, which can affect the results of the study in a negative way. To mitigate these risks, the same persons that conducted the interviews analysed it as well.

Bryman & Bell (2011) defines validity as the ability to ensure that the measured concept actually reflect the concept that is supposed to be measured. It can be argued that the external validity within the study is limited, since only a few relationships of different supply chains is considered. Although, the similarities between supply chains in the same context will enable usage of the findings in the study.

To verify our findings, they were presented and discussed at a workshop for the FFI project, with participants from suppliers and OEMs in the Swedish automotive industry. This helped verify the findings as well as provide additional input for some analysis.

2.5 Limitations

This study only featured forecast data sent to one supplier, which meant that the analysis was unable to make comparisons to the situations of other similar suppliers and provide an idea of whether this case is representative for the Swedish automotive industry as a whole.

For the study, we did not have access to data regarding the accuracy of the sales forecast for any of the customer organisations. Therefore, component demand data was used as a proxy to discuss the impact of sales forecasting methods. This is not necessarily representative, as we showed that some of the processes between the sales forecast generation and the final component demand forecast can introduce significant variations and errors to the forecast. Additionally, the lack of access to sales forecast accuracy data meant that we could not draw any conclusions regarding the exact impact of the flaws in the processes transforming sales forecasts to component demand forecasts in terms of loss of forecasting accuracy.

While the study had access to significant quantitative data for the case studied, the qualitative data collected was somewhat limited. Therefore, the connections and implications found should be seen as examples and indications of what could happen, and not as generalizable results that can be directly applied to a different case.

3. Theoretical framework

Our theoretical framework will cover literature in the areas of planning, forecasting and information sharing, covering both the processes and ICT-technology used to support them.

3.1 Supply chain structure and information sharing

The supply chain can be defined as "...a set of relationships among suppliers, manufacturers, distributors, and retailers that facilitates the transformation of raw materials into final products." (Beamon, 1998). The structure and production philosophy of the supply chain is dependent on the market that it serves, and Christopher (2016) discusses two main philosophies and when they are applicable; *lean production* and *agile*. The author argues that lean production is suitable when demand variation is low and lead-times long, as it utilises long term planning to optimise resource usage and create efficiency. Agile, on the other hand, is suitable when variation is high, but lead-times short allowing quick response to market variations. In cases where there is both variation and long lead-times a hybrid strategy of *postponement* is suggested, utilising a lean production philosophy up to a decoupling point from which production is done with an agile philosophy. One example of such an arrangement is found in the paint industry where a limited number of base colours produced according to lean philosophies can be mixed into a near infinite number of colours at the retailer.

While these different approaches to supply chain strategy are suitable under different market conditions, Mason-Jones et al. (2000) argue that elimination of system-induced uncertainties is crucial to the success of all three. This would in turn mean that continuous and accurate information flow is important in improving the efficiency and stability of the supply chain. Lee & Hwang (2000) discuss different types of information shared between companies in a supply chain. The specific types of information discussed in their article are: *Inventory level*, *sales data*, *order status for tracking/tracing*, *sales forecast* and *production/delivery schedule*. In essence the purpose of sharing these data is to create transparency and creating a common understanding of current operations and how the near future might look. For this study, sales forecasts and production/delivery schedules are the most relevant types of sharing, as they are forward looking and facilitate coordination of activities.

Lee & Hwang (2000) argue that these two types of forecasts can help both customer and supplier in planning their production using Quantity Flexibility contracts, where the customer has flexibility in deciding delivery quantity and the supplier can get a warning of shifts ahead of time through the forecasts. Huang, Hsieh & Farn (2011) call the phenomenon "rolling forecast", where customers share and continually update their demand forecasts. Henceforth the phenomenon will be referred to as Quantity Flexibility contracts, or QF contracts. While seldom discussed in academia, the practice is popular in industries (Huang, Hsieh & Farn, 2011). At an agreed point in time, forecasts in QF contracts become fixed orders. Lau, Xie & Zhao (2008) found that early order commitment (EOC) provide benefits in reducing inventory levels. Benefits from EOC and sharing of future forecasts are however mainly seen on the supplier end, whereas the forecasts and commitments are made by the customer. The value of utilising QF contracts are directly contingent on the accuracy of forecasts provided by the customer, which can prove problematic if customers act more out of self-interest rather than fully collaboratively (Huang, Hsieh & Farn, 2011).

Lee and Hwang (2000) highlight a potential issue with QF contracts, as there is an incentive for the customer to overstate future demand to ensure that they can get the quantity they need. This forces the supplier to carry additional inventory at their own expense as they will act on the forecasts available. Huang, Hsieh & Farn (2011) also identify a tendency for customers to adjust forecasts to protect their own interests, especially when the customer is more powerful than the supplier.

Tsay and Lovejoy (1999) take a supply chain perspective on QF contracts, concluding that QF contracts in essence is about distributing flexibility and the inventory burden. Inflexible contracts result in the customer needing to carry additional inventory, and highly flexible contracts result in the supplier needing additional inventory to guarantee delivery precision. The authors also highlight that QF contracts require significant changes to the procurement process, potentially resulting in organisational resistance in changing current behaviours. They conclude that QF contracts constitute a trade-off between procurement prices and inventory costs, responsibilities often distributed to different groups in the organisation potentially resulting in sub-optimisation of the usage of QF contracts. Tsay (1999) studies the usage of QF contracts in manufacturer-retailer relationships based utilising cost parameters for both the manufacturer and retailer, concluding that QF contracts can be used to increase net system profit. However these gains were only demonstrated when there were shared beliefs, and no information asymmetry between the parties.

As for the practicality of transferring data, Christopher (2016) mentions *EDI*, Electronic Data Interchange, as a way to create visibility and share demand information within the supply chain. Lee and Hwang (2000) use QF contracts as an example of when EDI usage is suitable, as these contracts are dependent on fast transfer of updated information for the supplier to be able to plan their production.

3.2 Electronic Data Interchange

EDI is a form of structured business communication for transmitting information in a standardised format (UNECE, 2019). In many supply chains EDI is crucial in ensuring smooth information sharing (Christopher, 2016). Transmitted information, such as demand information, is used in planning operations. A commonly used format is the UN/EDIFACT standard (UNECE, 2019), providing specifications for the structure and content of EDI messages to ensure correct transmission and interpretation of data. In order for electronic data interchange to be effective, a standard structure for messages is needed (UNECE, 2019). One framework standard for interorganisational data exchange is the UN/EDIFACT (United Nations/ Electronic Data Interchange for Administration, Commerce and Transport) (UNECE, 2019). This study is mainly concerned with the usage of data transmitted by one of the message standards in the UN/EDIFACT, namely the DELFOR (Delivery Forecast) message. DELFOR messages are used by customers to give a forecast of their future demand to their suppliers, so that they can plan accordingly. While EDI can be a powerful tool Lee and Hwang (2000) state that the existence of multiple standards can create flexibility issues as managing the usage of multiple standards can be difficult, should the company operate in multiple industries. There are challenges associated with the usage of EDI, but there are also potential benefits.

Hart and Saunders (1997) identified mutual trust between the actors as an important factor in determining how extensive and successful EDI usage between them would be. They identified that in relationships where persuasive and collaborative approaches, rather than coercive approaches were used. Dearing (1990) argues that business can gain three types of benefits from the usage of EDI; direct, indirect and strategic. Direct benefits come from automating and making information transfer electronic and enabling better storage of this information. Indirect benefits come from enabling organisations to change the way that they operate, such as switching to JIT production. Strategic benefits come from the possibility to create closer ties with customers and suppliers, and long term collaboration and integration to create cost benefits on both ends of the relationship.

To improve on EDI usage, metrics for meta-analysis of EDI messages have been proposed, one such metric is the FAI metric presented by Odette in 2012 (Odette, 2012). In a way, this metric can be seen as a way to facilitate transparency and communication between business partners to build the strategic benefits discussed by Dearing (1990). By using FAI and WTS data as a basis for discussion, companies could improve the quality of their communication of business data by jointly working to improve forecasts.

3.3 Measurements for forecasting errors

FAI is aimed at giving organisations a better understanding of the accuracy of forecasts, by giving possibilities to measure and compare the quality of the forecasted quantity to the actual required quantity (Odette, 2012). FAI functions as a 0 to 100% scale measuring the accuracy of delivery forecasts, with 100% indicating perfect forecast accuracy. The mathematical definition of FAI can be found in appendix 1, when calculating aggregate FAI for multiple components/customers, individual FAI scores are weighted by share of sales. The purpose of the metric is to be used in stabilising efforts to mitigate demand volatility and counteracting the 'bullwhip' effect in the supply chain. FAI is also aimed at being a tool for feedback in S&OP and for improved transparency, communication and feedback in the customer-supplier relationship (Odette, 2013). To complement the FAI measurement a WTS was introduced to indicate whether inaccuracies in forecasts were due to over or underestimation of demand. The mathematical definition for the WTS can be found in appendix 1. WTS is a number between -1 and 1, with 1 meaning that every misestimate is an overestimation and -1 meaning that every misestimate is an underestimation. A WTS of 0 means that there is no tendency towards either overestimations or underestimations.

A similar measurement, Forecast-Qualitätskennzahl, has been established by the German 'Verband der Automobilindustrie' (VDA). In their report, VDA (2008) defined a measurement that measures the deviation of forecasts. In the same report guidelines for what constitutes good and poor performance. This will be presented in figure 2. The VDA eventually refined Forecast-Qualitätskennzahl, publishing a report defining FAI and WTS (VDA, 2010). Forecast-Qualitätskennzahl, in turn, is similar to Mean Absolute Percentage Error (MAPE). MAPE, while a good measurement of forecasting errors in most cases, has a tendency to favour overestimations as underestimations are bounded by 100%, whereas overestimations are unbounded (Armstrong & Collopy, 1992). FAI, however, avoids this issue by limiting overestimations at 100%.

Time Horizon	Demand Period	Forecast Period	FAI Performance	Classification
Short	Days	Weeks 0 to -2	>97%	Good
			92-97%	Medium
			<92%	Poor
Medium	Weeks	Weeks -3 to -8	>95%	Good
			90-95%	Medium
			<90%	Poor
Long	Months	Weeks -9 to -x	>90%	Good
			85-90%	Medium
			<85%	Poor

Figure 2. performance levels for forecasts. Adapted and converted to FAI measurements from VDA (2008).

3.4 Forecasting

To be able to make decisions regarding future activities within a manufacturing organisation, information and assessment of the future state is needed. By evaluating the external factors that could influence future operations, qualified decisions can be ensured to a greater extent. Jonsson and Mattson (2009) define a forecast as an assessment of possible external factors that could affect a company, and the company cannot control themselves. Some external factors, such as market demand for certain products due to marketing and pricing are possible to impact, while other external factors like market conditions are difficult to influence.

Jonsson and Mattson (2009) state that forecast methods used in demand planning are mainly qualitative and quantitative methods. Qualitative methods are primarily based on subjective estimations made by experienced workers. These can be anything from basic guesses to more qualified assessments. This method can be compared to quantitative methods, which are largely dependent on calculations. The calculations can originate from different types of historical data related to usage or sales of material. According to Jonsson and Mattson (2009) forecasts are, by default, always incorrect. The ability to conduct more accurate forecasts must be weighed against the required resources. Usage of resources are related to costs and needs to be lowered as much as possible. By comparing the value added by accurate forecasts to the costs it is possible to decide whether an organisation should invest more in creation of forecasts. Vollmann et al. (1988) argue that organisations should aim to reach as low cost per forecast as possible. Organisations needs to have simple and effective forecast methods to be able to lower the costs related to forecasts.

According to Jonsson and Mattson (2009) a company can use the master production scheduling to plan the sales and production operations. By defining the quantities that should be delivered, it is possible to plan in which period the quantities should be manufactured. To be able to deliver all required orders, it is needed to specify all components and materials included in the finished product. Jonsson and Mattson (2009) further state that material requirements planning can support the material planning by calculating when material requirements are expected to arise and orders are needed to be released.

In a supplier perspective, customers send forecasts of longer periods of time which enable the supplier to plan their upcoming production processes. Further on, when more accurate demand information becomes available the customer demand can vary from the original plan. This leads to deviations and the supplier has to recalculate their production schedule. Order forecasts that changes with short intervals can make the supplier's MRP system nervous, due to the difficulties to plan material requirements and production in a good way. (Li and Disney, 2017) According to Li and Disney (2017) the most effective method to cope with these kind of variations is to use some sort of buffer.

Forecasting varies between different organisations. Rieg (2010) uses a conceptual framework of three independent variables that affect forecasting accuracy:

- Statistical methods
- Hardware & software
- People, processes & organisation

These three are then supplemented by a moderating variable; Uncertainty/volatility. Statistical methods is the choice of forecasting method(s) and hardware & software is the computer equipment used to assist the forecasting process. The impact of people, processes and organisation comes from among other factors training in the forecasting processes (Merrik et al., 2006). Gruber & Venter (2006) identified that learning effects do occur in forecasting, and that there are significant differences in how forecasting is conducted between different organisations.

According to Armstrong (2001), forecasters often make significant mistakes in the forecasting process. Many of these mistakes are related to not utilising statistical methods correctly or basing forecasts on incorrect assumptions. The author underlines the importance for practitioners to safeguard the integrity of the process, and suggests checklists to ensure proper procedures as a way to do so.

There are alternative, machine learning approaches to forecasting. In a meta-study, Zhang et al. (1998) evaluated Artificial Neural Networks (ANN) and featured a summary of articles evaluating the forecasting performance of ANNs compared to traditional statistical methods for various time series. The authors summarised the conclusions of 22 articles, with somewhat mixed results. 3 articles concluded ANNs performed worse or significantly worse, 8 concluded ANNs performed better or significantly better, 3 concluded ANNs were comparable and 8 concluded ANNs were situationally better and otherwise equal or slightly worse. Kang (1992) found that ANNs outperformed other methods when the time series featured seasonal or trend patterns. Kang (1992) also found that ANNs needed less data available to give accurate forecasts.

3.5 Usage of forecasts in Production/logistics planning processes

According to Lalami, Frein and Gayon (2017), the aim of production planning is to identify how many products that is needed to be produced, when they have to be produced and in which production plant the production should take place. Meyr (2004) has examined the supply chain planning in an automotive industry and defines the general flow of materials upstream in an automotive supply chain as convergent. Coordination difficulties is common in these type of supply chains, due to production capacity, manpower issues and incoming goods. To manage these difficulties an organisation needs to adapt not only an effective internal information flow, but also enable collaboration in terms of information sharing with other parties within the supply chain. Meyr (2004) states that planning processes differs between companies, and further mention forecast-driven and order-driven planning as two possible ways to manage the production planning. Forecast-driven planning is usually used in long- or mid-term decision, and order-driven planning is used in short-term decisions. Wei et al. (2017) describes three hierarchical levels within supply chain management (strategic, tactical, operational), where each level is related to different decision processes. Decisions at the strategic level is usually high level decisions, including decisions such as location of production plants or create new transport networks. At the tactical level, the process itself is defined by addressing cost control, customer satisfaction and risk management. These issues are connected to activities like production schedules, transportation and warehousing. The operational level refers to the regular day-to-day processes, and concern a more detailed plan of the work-in-progress, inbound and outbound logistics.

Lalami, Frein and Gayon (2017) defines a planning process named rolling horizon planning. When this type of planning process is used, the production plan is updated periodically by referring to the most reliable information available. The reason to update the production plan is according to the authors, either because of a shift of planning horizon or uncertainty. Demand forecasts is usually used in production planning and by regularly reviewing the forecast, it enables the organisation to be reactive to forecast errors.

Myrelid (2017) found that the quality of demand schedules shared by customers to their suppliers affect the production planning of the supplier. Among the determinants of quality used, was reliability which is the accuracy of the delivery schedule compared to final deliveries. Reliability is used in the same way that ‘accuracy’ is used for this study, and the study performed by Myrelid (2017) confirms the connection between customer demand schedules and supplier production planning. Karlsson & Ragnarsson (2014), a previous thesis within the same overarching project as this thesis, found that suppliers to a large degree rely on information sent by their customers, and are very limited in their own utilisation of an S&OP process. Some suppliers deem information sent by the customers as insufficient to base their own long term planning on, citing difficulties in making accurate decision for machine acquisition and employee training due to short planning horizons. This implicates that in most cases, if the customer is unable to create accurate forecasts, suppliers will be heavily affected.

4. Case description

The subject studied is forecast accuracy in demand forecast (DELFOR) messages sent from the customers of a selected supplier to the supplier. The development of demand forecasts is done according to the general process described below at all three of the customers studied.

The raw data used to generate the forecast is collected from sales forecasts. These forecasts are then run through the MRP system, where production and/or inventory policies, lead times, unit loads and other factors are taken into account. Through this process, the initial sales forecast is broken down and processed to generate a delivery forecast which is subsequently sent to the supplier. These forecasts will contain variations in demand volumes. For the purpose of this study, variations is used to describe the differences in final order volumes, either as temporary increases or decreases, or long term more trend-like changes. Important to note is that this study does not examine variations in end customer demand, but only the variations in demand from the customer organisation to the supplier. In the process described above, variations can stem from two different sources. Firstly, variations can be a product of changes to the end customer demand, whereby the total production volumes of the supply chain as a whole change. Secondly, variations in end customer demand can be amplified or reduced internally, through the planning process to give the final variation. Examples of factors that may affect the variation are production batching, order batching, inventories, safety stock and MRP nervousness. The purpose of the forecast is to predict variations ahead of time.

Forecasting accuracy is the ability to predict these variations ahead of time, and subsequently indicate correct demand volumes to the Supplier as far ahead of time as possible. In this study, possibilities to affect end customer demand will not be considered, but only the possibility to predict them through sales forecasts, and how these are then processed and used to generate demand forecasts sent to the Supplier. To facilitate for the reader, this study differentiate between the definition of *component* and *product*. *Component* is used to refer to components created and delivered by the Supplier or pre-assembly companies. When components are received by the OEM and put together it creates a *product*.

4.1 Supplier studied

The supplier studied for the purposes of this study is located in Sweden, supplying metal components in the automotive industry. The Supplier is a wholly owned subsidiary of a major OEM, operating independently under a different brand. Over the past years, the Supplier had an average yearly revenue in the area of SEK 1.8B. The Supplier is a tier 1 and tier 2 supplier in the automotive industry delivering primarily to OEMs with some deliveries to companies doing pre-assembly for OEMs. Components used by the OEM studied in this case are sent to a pre-assembly company. The Supplier has over 400 employees operating at their plant. They supply components to several major OEMs in the automotive industry, mainly within the European Union. Roughly 70% of revenues are from within Sweden, 28% from the rest of the EU, and 2% from countries outside of the EU. The company product line consists of three main component groups; C10, D10 and H10.

The Supplier delivers components for both cars and heavy vehicles. Around 55% of revenues are from the heavy vehicles industry and the rest is from the car industry. A few large OEM constitute a majority of their revenues, whereas the supplier is just one of many for the OEMs power in the relationships is heavily skewed in favour of the OEMs. Most customers only buy components from one component group, resulting in limited overlap in the customer bases of the different component groups. There is some overlap in the customer bases of component groups C10 and D10 but none with H10

4.1.1 Logistics and order process

The supplier is using an arrangement similar to the Quantity Flexibility contracts described in the theoretical framework. Customers continuously send demand forecasts outlining their needs for the future through a delivery schedule. Once a delivery date is close, the schedule is "frozen" and the quantity cited in the delivery schedule acts as a formal order. The structure of these arrangements varies between customers. Some customers have a defined latest date to make changes ahead of delivery after which the order is frozen. Others have no such period, with the latest delivery schedule always acting as the order, this gives the customer more flexibility at the cost of uncertainty for the supplier. Customers generally send demands aggregated on a monthly level for demands far into the future, weekly demands at a medium time horizon and daily demands for the near future. For the customers studied, daily demands are sent for roughly the next two weeks.

The supplier attempts to offset some of this uncertainty through safety stocks. They keep safety stocks of finished components depending on weekly volumes. They also keep safety stocks of materials equalling no more than five days' worth of production. Stocks for screws and similar small components are larger as the costs associated with keeping them in the inventory is low. There are no interim storages for work components apart from a small buffer before final assembly (roughly 6 hours).

Lead times for inbound logistics vary from one day for some generic goods to three months for some special components. The plans sent to their suppliers are based on the forecasts received from customers and cover the same planning horizon (roughly one year).

4.2 Customers studied

4.2.1 OEM 1

OEM 1 studied is a multinational, major producer of heavy vehicles. This study focuses on one of their sites in Sweden. Production flow at this site is JIT type, with sequential delivery of most major components, among those are components from a pre-assembly company between OEM 1 and the supplier studied.

Material & information flow

Figure 3 outlines the flow of information and materials between OEM 1, the pre-assembly and the supplier in the supply chain studies. OEM 1 sends information about needs both in the form of DELJIT messages detailing the components, sequence and time for delivery, and DELFOR messages forecasting future demand. The pre-assembly company then makes a decision for their procurement based on the composite information from DELJIT and DELFOR messages from the OEM. This is then sent to the supplier in the form of a DELFOR message. Deliveries from the supplier to pre-assembly are not sequential and usually in daily batches. Both the supplier and pre-assembly company carry safety stocks to guard against issues in logistics or production, as penalty fees for failing final delivery to the OEM are high.

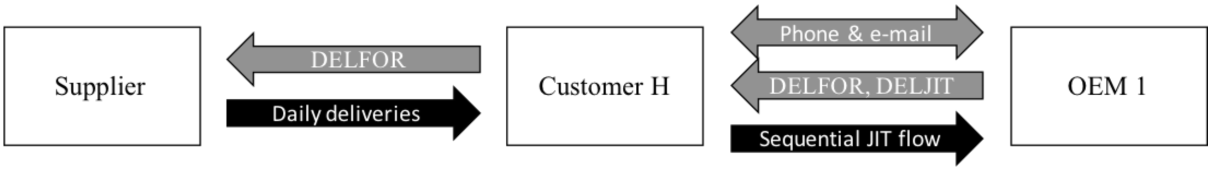

Figure 3. Material and information flows. Information flow(s) denoted by gray arrows, and material flow(s) by black arrows.

There is no direct formal flow of information between OEM 1 and the supplier. As both the pre-assembly company and the supplier were previously owned by OEM 1, many of the supplier contracts of both companies are held by OEM 1. Because of this, there is significant communication between the organisations on other matters, but in terms of production and material planning only EDI messages are sent. Figure 3 shows an overview of important production- and demand related material and information flows.

The total quantity of tied up capital in inventories and production throughout the segment of amounts to roughly 25 days' worth of production. This results in stability for OEM 1, but can conceal issues with production and communication in the supply chain. For example, at the time of the study there had recently been a disruption between the Supplier and one of their subcontractors due to a contract-related issue. Deliveries to the Supplier were limited or completely stopped for a period of several weeks, however the effect of this never reached OEM 1 in the form of missed or delayed deliveries.

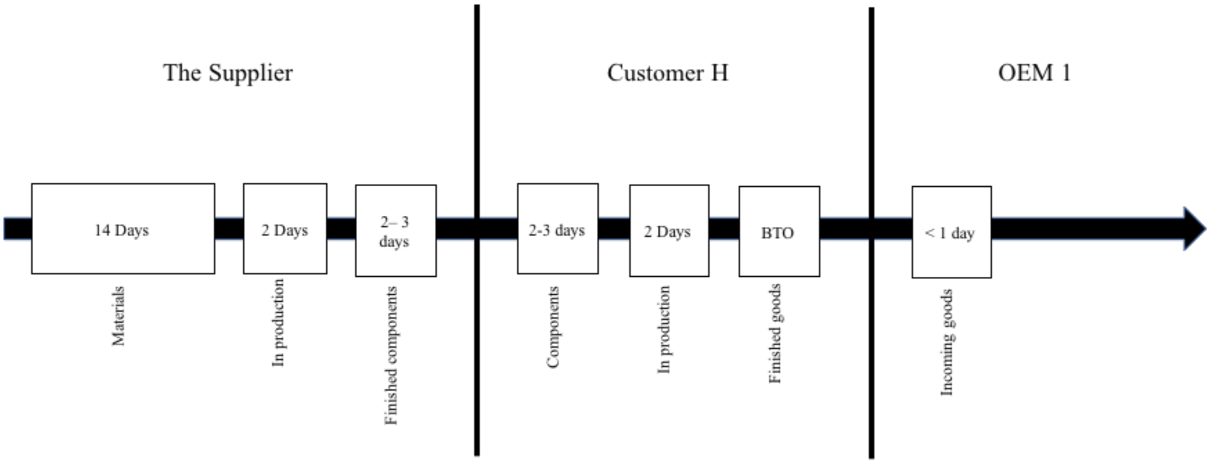

Figure 4. Inventories, buffers and materials bound in the segment of the supply chain studied.

There is a total of around 24 working days' worth of production in inventories for this segment of the supply chain. Of this, roughly 19 working days' worth of production is kept at the Supplier. Based on an approximation of 260 working days in a year, the inventory turnover rate of the Supplier for this component group is roughly 13.7. Based on financial data from the 2017 annual report of the Supplier, their overall inventory turn rate was 12.2 for FY2017.

4.2.2 OEM 2

For this study, interviews in the aftermarket service organisation, Customer E, as well as one of their main production facilities of a second OEM, Customer D, were conducted. OEM 2 is a global car manufacturer.

Material & information flow

Both Customer E and Customer D uses EDI messages in UN/EDIFACT format, primarily DELFOR, when communicating demand information with their suppliers. There are however some differences between the two in how they communicate with their suppliers, and in the nature of the supply chain, as one is a production supply chain and one is an aftermarket supply chain. Some of the differences and attributes of each supply chain segment studied will be presented below.

Customer E

Customer E is the aftermarket organisation of OEM 2, supplying spare parts globally for cars produced by OEM 2. In total they supply over 50 local offices/warehouses from their main warehouse, which is where goods from the Supplier are sent. The Supplier sends daily deliveries to the main warehouse, mostly following the DELFOR. However, Customer E and the Supplier have regular contact by phone and e-mail and if needed they forego the DELFOR messages, being willing to make changes and adaptations if either party deems it necessary. The Supplier delivers goods to Customer E every day, however, quantities are generally higher on Mondays and taper off over the course of the week. Deliveries from Customer E to each of the local offices and warehouses are generally less frequent, and based on inventories at each warehouse using EOQ with trigger points and safety stocks. Figure 5 shows an overview of the flow of information and materials/goods.

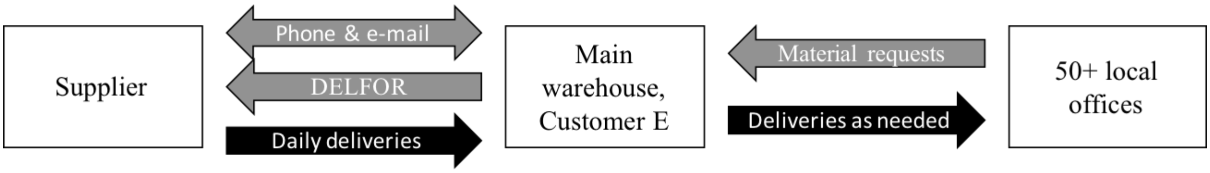

Figure 5. Material and information flows. Information flow(s) denoted by gray arrows, and material flow(s) by black arrows.

Figure 6 shows average inventories within the supply chain segment. Inventory levels are given as number of (working)days' worth of average demand for one of the high-volume components sent from the Supplier to Customer E. In total, there is approximately 32 working days' worth of materials and components in this segment of the supply chain at any given time. Of this, roughly 25 working days' worth of production is at the supplier. Based on an approximation of 260 working days per year, the inventory turn rate of the Supplier is 10.4 for this component group.

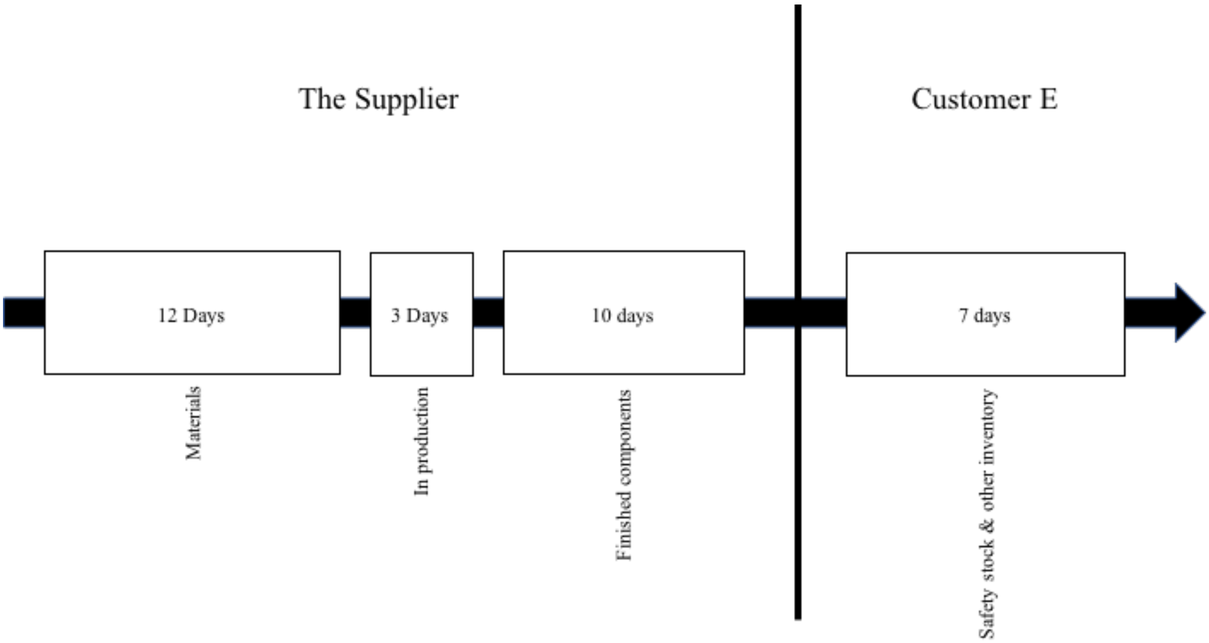

Figure 6. Inventories, buffers and materials tied up in production within the supply chain segment.

Customer D

Customer D is one of the main production facilities of OEM 2, and purchases components directly from the Supplier. There is no communication between Customer D and the Supplier outside of EDI messages and transactions, unless there are significant issues and most issues are solved by referring to the contract terms. There is little to no joint problems solving or adaptation outside of the contract terms unless it is the last resort. Goods from the Supplier to Customer D are delivered on a daily basis, according to DELFOR messages sent by Customer D. The Supplier is given 48 hours of frozen orders. Goods are batched and non-sequential. In total, 9 components and variants are delivered by the Supplier to Customer D, with 2 components amounting to roughly ⅓ of the total quantity each. Figure 7 gives an overview of the main modes of communication and deliveries.

Figure 7. Material and information flows. Information flow(s) denoted by gray arrows, and material flow(s) by black arrows.

Figure 8 shows inventories and capital tied up in production for the segment of the supply chain studied. Quantities are given in days' worth of average daily quantities. The numbers given are for the component(s) making up the largest portion of total quantity, as these flows are more stable over time as production batching and unit loads makes a smaller impact on quantities in inventories at any given time, as well as these components having the biggest impact on the total capital bound. The figure gives an idea of where there are buffers, and where the supply chain is most susceptible to disruptions.

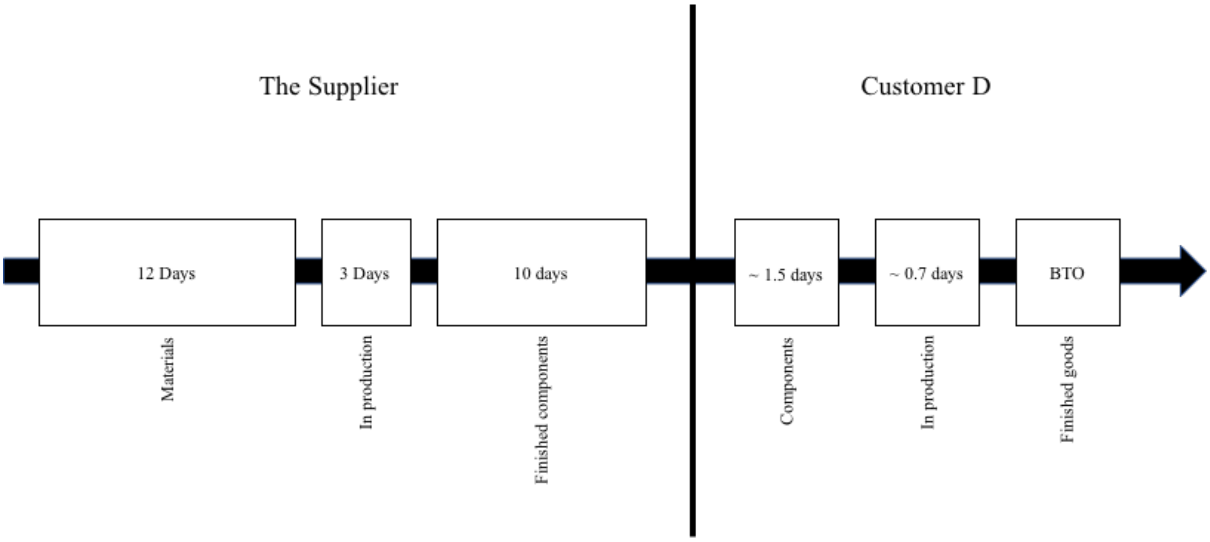

Figure 8. Inventories, buffers and materials tied up in production within the supply chain segment.

In total, there is normally 27 working days' worth of components in this segment of the supply chain at any given time, mainly at the Supplier.

Available data on forecasts

For the purposes of this study, access to a database containing all DELFOR messages received by the supplier from 1/1/2018 until 31/1/2019 was given. The data was accessed through a frontend application which allows aggregation of forecasts based on customer, delivery address, component, demand week and when the forecast was received. Separate to this database, information on component groups and translations of customer ids was available.

5. Empirical results

The empirical results will feature the general patterns found in the data to give a comprehensive overview of the current situation in terms of forecasting accuracy. A summary of data for each of the studied customers will also be given. Some of the more specific and in-depth data for the major customers will be given directly in the discussion for convenience reasons, as it is frequently referenced. In addition to the general data, summaries of key data and insights from each of the interviews conducted will be given in the empirical results.

5.1 General patterns in FAI and WTS

Below a selection of graphs constructed from aggregated data regarding the main component groups C10, H10 and D10 will be shown. Component group H10 consists of components delivered to the heavy vehicle industry, whereas groups C10 and D10 are two different types of components delivered to car manufacturers. Patterns found in these data, as well as implications and conclusions to be drawn from them, will be discussed in detail under the analysis chapter. We will characterise forecasting accuracy as the FAI score of the forecast, and forecasting inaccuracies as the difference between the FAI score and 100%. FAI and WTS scores are calculated for different time “lags”. The lag is the time from the date the forecast was sent to the Supplier to the date of the forecasted demand, e.g. for a delivery schedule sent in calendar week 32, the forecast at 8 weeks lag would be the forecasted demand for calendar week 40. Some calculations are made as a weighted FAI for several different lags. A FAI score labelled with lag (2/4/6) is a weighted calculation of the FAI scores of 2 week, 4 week and 6 weeks lags, respectively. In all cases where weighted FAI scores are used, three different lags are used and they are all weighted equally and the number is the average of the different time lags.

5.1.1 Patterns for the different component groups

Figure 9 shows a comparison of FAI scores for each component group for for different lags, ranging from pure 2 week delivery schedules to schedules 6-10 weeks ahead of time. In the data, we can see that FAI scores for group H10 are more than 9 percentage points higher for the 2 week short term prognosis. However, differences in FAI scores become smaller for longer planning horizons.

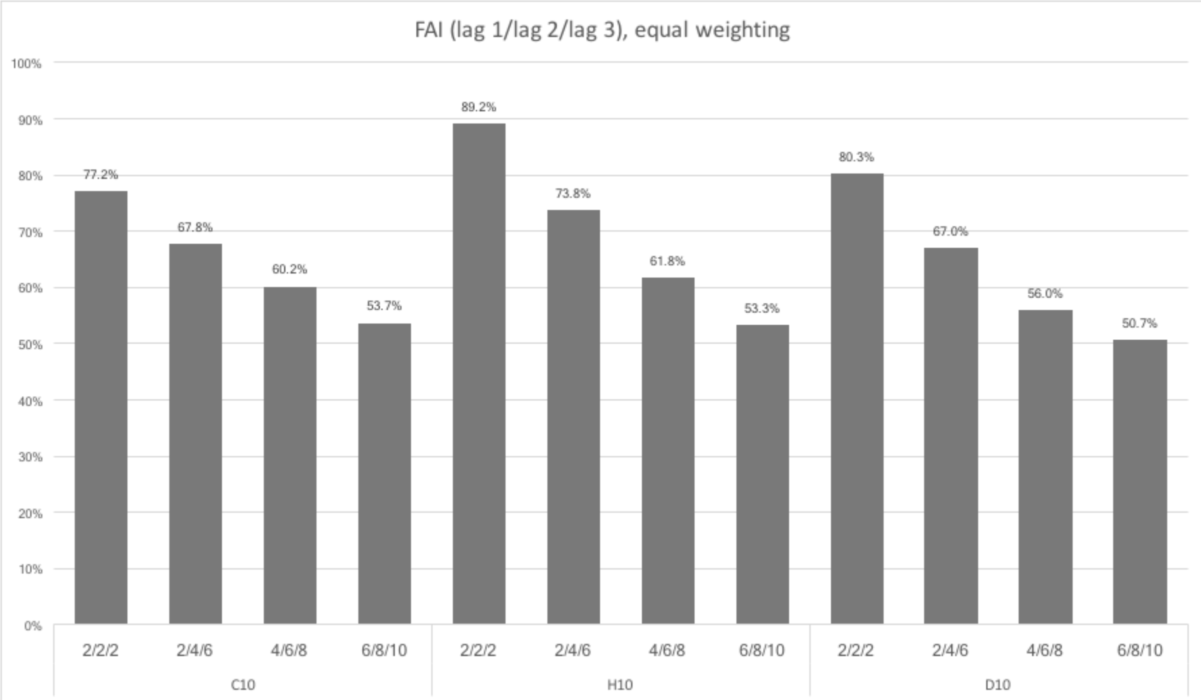

Figure98. FAI scores for each component group, for different lags. Lags are given in weeks.

Data for the WTS connected to the FAI scores in figure 9 can be found in figure 10. The WTS scores for component groups C10 and D10 are significantly above 0, revealing that customers ordering these components consistently overestimate their demand in delivery schedules. For group H10 WTS scores are close to 0. Customers ordering these components also have no tendency to consistently over- or underestimate their demand.

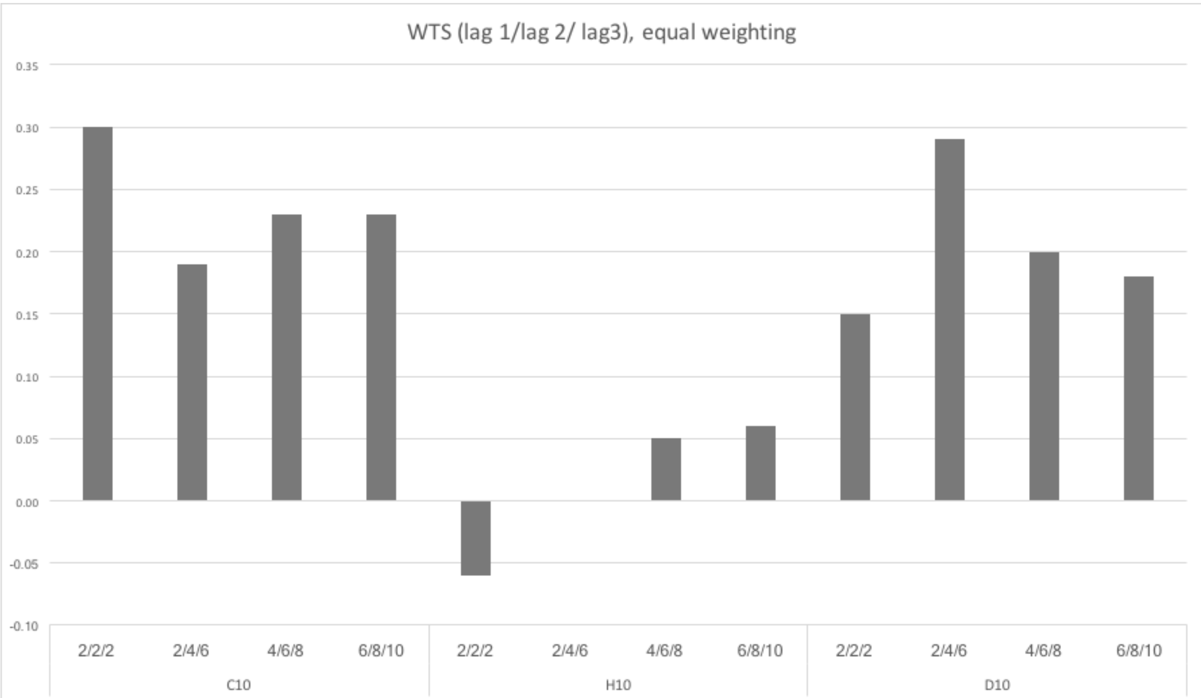

Figure 10. WTS numbers for each component group, for the same lags as used in figure 8. Lags are given in weeks.

Figures 11, 12 and 13, show the FAI scores for each component group from delivery schedules during the year 2018. The graphs start in week 8, as six weeks of data is required to make the calculations since the longest lag is 6 weeks. None of the component groups show any clear patterns for how the FAI has changed over the course of the year. There are varying levels of volatility, with H10 being the most stable, and C10 being the most volatile. All three component groups have significant changes in FAI between the weeks 28 and 31, which are traditionally vacation weeks for factory workers in Sweden. This could explain the difficulty in forecasting production volumes for these weeks, subsequently leading to lower FAI scores.

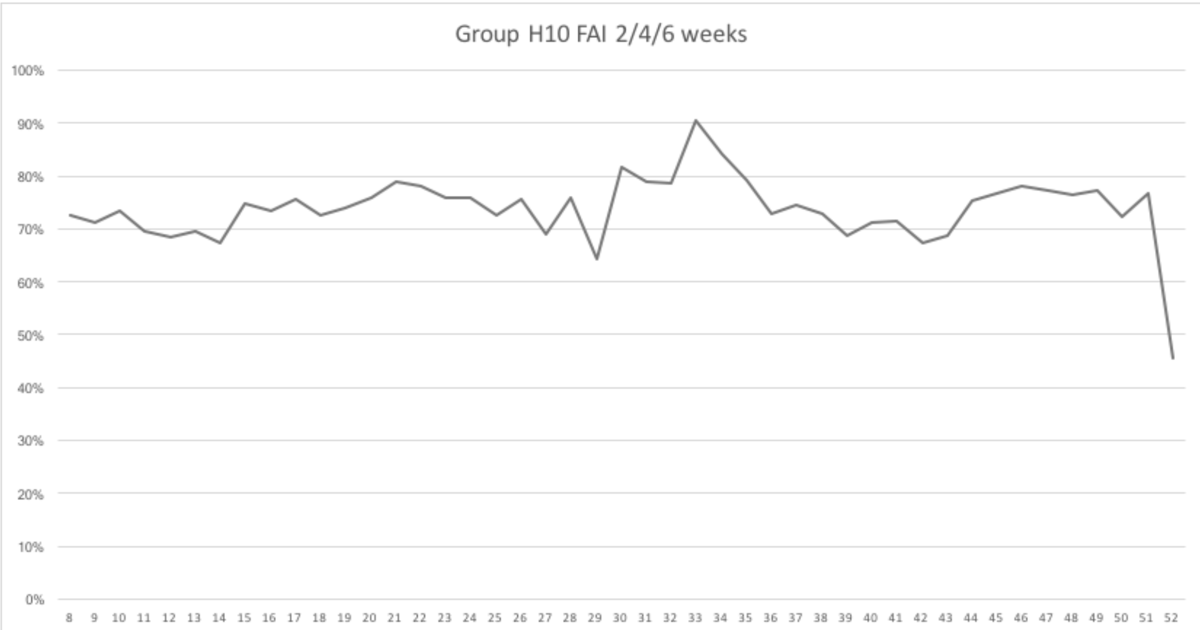

Figure 11. FAI scores for group H10 during 2018, using 2, 4, and 6 week lags. Scores are given for each calendar week from 8 to 52 (6 Week FAI can be calculated at Week 8 at the earliest

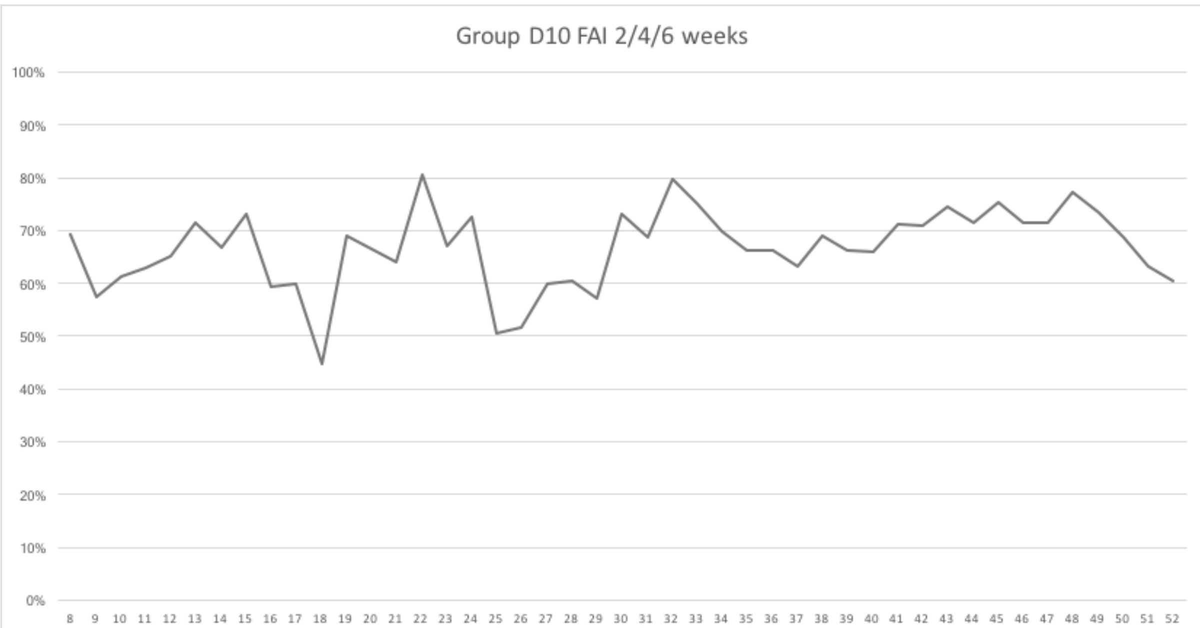

Figure 12. FAI scores for group D10 during 2018, using 2, 4, and 6 week lags.

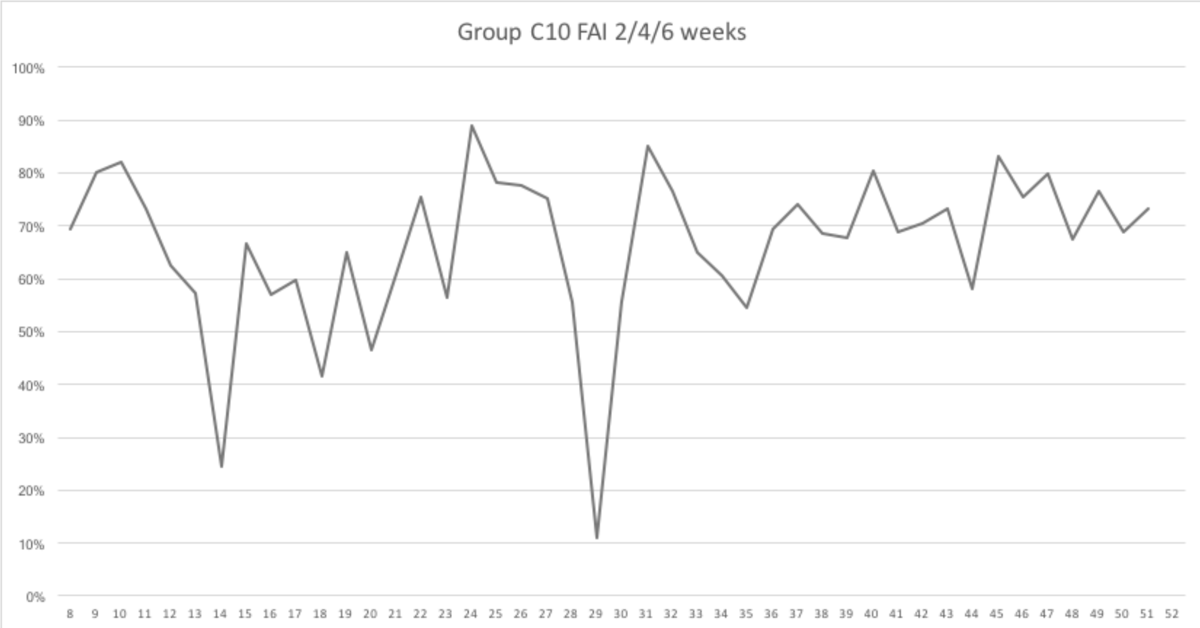

Figure 13. FAI scores for group C10 during 2018, using 2, 4, and 6 week lags.

Figure 14 shows a summary of FAI scores with standard deviations for each component group with different lag settings. The standard deviation here becomes a measurement for the consistency in accuracy of forecasts, with a low standard deviation meaning that forecasts are roughly as accurate every week. We measured this to capture the stability and consistency of forecasting methods employed. While comparisons of the standard deviations between different component groups can be influenced by the volatility of demand for the final product, the standard deviation still gives a rough idea as to how stable and consistent the forecasting of customers is. The average FAI scores and standard deviations further highlight the patterns seen in figures 11, 12 & 13, with forecasts for H10 generally being more accurate as well as more consistent in their level of accuracy.

Component group	Lag settings (weeks)	FAI	STDEV	WTS
C10	2/2/2	77.2%	15.0%	0.30
	2/4/6	67.8%	14.9%	0.19
	4/6/8	60.2%	16.9%	0.23
	6/8/10	53.7%	16.7%	0.23
D10	2/2/2	80.3%	11.3%	0.15
	2/4/6	67.0%	7.5%	0.29
	4/6/8	56.0%	8.8%	0.20
	6/8/10	50.7%	10.2%	0.18
H10	2/2/2	89.2%	5.1%	-0.06
	2/4/6	73.8%	6.4%	0.00
	4/6/8	61.8%	7.1%	0.05
	6/8/10	53.3%	7.4%	0.06

Figure 14. Summary of average FAI scores with standard deviations.

5.2 FAI statistics for major customers

Figure 15 shows the same information as figure 13 but only for the most significant customers of each group (roughly 10% or more of total volume for that component group). Apart from Customer B and Customer E, all major customers had equal or better FAI scores compared to the average of their respective component group. Also worth noting is that differences between the component groups are smaller when only major customers for each group are considered. Customer H is the company doing pre-assembly for the OEM studied, and Customer G is a company in the same corporate group as the OEM studied. Comparing the standard deviations for FAI scores of major customers purchasing from the same component groups can give an idea of how stable the forecasting methods for each customer are.

Customer (component group)	Lag settings (in weeks)	FAI	STDEV	WTS
A (C10)	2/2/2	81.3%	18.1%	0.27
	2/4/6	72.9%	19.0%	0.17
	4/6/8	66.9%	21.2%	0.25
	6/8/10	62.3%	23.0%	0.26
B (C10)	2/2/2	70.0%	31.7%	0.07
	2/4/6	61.6%	24.8%	0.11
	4/6/8	52.2%	27.7%	0.17
	6/8/10	49.0%	24.1%	0.23
C (D10)	2/2/2	90.0%	15.2%	-0.13
	2/4/6	71.6%	14.7%	-0.22
	4/6/8	60.0%	18.3%	-0.12
	6/8/10	55.6%	19.2%	-0.02
D (D10)	2/2/2	86.4%	12.3%	0.21
	2/4/6	83.3%	10.2%	0.30
	4/6/8	74.3%	9.5%	-0.19
	6/8/10	67.3%	13.8%	-0.28
E (D10)	2/2/2	78.6%	20.7%	0.31
	2/4/6	61.5%	12.2%	0.46
	4/6/8	50.2%	12.2%	0.38
	6/8/10	47.0%	13.0%	0.33
F (D10)	2/2/2	89.8%	17.7%	0.36
	2/4/6	84.4%	18.9%	0.16
	4/6/8	78.9%	21.4%	0.14
	6/8/10	71.6%	21.9%	0.23
G (H10)	2/2/2	87.2%	6.8%	0.13
	2/4/6	75.9%	7.0%	0.03
	4/6/8	67.3%	7.2%	0.04
	6/8/10	60.4%	7.3%	0.03
H (H10)	2/2/2	90.1%	9.3%	-0.25
	2/4/6	76.6%	7.6%	-0.04
	4/6/8	66.2%	8.0%	0.02
	6/8/10	57.9%	10.7%	0.02

Figure 15. Summary of FAI scores for major customers of each component group.

The two customers with the worst FAI performance were Customer B and Customer E. Customer B was expected to have worse performance, as they are not as mature in their usage of ERP systems and EDI communication as the other customers. In addition to this, transports to Customer B are very long distance transports, resulting in batching and less frequent transports. Changing the delivery date of one of these batches one day forward or backward, for example, will have a large effect on FAI. This is shown by the standard deviation, as some forecasts are fully accurate, whereas others are very inaccurate. This study focused primarily on the supply chain segments connecting the Supplier to OEM 1 and OEM 2, and as such Customer D, Customer E and Customer H are of particular interest. A more detailed presentation of their respective forecasting accuracy, as well as any unique patterns for each will be presented below.

5.2.1 Customer D

Customer D has a high forecasting accuracy when compared to other customers of the Supplier, particularly for long forecasting horizons. Figure 16 summarises the forecast accuracy of Customer D for different forecast horizons ranging from 4 to 26 weeks. The low forecasting accuracy for 8 week forecasts is likely due to when Customer D splits their demand from monthly to weekly. Depending on the weekday, the demand for same weekday 8 weeks ahead may be given with different levels of aggregation, which will confuse the algorithm used by the software when calculating accuracy. For example, some forecasted demands will appear as monthly demands and some as weekly, but both will be treated as weekly demands by the algorithm and compared to weekly reference demand when calculating FAI. The 8-week accuracy is likely due to calculation difficulties, as bucketing is somewhat inconsistent at this point, and should not be considered as too serious as in practice planners can clearly distinguish between weekly and monthly demand numbers.

Forecast Lag (in weeks)	Customer D FAI, high volume
4	92.2%
6	90.5%
8	58.7%
10	76.9%
12	78.2%
14	79.3%
18	80.7%
22	77.2%
26	73.8%

Figure 16. forecasting accuracy of Customer D for different forecast horizons.

Customer D has a comparatively high forecasting accuracy for the components sent most frequently from the Supplier. Particularly for forecasting horizons beyond 12 weeks, where many other customer quickly fall off in terms of forecast accuracy, Customer D manages to maintain a high level of accuracy.

5.2.2 Customer E

Customer E exhibits a very unique pattern compared to the other customers, particularly in the fact that there are significant changes to their performance across the period studied.

Figure 17. 2 week FAI for customer E for 2018.

As can be seen in figure 17, 2 week FAI for Customer E follows completely different patterns before and after week 29, which is during the Swedish industrial vacation period. Up to and including week 29, Customer E had an average FAI of 60.7%. From week 30 and onwards their average FAI was 96.0%. The difference is remarkable, and in the underlying data it appears to be almost momentaneous. Interestingly, Customer E had a lower ratio of changes within 2 weeks of delivery (number of orders changed less than 2 weeks before delivery compared to the total number of orders) than the median for all customers. Their changes were however more significant in terms of volume. A few orders appear to have been modified by a factor of 5, mere days before delivery. In addition to lowering the frequency of late changes, their magnitude was also lowered. The nature of their misestimates also changed. Prior to week 30, almost all misestimates were overestimations. After week 30 WTS scores were more balanced, with a slight tendency towards underestimations, as can be seen in figure 18.

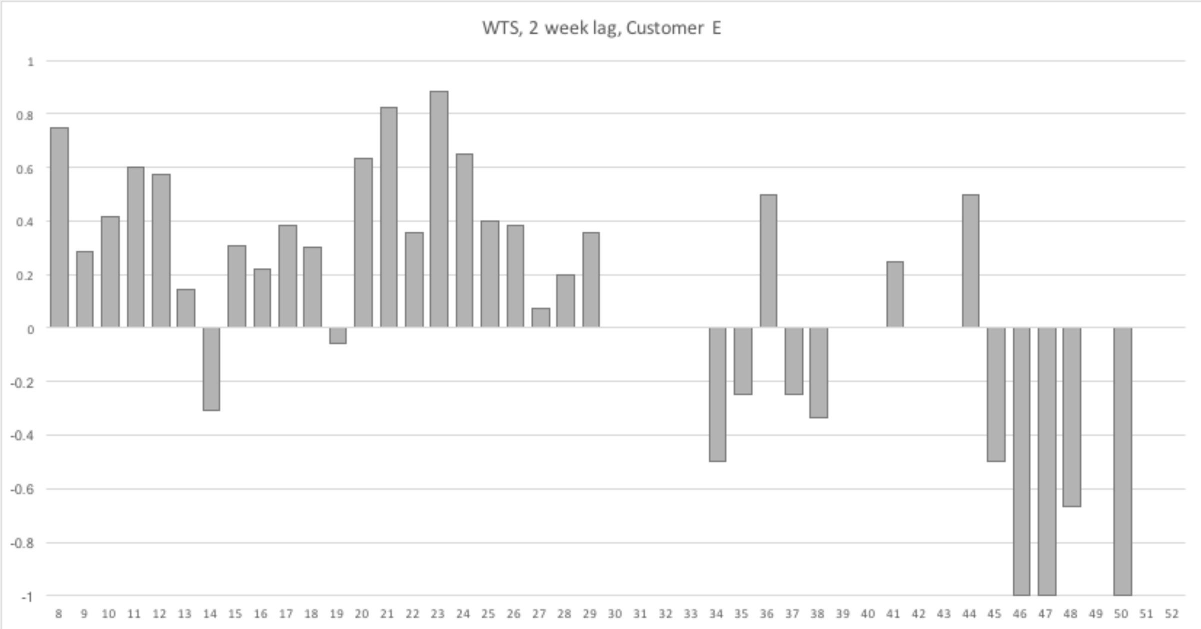

Figure 18. WTS numbers for Customer E over the course of 2018.

Looking at the forecasting accuracy of Customer E for different planning horizons, from 4 weeks up to 26 weeks, reveals some interesting patterns to be considered. The forecasting accuracies for the different horizons are given in figure 18. The accuracy of forecasts appear to be roughly the same, regardless of the planning horizon. Customer E does not appear to have more reliable information regarding demand 4 weeks ahead than they do for demand 26 weeks ahead.

Forecast Lag (in weeks)	Customer E FAI, high volume
4	66.0%
6	63.6%
8	57.6%
10	55.2%
12	57.7%
14	56.0%
18	63.9%
22	64.0%
26	64.4%

Figure 19. forecasting accuracy of Customer E for different forecast horizons.

5.2.3 Customer H

Customer H has a comparatively high forecasting accuracy for horizons between 4 and 10 weeks. For longer horizons their forecasting accuracy decreases rather quickly to level out at roughly the same accuracy as most other customers. Figure 20 summarises forecasting accuracy for Customer H for different planning horizons. Similar to Customer D, Customer H also has one planning horizon with very low accuracy. This is also due to changes in demand buckets 18 weeks ahead of delivery, similar to the dip in accuracy at the 8 week horizon for Customer D.

Forecast Lag (in weeks)	Customer H FAI, high volume
4	83.3%
6	76.4%
8	73.7%
10	69.3%
12	63.7%
14	59.0%
18	23.6%
22	57.0%
26	46.4%

Figure 20. Forecasting accuracy of Customer H for different forecast horizons.

5.3 Interview data

Interviews were conducted at OEM 1 and OEM 2. Interviews were done at two different organisations within OEM 2. Interviews at OEM 2 were done both at the aftermarket organisation as well as at one of their main production plants. The relationships and the nature of material flow and demand profiles were expected to be different between the two OEMs, but also between the two different internal organisations within OEM 2.

5.3.1 Interviews at OEM 1

Material planner at OEM 1

As an exploratory interview at OEM 1, a material planner, from here on referred to as the Planner, was interviewed to better understand the information, and material, flow between OEM 1 and Customer H. The Planner is the main contact person for questions and concerns from Customer H, and forwards or otherwise addresses concerns that Customer H raises. In addition to the formal information flow of DELFOR and DELJIT messages, the planner also maintains continuous contact with Customer H. Orders, and sequencing, are frozen 3 weeks ahead of time, and any changes beyond that point have to be done manually and approved by Customer H before the order can be changed. OEM 1 has very limited information on the current situation in production at the Supplier and only has extensive information one step backwards in the supply chain.

Outside of the 3 weeks of frozen production schedule, OEM 1 also sends forecasts outlining approximate needs for the coming 1 months. Changes that are made within the freeze period are due to changes in the specifications from the end customer. The components that are part of the flow from the Supplier to OEM 1 through Customer H are rarely subject to change in specification. Almost all changes to this flow within the freeze periods are due to cancellations of end customer orders, which are rarer. The Planner did however state that there had previously been some issues with certain end customers completely changing orders a few weeks before delivery to the extent where it did affect the flow from Customer H, and in turn from the Supplier.

The modules delivered from Customer H to OEM 1, are large and inefficient to store. As such, at most one day's worth of production can be stored at the OEM 1. Therefore, any stop in production will lead to deliveries being postponed at Customer H until production can catch up, which can lead to carry-on effects. There is also a possibility for the logistics firm to store some modules at their hubs in case of a major stoppage. There has however been no major production stoppages in recent history.

If Customer H has any questions regarding delivery schedules they contact the Planner, who either forwards the question to the relevant function and then sends the answer back to Customer H, or established direct contact between Customer H and the relevant function for more complex issues. Any issues regarding changes to delivery schedules also pass through the Planner. If Customer H has any issues with changes in delivery schedules, they are mostly concerned with changes made with short notice, and rarely anything concerning forecasts.

Volume and program manager

To improve insight into the actual forecasting process, two employees working with production program management were interviewed to build an understanding of the forecasting process and potential sources of issues further upstream in the supply chain.

OEM 1 has sales offices in each geographical area where they are present. The sales organisation creates volume forecasts for each of the two main product lines for every market. The forecast follows a cyclical process where initial estimates are collected, and then discussed in terms of reasonability before to arrive at a final forecast that is sent to the planning department which updates the total production program two times per month. The sales department collects data from their customers as a part of their process to build forecasts. Information about major infrastructure or industrial developments is also incorporated as this will increase demand of heavy vehicles. The collected data is compiled to give an idea of the potential development of demand going forward, and is put into relation to historical sales figures. In the end, however, data pertaining to future demand is qualitative in nature and the forecasts are heavily reliant on experience and the personal judgement of the forecasting personnel. OEM 1 has started looking into how they can utilise more quantitative data in their forecasts, such as GDP and other indicators of economic performance of each market to predict future demand. Other companies within the same corporate group have been using such measurements successfully in their forecasting process, improving accuracy of forecasts.

Due to the complexity of the product structure and its variants, forecasts for each variants are created by automatically breaking down total volume forecasts for each country using historical data on distribution of each variant. Based on the production program, each factory then breaks down the production into material requirements, taking into account lead times, unit loads, inventory levels among other factors to create demand forecasts for each individual supplier.

The size and complexity of the company, its markets and product range makes it virtually impossible for anybody to have a comprehensive picture of everything.

5.3.2 Interviews at Customer H

Assembly planning manager

Delivery schedules are sent from OEM 1 to Customer H one time per day via EDI. The assembly planning manager analyse the plan each morning to be able to plan the daily production. He believes that the quality of the delivery schedules sent from OEM 1 is good. Customer H can experience some issues if the mix of requested components is changed, due to long lead time from some of their suppliers. They got the ability to handle small changes if they are small and not to close date of delivery. The assembly planning manager has daily contact with the material planner at OEM 1 to mitigate potential issues in the material flow. The material flow to OEM 1 is perceived as generally being stable, with some exceptions. OEM 1 manufactures some vehicles that are sent in “lego boxes” from Sweden to certain geographical markets. Orders for “lego boxes” from the international factories are batched before they are sent to the Swedish production plant. This subsequently results in an equivalent batch order for components being sent further down the supply chain. This can result in some difficulties for Customer H, however they are not seen as critical.

Delivery forecasts sent to the suppliers are created by the ERP system by breaking down the delivery schedule received from OEM 1 into component level. Lead times are added to the forecasts and sent to the supplier. Creation of forecasts are only based on the order info received from OEM 1. The assembly planning manager mentioned that the accuracy of the forecasts are not measured by Customer H.

5.3.3 Interviews at OEM 2

Interviews at the aftermarket organisation (Customer E)

Material planner

The planner mentioned that the issue of poor stability in prognoses and delivery schedules had been raised by the Supplier for some time, and Customer E themselves had also realised that their lack of stability had caused problems for their suppliers. As a solution to this the freeze time for orders was prolonged from 1 week to 2 weeks. This significantly improved the quality of short term delivery schedules. The material planner perceived that the effects on their own organisation as a result of this change had been minimal. The change was possible to implement overnight and the material planners have not seen any direct effects on their daily work as a result.

Apart from the delivery schedules, the material planner maintains regular contact with the Supplier. In case of a variation in demand or other disturbances in the flow, the material planner and the main planner for the flow to Customer E at the Supplier worked together to come up with a solution to handle the situation.

Forecasts

The forecast planner mentioned that forecasts used at Customer E are created from consolidated data from the 50 local offices. Each local office calculates a sales forecast based on the historic sales from the specific local office. All forecasts are aggregated at the central warehouse to calculate the total amount required of each component. The warehouse in Gothenburg is the central warehouse, responsible for resupplying local warehouses around the world.

Customer E uses two different types of orders in their organisation to manage the inventory at their warehouses. The first type is procurement orders. Each of the largest warehouses is responsible for supplying some components to every local warehouse around the world. Allocation is based on the sourcing strategy, single- or multiple sourcing, and the geographical location of the supplier. The forecast planner states that locally based procurement is needed to be able to maintain a good collaboration with the suppliers. The aftermarket organisation usually purchase components from the same suppliers as the OEM factory does.

The other type of orders are refill-orders. They are used to replenish the inventory of components at the central warehouses and local offices. The team that are responsible for the refill-orders are located in Gothenburg and manage the material flow between the central warehouses and the local offices. Each local office uses a standardised way to calculate a forecast based on their own sales data the last 12 months, weighted on the last couple of months. Each distribution centres uses re-order point to plan future replenishment. By considering safety stock, lead time and EOQ, it is possible to identify when specific materials are required. The replenishment team access the forecast data through the organisation's global ERP-system. The needs from the distribution centres are consolidated at the central warehouse and added to the delivery schedule sent to the supplier. If the required amount of material are changed at any local office, the delivery schedule are instantly changed.

The forecast planner mentioned sales-campaigns, seasonality and trends as external differences that affect the process when forecasts are created. If a sales-campaign takes place, the purchaser override the forecast data from the distribution centres and creates a forecast based on their own experience.

There are no explicit measures taken to ensure proactivity when forecasts are made. Normally, forecasts are made based on weighted sales figures from previous months and years. The interviewee expressed a desire to develop their forecasting to incorporate measurements such as the number of cars in use, service intervals and average lifetime of each part to better foresee future changes in demand. Currently their approach is perceived as reactive, managing variations in demand once they appear rather than preparing in advance.

Interviews at production plant (Customer D)

Material planner

Compared to the aftermarket organisation, the production plant has significantly shorter freeze times for orders, with 24 hours guaranteed in the contracts, but 48 hours generally being given. This is to increase flexibility for the OEM, allowing them to quickly reacting to any change in demand by adjusting their production. Internally, the production sequence is only frozen for a few hours. The delivery schedules sent to suppliers is based entirely on actual customer orders for the coming 2 months, approximately. The full delivery schedule encompasses 250 production days, 50 weeks, with large parts being based on prognosis. The prognoses are updated monthly, and are built based on a mix of historical data, along with adjustment for current, and probable future market trends. Final orders for all materials and components are always based on actual production requirements for each day, rounded up to nearest unit load. They do not use EOQ (Economic Order Quantity) to dimension their orders. Customer D keeps some safety stocks of materials and components, with volumes being based on experience and the nature of the material or component. For example, fragile components that could break during transport or handling are generally kept in higher volumes.

Unlike the aftermarket organisation, production does not send any complementary information to their suppliers. Their stance is that, ideally, the supply chain should not feature any information flow outside of information flow. This is naturally not the case, but it is up to the suppliers to contact the materials planning department if they want to raise any issues. There is no proactive communication from Customer D, operating with a no news is good news mindset. In general, Customer D sticks closely to the terms agreed to in the contract expecting both parties to fulfil their commitments without interventions by the other party. As long as variations in volumes are within what was stipulated when the contract was drawn, they do not send any information apart from the delivery schedules. If the prognosis indicates that they will go above the agreed capacity in the contract they work with the affected suppliers to draw a new agreement to ensure fulfilment of their needs.

Volume and Program Manager

The sales organisation of Customer D is divided into several geographical regions. The division of geographical regions are based on each markets expected sales. In high-volume markets each country represents one region and in low-volume markets each region is based on typical characteristics, such as technical preferences. The local offices in each region acquire production slots, based on their forecast of potential sales. If they are unable to fill their assigned production slots, it is possible to collaborate with other local offices within a region and exchange production slots with one another.

Each specific local office creates a forecast of their potential sales based on historical sales together with market trend analysis and economic situation in their sales region. To ensure that fluctuations and trends in the market can be fulfilled, adjustments of the forecasts are made continuously and the forecasts are updated twice per month. The forecasts are consolidated in each market and communicated to the Volume and Program Manager. He creates an overall weekly production plan of which quantities of which product model each factory needs to produce.

The overall production plan does not manage the complexity of product structures and customisation. Instead, the total volume of the overall production plan is automatically broken down into separate needs of specific components. Depending on unit loads, inventories and lead times, the required amount of each component is transferred to delivery schedules sent to the Suppliers.

5.3.4 Interviews at the Supplier

To further explore effects resulting from variations in demand forecasts interviews were conducted at the Supplier.

Interview 1

The first interview focused on general processes around planning and production, with some aspects of demand variation being discussed.

Production and material planning

Production schedules are generated by MRP and released to production every day. Data regarding order information is updated only once each day to ensure that data is kept in synch between the information system, logistics and production. All production plans are aggregated each day and the total production volume of each component is calculated and planned. The Supplier asks at least 4 days of frozen plans from each customer, but would like to have longer freeze times as lead times from suppliers can be long for some components. Currently, production lines are currently running at around 80% of maximum capacity, which is lower than what it had been previously, where production was overloaded due to backorders. For component group H10, some variants share the same initial production steps, only being differentiated in the final stages. A few variants are significantly different from all others and have their own production steps. The possibility to postpone differentiation for some variants helps in managing variations as the total throughput time can be upwards of one week. For components that are differentiated later on in production, changes to the product mix can be made within the last week.

Effects of variations

The interviewee perceives that short-term variations have a larger effect than long term variations in their organisation. Variations more than 2 weeks ahead can generally be dealt with through replanning of production and material orders to subcontractors, or by running extra shifts to build a buffer ahead of time. For variations communicated shortly before delivery, replanning might not be enough, or too slow, and variations need to be mitigated by safety stocks.

Most customers have their plans frozen 4 days ahead of delivery, which can result in late changes to production schedules and product mix. Furthermore, the subcontractors ask for longer freeze times. Therefore, when a late change to a customer order arrives, material flow from the subcontractor is already frozen. Due to this the Supplier generally orders more than the believe necessary to ensure that customer order fulfilment. As a result, the Supplier has high inventory levels resulting in additional cost. Additionally, most of the contracts with the subcontractors are held by the OEM, resulting in arrangements sometimes not fitting the Supplier. Most prominent is the fact that the Supplier has very limited flexibility and power in these relations on their own, which can leave the Supplier powerless when it comes to creating solutions to manage short term demand variations.

To guard against variations in customer orders and disruptions in production the Supplier aims to finish production of customer orders ahead of delivery, keeping finished components in storage until delivery. For high-volume components, orders are ready around 3 days ahead of delivery for some high-volume components. For lower volume components safety stocks are kept instead as demand is irregular and production batches are larger than order volumes. In general, the Supplier keeps large inventories of materials as well as finished components to guard against variations. At the time of the study there had recently been a week where Customer E had ordered roughly twice their average weekly volume, which had to be "absorbed" by their inventory. Furthermore, the Supplier perceives that it is necessary to keep large inventories to ensure that they can supply customers even if the product mix of the demand changes.

Forecasts are perceived to be roughly equal in quality between most customers and most customers also send complementary information regarding likely short-term upswings in volume due to, for example, promotional periods or new product launches. This is perceived as very helpful in preparing and planning for these spikes in demand.

As production is at 80% of max capacity currently, and has been even higher previously, the Supplier is sensitive to significant upswings in demand. As a result of this, and the previously mentioned long lead times from subcontractors, the Supplier keeps a significant inventory of materials and finished components. Inventory levels vary during the year, but are generally above 10% of total assets in terms of value. Most of the value bound in inventory is in the form of finished components.

Interview 2

The second interview focused more on variations and their effects on the Supplier, putting extra emphasis on the changes in forecasting accuracy from Customer E. The interview was conducted with a production planner for component group D10.

Effects of changes made by Customer E

The change made by Customer E to prolong the freeze period from 1 to 2 weeks ahead of delivery has made variations much smaller and the flow more easily managed during the autumn and winter. So far, the change has made day-to-day planning easier and has allowed for better stability in production and inventory. There are however still some concerns regarding forecasts from Customer E. As Customer E is a global aftermarket organisation, with over 50 local offices around the world, each with their own demand, the Supplier often receives information about significant spikes in demand quite late. If a local office decides on a promotional period for a certain component this is only communicated to headquarters in the form of requests for material. Because of this, from the Suppliers perspective these demand spikes often appear out of nowhere with little to no explanation as to what is happening and the long term effects on volume. By comparison, Customer D, one of the production plants of the same OEM as Customer E, was able to provide better information on future increases in demand. This was perceived to be due to the nature of end customer demand, with Customer D producing to fulfil a relatively known demand, and Customer E keeping replacement parts.

Managing variations

As the supplier closes production for 4 weeks during the summer due to vacations, maintenance and renovations they need to have built up a buffer of finished components ahead of time. This buffer is built up during the spring, and results in a heavy strain on production, making them susceptible to upswings in demand. While they will have components in their inventory to meet the immediate demand, building a sufficient buffer for when they close production could prove difficult and expensive. The Supplier may have to order overtime production or forego weekly maintenance routines to meet production requirements. In addition to this general sensitivity to upswings in demand, the Supplier is particularly sensitive to variations the last 3 weeks before they close production. Materials are purchased from foundries in Germany and transported by train, with materials taking around 2 weeks to reach the Supplier. Changes during the last three weeks before closing production cannot be met by ordering more material by train, but would have to be sent by express delivery, which creates additional costs for the Supplier. Some variations might be too late to account for at all before production closes, which could create a risk of inventory levels not being able to cover the 4 weeks of shut down production.

An additional aspect of the train transport is that batch volumes are either a half or a full cart. For certain low-volume components this could be equivalent of months of production. Cancelled orders of low volume components can therefore result in the Supplier having significant volumes of material in their inventory without any real demand in the near future. Additionally, for component group D10, the smallest production batch is around 2000 units, whereas the unit load to customer is just over 100. This results in large inventories of low volume components, which make up a significant portion of inventory costs but not of revenues.

Interview 3

To identify any differences in the effects on production for component groups D10 and H10, an interview with a production planner of component group H10 was conducted.

Similarly to production planning of component group D10, the production of component group H10 is generally not impacted significantly by variations in customer demand and changes to customer orders. In almost all cases, there are enough finished components in the inventory to cover for any changes to customer orders. The extra components are taken from the inventory, and that volume is then added to the next production batch of that specific product. While this does affect the production schedule slightly as batch sizes may increase soon before production start, it does not affect downtime and therefore has no significant effect on production costs. Customer demand volumes are perceived as generally being stable over time, however orders are sometimes moved forward or backwards in time, resulting in variations. This does not result in any significant issues for production planning, as inventories are able to absorb the variations allowing production to be stable.

Interview 4

To build a better understanding of how variations in customer demand impacts the Supplier outside of production, an interview was conducted in the purchasing department.

The main materials for each component are sourced from smelteries, both from within Sweden and from the rest of Europe. Currently, smelteries in Germany account for the largest share of material. The smelteries have different geographical locations, resulting in different lead times. However, lead times from the smelteries delivering the largest quantity are roughly one week. The supplier has not experienced any issues with the smelteries in terms of delayed deliveries or contract disputes. As the Supplier is relatively small in terms of revenue compared to both their main customers and the smelteries, there could be a risk of having no flexibility or leverage in either direction. The interviewee believes that the fact that they are a wholly owned subsidiary of a major OEM has helped them in being given better service and leverage than what their share of the revenue of the smelteries would otherwise warrant. The interviewee has not experienced that they need to adapt in any way to manage the power relationship with the smelteries.

The supplier has not had to order any significant number of express transports from the smelteries as a result of material shortage in their own production. As a whole, variations in customer demand is not perceived as impacting the order process in such a way where additional costs are accrued due to late changes.

6. Analysis & discussion

The discussion will feature three different segments, each focussed mainly on one research question. 6.1 will cover research question 1, 6.2 covers research question 2, and 6.3 covers research question 3.

6.1 Analysis of patterns in FAI and WTS

6.1.1 General patterns in FAI

As described in the empirical results, customers of group H10 had significantly better FAI scores for short planning horizons compared to customers of component groups C10 and D10. A potential explanation for this is that the customers are active in different industries. The OEM studied within the heavy vehicle industry has their production frozen for a 2 week period, meaning that no changes to production planning will be done within this period. However, this information still needs to flow through the pre-assembly company, and forecasts from the pre-assembly company exhibit some variation within these 2 weeks. OEMs within the car industry generally have shorter freeze times, where the production can be changed on short notice, even a day or two beforehand. This can explain the differences for short planning horizons. However, as the full production mix is known by the OEM for components in the H10 group, 89.2% FAI seems rather low compared to the targets set by the VDA. These inaccuracies cannot be explained by changes originating from final assembly line, but are created somewhere along the way before communication reaches the supplier.

For the weighted 2, 4 & 6 weeks prognoses, component group H10 once again shows higher FAI on average, and barring a few weeks at the end of the year H10 has a higher FAI than both C10 and D10 for almost every single week. In addition to this, FAI appears less volatile for H10 with smaller changes in FAI week to week. The extent to which this is caused by the differences in industries and end customer demand profiles, and to which extent it is a component of different forecasting processes or other internal factors cannot be discerned from this single data set.

WTS scores indicate systematic overestimation of demand for component groups C10 and D10, but not for H10. There are customers carrying significant shares of total volumes in all three component groups, and according to the reasoning of Hwang & Lee (2000) and Huang, Hsieh & Farn (2011) uneven power tends to lead to manipulation of forecasts by customers to protect their own interests. The theory could hold part of the explanation as to why there are overestimations for groups C10 and D10, but the pattern for group H10 contradicts theory. This likely indicated that there are more variables that affect forecasting accuracy and tendencies in customer demand forecasts. The main difference between H10 and the two other component groups is the industry of the customers. While all customers are within the automotive industry, differences between the heavy vehicles industry and the car industry could explain why patterns differ. Customer behaviour can be expected to be different, and as such the end customer demand likely has different patterns when it comes to the demand variations that the OEM faces. How end customer demand varies affects the ability to make accurate forecasts and could be a contributing factor in why forecasting patterns vary between the different component groups. Differences in components, with H10 being lower volume and higher unit price, or differences in relationships and trust could also be explanations. With significantly higher unit prices, overestimating the needed quantity for component group H10 would prove more costly through inventory costs and bound capital. If there is also significant trust between the customer and the Supplier, where the customer always trusts in the ability of the Supplier to deliver the desired quantity as well as being able to manage a short notice increase in quantity due to a market-side increase or an internal factor such as replanning, there would be no reason for the customer to indicate higher volumes than they plan for in their forecasts.

Additionally, as was discussed earlier, the large customers generally have higher forecast accuracy than the average for their respective component group. The demand for component group H10 is more consolidated with the major customer amounting to a larger portion of total demand. This could also be a reason to why the average FAI scores for component group H10 are higher.

6.1.2 Patterns in FAI for major customers

Differences in FAI between component groups when only major customers are considered, are smaller than those of the component groups overall. The major customers order regularly, as a part of their main logistics flow, and disruptions to this flow would prove costly. It would therefore be in their interest to provide forecasts of sufficient quality to guarantee that there are no disruptions to the flow. While some smaller customers also order on a regular basis, their size likely limits the resources they are able to dedicate to forecasting and development of processes for these types of supporting activities. As Armstrong (2001) states, a lot of forecast inaccuracies stem from the forecasting process not being sophisticated or rigid enough. This could potentially be a reason why some of the smaller customers are less accurate in their demand forecasts. However, no small companies were studied in detail, so there is no concrete information on their forecasting process available for this study. Moreover, high volumes are expected to in itself stabilise variations, which will be discussed further later on in the paper. However, other studies indicate that there is still room for improvement.

The inaccuracies found in the forecasts sent by the major customers are not insignificant. In their development of the predecessor of FAI, VDA (2008) established that the equivalent of above 97% FAI for a 2 week planning period was to be considered good, 92%-97% medium and below 92% poor forecast accuracy. Over the course of the entire year, all major customers would be classified as having poor performance. The only major customer performing adequately for an extended period of time is Customer E after week 30 until the end of the year, falling just short of ‘good’ performance. It should be mentioned that the targets set by VDA mainly refers to the production of cars and not trucks. While the VDA operates in the German automotive industry as a collaborative coalition and is not active in the Swedish automotive industry, the overall market climates are similar enough to be considered negligible. As such, Swedish manufacturers should be able to achieve the same levels of performance as the forecast accuracy proposed as targets by the VDA. This is not the case, and the poor FAI performance is likely due to the organisations themselves and systemic errors and not random market variations.

Reasons and effects connected to poor FAI performance

As mentioned before, Lau, Xie and Zhao (2008) found that most of the benefits of forecast sharing are felt by the supplier. Costs and benefits connected to demand forecasting are disjunct and separated by organisational barriers. All of the major customers are large enough in size to have the organisational resources to develop their forecasting processes to match their needs from it. However, there are more benefits from accurate forecasting that are not necessarily seen directly by the customer, yet the cost of the forecasting process falls on them. This could potentially result in under-spending on forecasting processes as customers are unlikely to spend resources purely for the benefit of their suppliers. No single major customer had an average 2 week FAI of above 92% for the entire year, which would constitute medium performance according to the classification made by the VDA (2008). However, the fact that Customer E had an average FAI for 2 week lag of 96% after week 30 shows that better FAI scores should be attainable, in particularly as Customer E went from being exceptionally poor, having large variations late, to being the best out of all major customers momentaneously.

The reason that the major customers are not making more significant efforts to improve forecasting might not be rooted in a lack of resources or ability to improve, but rather that they see no urgency to do so or missing. As long as there is no loss of supplier delivery precision due to poor forecasting, there is little need for the customers to improve their forecasting. The created uncertainty due to inaccurate forecasts causes difficulties in maintaining delivery precision, however the effects are not necessarily dealt with by the customer. The penalty fees for failed delivery shifts responsibility to the supplier, resulting in built in over-flexibility through safety stocks and slack in production, creating a situation where there are no incentives for the customer to do anything about the situation. As long as the customer acts in accordance with the supplier contract, all responsibilities for dealing with the uncertainties will be on the supplier. There is limited reason for the Customer to go beyond what is strictly necessary for their organisation, which does not necessarily coincide with what the Supplier desires.

The raw data used to generate the DELFOR forecasts is sales forecasts. The customer naturally wants to have accurate sales forecasts for long term production and capacity planning, and are not detailed in terms of variants. The final volumes for each component will be set when the production schedule at the OEM becomes firm. Companies' order books relate to how far they are in need of forecasts. Instead of using forecasts, companies with order books are aware of the firm orders and can use them in production planning. In most cases production decisions at the Supplier will have to be taken before definite information regarding quantities is known to them. In most cases, forecast information is used for long-term or rough planning at the Customer, whereas it may be used for operational decisions at the Supplier. This difference in how and when the information is used can create problems, as the sales forecasts are generated by the Customer, with their own needs in mind. The end result is that the Supplier never has perfect information to make their decisions and need to take measures to manage changing demand after production has started.

6.1.3 Patterns in WTS

On average, across all forecasts, there is a tendency to overestimate future needs in forecasts. However, this trend is not universal, as there are some customers that do not exhibit this pattern. While overestimations in long term prognoses could to some extent be explained by optimistic sales forecasts and a general tendency to be over optimistic, many customers have WTS well above 0, indicating a tendency to overestimate even on short planning horizons. As argued under 'Reasons and effects connected to poor FAI performance' customers likely do not care about their forecasts beyond getting their components on time and in adequate amounts. Knowingly overstating demand could then be used to ensure that the suppliers build excess capacity into their production and logistics. This helps the customer ensure that the supplier can always meet their quantity requirement, but also leads to extra costs for the supplier. The only major customers that do not have a WTS significantly above 0 in their short term plans are Customer B, Customer C, Customer G and Customer H. For Customer C, Customer G and Customer H, there is a pre-assembly of the parts before components are sequenced and brought to the final assembly line at the OEM. Customer C and Customer H are external pre-assembly companies and Customer G does pre-assembly in-house. The two external pre-assembly companies are the ones least prone to overestimation, with a tendency towards underestimations.

We see overestimates as a sign of uncertainty or lack of confidence. We see several plausible causes for this systematic bias; uncertainty in demand, lack of confidence in data used for material forecasting, lack of confidence in own ability to forecast and lack of confidence in supplier's ability to deliver. For short planning horizons, variations in demand should be low, and close to negligible. However, if the manufacturer has very low safety stocks and other buffers to cut costs, any variation could be significant. It is possible that the manufacturer knowingly always makes forecasts that are in the high end of what is deemed possible, utilising the forecast as a type of buffer to guard against short term upswings in demand from their customers. If demand goes up, the added volume in the forecast guards against delays in delivery. If there are no changes or if demand goes down the manufacturer adjusts their forecast down. Late reductions to order quantities are perceived as easier to deal with by the Supplier, compared to late increases. While late reductions may lead to excess inventory, it allows for the Supplier to manage the change without the need for ordering overtime or express deliveries of material from the subcontractors. From the data studied, it seems that for customers that do not have a tendency to overestimate, there is a layer of pre-assembly between the OEM and the Supplier which carries with it buffers, supply chains where the Supplier is a tier 2 supplier to the OEM. Based on the supply chain segments studied, it would appear that tier 1 suppliers have larger buffers compared to the OEM. OEMs are therefore at greater risk of stockout if there is a late increase to their materials requirements that cannot be met by their supplier(s). This could influence their forecasts to tend to be on the high end of the expected range of probable quantities.

6.2 Potential sources and improvements to poor forecasting accuracy

To explain the sources of inaccuracies in forecasts we will consider two processes and how they can affect the accuracy of forecasts sent in DELFOR messages to the Supplier. Firstly, the data that eventually will constitute the DELFOR forecast is sourced from the company sales forecast. The quality and accuracy of the sales forecast directly impacts the ability of production managers to create accurate forecasts for the suppliers.

6.2.1 Sources of error and areas for improvement in sales forecasting

In all three customer organisations studied, DELFOR forecasts are based on forecasts generated by the sales organisation. These forecasts attempt to capture the future movements of product demand, based on a wide range of data.

As the (long term) production planning, and subsequently demand forecasts are based on the sales forecast, if the accuracy of sales forecasts is poor the accuracy of demand forecast will also be poor. The effect of processes between the sales forecast and the demand forecast will be discussed further in the next segment. Differences in forecasting accuracy between customers could stem from several different causes; the inherent variations in end product demand impacting ability to conduct accurate sales forecasting, the methods used for sales forecasting and the processes generating the component demand forecast based on the sales forecast. As these are independent variables that are difficult to isolate when examining the data, drawing definite conclusions regarding the exact impact each of them carries becomes difficult. However, based on observations made, some hypotheses and implications can be found.

Figure 21 shows the FAI for different forecast lags, ranging from 3 weeks to 26 weeks. The dips in FAI for Customer D and Customer H at 8 and 18 weeks, respectively, is due to changes in planning buckets that impact the calculation of FAI for these lags. Do note that forecasts from Customer H are in essence the forecasts made by OEM 1, as Customer H does not make any forecasts of their own, but only breaks down the ordered systems into components and adds their internal lead times and doing unit load rounding before sending the forecast on to the Supplier. As systems delivered from Customer H to OEM 1 are unique and connected to a specific customer order, there should be no mutation of the data before it reaches Customer H. For forecasts, OEM 1 simulates customer orders based on overall sales forecasts and historical product variant and customisation data. The three studied customers exhibit significantly different patterns for their FAI. Customer D and Customer H have order books that are relatively filled for at least the coming 8 weeks at any point in time, resulting in high accuracy for lags shorter than 8 weeks. Outside of this horizon, FAI drops for both, however Customer D maintains a consistently higher FAI even outside of this period. During interviews, the interviewee at Customer D emphasised their close integration of non-time series based quantitative data in sales forecasting. Data such as GDP forecasts were actively and directly used in calculating sales forecasts for the future and seen as a core part of the forecasting process, whereas this did not appear to be the case for Customer E and OEM 1 based on the interviews. GDP as measurement is relevant in those cases when sales forecasts are created on a longer horizon than regular weekly forecasts. Shorter horizons are analysed in study, which implies that the effects of GDP are difficult to examine. However, we believe that the process of actively searching and utilising complementary data will increase contextual understanding. While processing and integrating complementary data, the context of the forecast will be better understood and the forecasted demand may be scrutinised more closely and potentially revised.

Forecast Lag (in weeks)	Customer D FAI, high volume	Customer H FAI, high volume	Customer E FAI, high volume
3	93.2%	86.7%	64.2%
4	92.2%	83.3%	66.6%
5	90.5%	82.0%	63.6%
6	90.5%	76.4%	63.3%
7	89.4%	76.9%	60.9%
8	58.7%	69.3%	56.5%
9	77.8%	67.3%	56.3%
10	76.9%	63.7%	53.3%
11	75.7%	67.3%	54.5%
12	78.2%	63.7%	54.5%
13	81.0%	62.9%	56.6%
14	79.3%	59.0%	53.7%
15	78.7%	57.0%	59.8%
16	80.5%	55.4%	58.9%
17	82.2%	57.4%	61.9%
18	80.7%	23.6%	62.4%
19	79.7%	57.0%	65.1%
20	78.3%	61.0%	61.2%
21	77.7%	62.4%	61.2%
22	77.2%	57.0%	60.8%
23	74.6%	54.1%	60.4%
24	74.0%	52.8%	61.0%
25	74.4%	51.5%	63.6%
26	73.8%	46.4%	61.8%

Figure 21. FAI for highest volume components for Customer D, Customer H and Customer E, respectively. Accuracy given for forecasts ranging from 3 weeks to 26 weeks ahead of delivery.

Customer D is already utilising proactive measures in their forecasting, such as market trend analysis, to improve their long term forecast accuracy where there are no firm orders in the order book to use. Customer D, in addition to Customer F, which uses the same forecasting process have a significantly better accuracy in their long term forecasts, longer than 3 months, when compared to other customers of the Supplier. This data is of course insufficient to draw firm conclusions on the value and applicability of quantitative market data in forecasting. However, the higher forecasting accuracy of Customer D and Customer F, along with interviewees at both Customer E and OEM 1 expressing quantitative market data as a probable "next step" in their forecasting could be indicative of the value of quantitative market data for forecasting. Logically, data regarding probable market developments should prove useful in improving forecast accuracy, if the data is reliable.

Better long term forecast accuracy can help both the Customer (read manufacturer) and the Supplier in balancing production lines and making accurate decisions regarding capacity planning. With accurate long term capacity planning, the supply chain can dimension processes in such a way where the need for express transports, over time or unbalanced production lines carrying extra costs or inefficiencies.

In terms of forecasting performance within each of the three supply chain segments studied we have identified differences in forecast accuracy for forecasts more than 4 weeks ahead of time. Out of the three supply chain segments studied, the one between Customer E and the Supplier had the worst long term forecasts. Customer E currently forecasts based on historical sales data and as future variations in demand do not necessarily correlate to past variations they become difficult to predict using historical data. OEM 1, whose forecasts are visible to the Supplier through Customer H, showed significantly better accuracy for long term forecasts when compared to Customer E. However, even taking into account the time lags created by the lead times of Customer H, the long-term forecasts of OEM 1 have a lower accuracy when compared to the accuracy of forecasts made by Customer D & F. The general process of forecasting is very similar between OEM 1 and Customer D & F, with forecasts for total volumes being broken down into variants based on statistics on frequency of each variant. The key difference is that Customer D & F utilise both quantitative and qualitative proactive data when creating forecasts, whereas OEM 1 mainly utilises qualitative proactive data.

However, there are more different components and variants sent from the Supplier to Customer H and subsequently to OEM 1, when compared to the number of different components and variants sent to Customer D & F. This could have an effect on the ability to perform well in forecasting, however when only high-volume components for each of the two supply chain segments are compared, the difference in accuracy is even more remarkable, particularly for forecasts 3-6 months ahead of time. Forecasts with long horizons makes it difficult to create weekly-based plans. Both of the segments have significant dips in accuracy for one of the forecasting horizons (8 weeks for Customer D, and 18 weeks for Customer H). For Customer D, 8 weeks is the point at which weekly demand figures are split into daily deliveries. The software used determines whether the forecast demands should be compared to daily or weekly reference demands, and the progressive transition from weekly to daily demand buckets likely causes weekly reference demand being compared to daily demand forecasts, or vice versa, for 8 week forecasts. It is however evident that Customer D has a significantly better forecast accuracy for high-volume components from the Supplier. Both the forecasting process and the production systems that make use of them are complex, and the exact value and impact of different methods and data sources become difficult to isolate and evaluate.

	Time series	Qualitative market data	Quantitative market data
Customer D	X	X	X
Customer E	X	-	*
OEM 1 (Customer H)	X	X	*

*Figure 22. data types directly integrated in sales forecasting. X denotes data currently being used, * indicates that the organisation is evaluating the value and applicability of the data type in their processes.*

While the nature of end customer demand will result in direct comparisons of demand forecasts never being completely fair, component demands from Customer D and Customer H both stem from production lines with set production rates that rarely change. In light of this, the difference in accuracy is remarkable and difficult to explain with only variations in end customer demand. Also note that where there are limited to no firm or preliminary orders to base forecasts on (roughly 12 weeks and onwards), the forecast accuracy of Customer H falls off. Customer D, on the other hand has a rather consistent level of accuracy across all forecast horizons beyond 12 weeks. This could potentially be explained by high quality qualitative data from end customers being scarce for long horizons, whereas data quality of more quantitative data such as macroeconomic forecasts and analysis still maintains reasonably high quality for these horizons. This would indicate that incorporation of proactive data increases forecast accuracy for horizons longer than 4 weeks, as shown by comparison between Customer E and Customers D & H. However, qualitative data does not seem to have any impact beyond 12 weeks, where the forecasting accuracy falls off. For Customer E, on the other hand, only looking at retroactive data appears to result in forecasts being roughly as accurate regardless of forecast horizon. All indications from the data are summarised in figure 23. Based on the data available, it appears that more advanced or more closely integrated analysis of quantitative proactive data contributes to improved forecasting accuracy for horizons around 3 months and beyond, whereas qualitative customer data appears to matter little outside of preliminary orders in the order book.

Type of data used	Implied impact on forecast accuracy
Retroactive data	No difference in forecast accuracy across forecasting horizons
Retroactive data + qualitative proactive data	Improved accuracy for 4 – 10 week forecasting horizons, little to no effect beyond that compared to only retroactive data
Retroactive data + qualitative & quantitative proactive data	Improved accuracy compared to only retroactive data or retroactive and qualitative proactive data across all planning horizons, particularly for longer horizons

Figure 23. Summary of indicated impact on forecast accuracy depending on type of data used in forecasting.

As this study was limited in the number of cases and different supply chain segments studied, no concrete general conclusions regarding the impact of different data types on forecast accuracy across different horizons can be drawn. However, based on the cases studied, the effects appear significant and warranting further study.

Having high forecast accuracy for long planning horizons allows suppliers to make accurate plans of their own further ahead of time. As exemplified by interviews, the large increase in volume ordered by Customer E communicated soon before delivery at the time of the study would have been impossible to deal with without significant safety stocks. If such large variations could be seen further ahead of time, the need for the Supplier to constantly carry such large numbers of finished components and materials would decrease. This would in theory allow them to manage many of the variations in end customer demand through more effective capacity increases or decreases rather than ordering overtime or express transports and additional safety stock. This carries with it potentials savings in cost of operations as well as in avoiding loss of revenue as a result of inefficiencies or disturbances in production due to inaccurate planning. These potential saving would have to be weighed against the costs of implementing and maintaining new forecasting processes that utilise proactive data, either qualitative or quantitative.

Returning to the conceptual framework developed by Rieg (2010), focusing on statistical methods, hardware/software and processes, where the author found no improvement in forecasting accuracy over a period of 15 years. The methods studied were time series based forecasting methods, implying that methods based on historical data have potentially reached their potential in terms of accuracy.

In an attempt to analyse the potential to use measurements such as GDP growth, inflation adjusted car sales revenue was compared to real GDP growth for Sweden and some of the major economies in Europe. Car sales revenues were gathered from Eurostat data. GDP growth and inflation were gathered from IMF (International Monetary Fund) data. The results are summarised in figure 23.

Country	Correlation of inflation adjusted GDP and inflation adjusted car sales revenue between 2012 and 2016
UK	0.996
Sweden	0.993
Spain	0.976
Germany	0.927
France	0.837
Italy	0.674

Figure 24. Correlation coefficient between GDP growth and car sales for selected economies.

GDP and car sales appear closely correlated for most of the countries, implying that GDP could be used effectively to create future forecasts. Of course, this is for the total revenues of all companies in the sector, and depending on competitive developments may not be true for the individual company. In the companies studied, the sales forecast is made for the main product models. Improvements to the sales forecast would lead to improvements to the accuracy of total volumes in forecasts and in volumes for each of the main product lines. Within each product line there are different models and variants, and the distribution of purchases between these variants can change over time. Changes to model and variant mix can still occur, but GDP should be possible to use to forecast future revenue and total volume increases or decreases with reasonable accuracy. A potential benefit of utilising GDP in forecasting is that there is extensive research done around GDP forecasts by external organisations that manufacturers can tap in to at a much lower cost compared to generating similar forecasts of predictions of their own.

While closer incorporation of non-time series data may improve forecast accuracy, previous studies have highlighted usage Artificial Neural Networks (ANNs) as a potential way to improve forecasting accuracy only using time series data. Results from such studies are not universally positive to ANNs, but overall most studies conclude that ANNs are better in all or some situations. In particular, seasonal or trend patterns as well as limited previous data appear to be better managed by ANNs. While production in the automotive industry may not be significantly seasonal in its nature, the aftermarket is. For example, more windshields are changed during spring due to stone chips after the snow melts. Production in the automotive industry is, however, trend dependent and market trend heavily influence production. For a new product launch ANNs should be quicker to adapt and provide accurate forecasts according to previous research, as some studies found they required less data to be accurate. While the potential improvements that could be made through implementation of ANNs in the forecasting processes are uncertain, the prospect certainly has potential and should be investigated further.

Current performance overall is far from the goals suggested by the VDA. If these goals are possible to achieve, forecasting performance in the Swedish automotive industry is exceptionally poor, as can be seen in figure 24.

	VDA 'Good'	**All Customers**	Customer D	Customer E	Customer H
Short (0-2 weeks)	97%	**85.40%**	86.60%	79.60%	89.70%
Medium (3 - 8 weeks)	95%	**58.72%**	78.40%	48.97%	67.47%

Figure 25. Average FAI for all customers, as well as for the customers studied compared to the goals set by the VDA.

However, due to difficulties in forecasting low-volume components accurately, which will be discussed later in the paper, this level of forecasting accuracy across all items may not be feasible. The lower volume components are more difficult to forecast accurately, and the benefit of doing so for each article is lower. Looking at each low volume component individually when forecasting is not feasible, whereas it is for high-volume components. Figure 26 shows FAI of the highest volume components.

	VDA 'Good'	Customer D, high volume	Customer E, high volume	Customer H. high volume
Short (0-2 weeks)	97%	94.4%	80.3%	91.7%
Medium (3 - 8 weeks)	95%	91.2%	62.5%	79.1%

Figure 26. FAI for high-volume components for each of the studied customers compared to the goals set by the VDA.

For high-volume components, Customer D is close to achieving the goals set by the VDA, and are already in the range the VDA defined as medium performance. This indicates that the goals are possible to reach. However, forecasting efforts should be directed at improving forecasts for high-volume components to keep costs lower. Moreover, general process improvements developed with high-volume components in mind will still have spillover effects that improve forecasting accuracy for low-volume components.

Based on the findings in this study, there are possibly two different approaches to improving forecasting accuracy. There are indications that closer or better integration of non-time series quantitative data could improve forecasting accuracy, and that implementation of ANNs could improve forecasting accuracy based on time series data. The value of closer integration of non-time series quantitative data is difficult to discern due to the complexity of the organisations and the forecasting processes. There are many different factors that affect the process, and it is not possible to say with certainty that this makes a significant different based on this study. All of the studied companies certainly utilise measures such as GDP in some way within their organisation, it is just a matter of if and how these types of data are utilised in the forecasting process. Our findings indicate that this could make a difference for long forecasting horizons, and as such we find that it at the very least warrants that companies look into their current forecasting practices and if they could utilise GDP and similar measures in a more effective way when forecasting sales.

6.2.2 Sources for errors and areas for improvement in processing and breakdown of sales forecasts

Effects of batching in production, ordering and logistics

In the case of OEM 1 and Customer D, the sales forecast is sent to production where it is broken down into demand for each component and variant based on historical data on distribution of variants. Changes to consumer behaviour in terms of popular add-ons and customisation options is something that may not be captured by the sales forecast, but still has an effect on the required materials, which can create additional variations for the suppliers. As both OEM 1 and Customer D employ a sequence flow in assembly, there are no de facto minimum production batches that affect the Supplier through sudden volume increases followed by long periods of low or no volume. Data from the production planning is then passed on to the procurement organisation that order based on inventory policies and unit loads. Unit loads were expected to have an effect on the forecasting accuracy of low volume components in particular. Figures 27, 28 & 29 show comparisons of FAI for high-volume components and low volume components for each of the three customers studied. For the high-volume components, an average of the three highest quantity components was chosen, and for the low volume components the three lowest volume components with regular deliveries (deliveries every week or close to every week) were chosen.

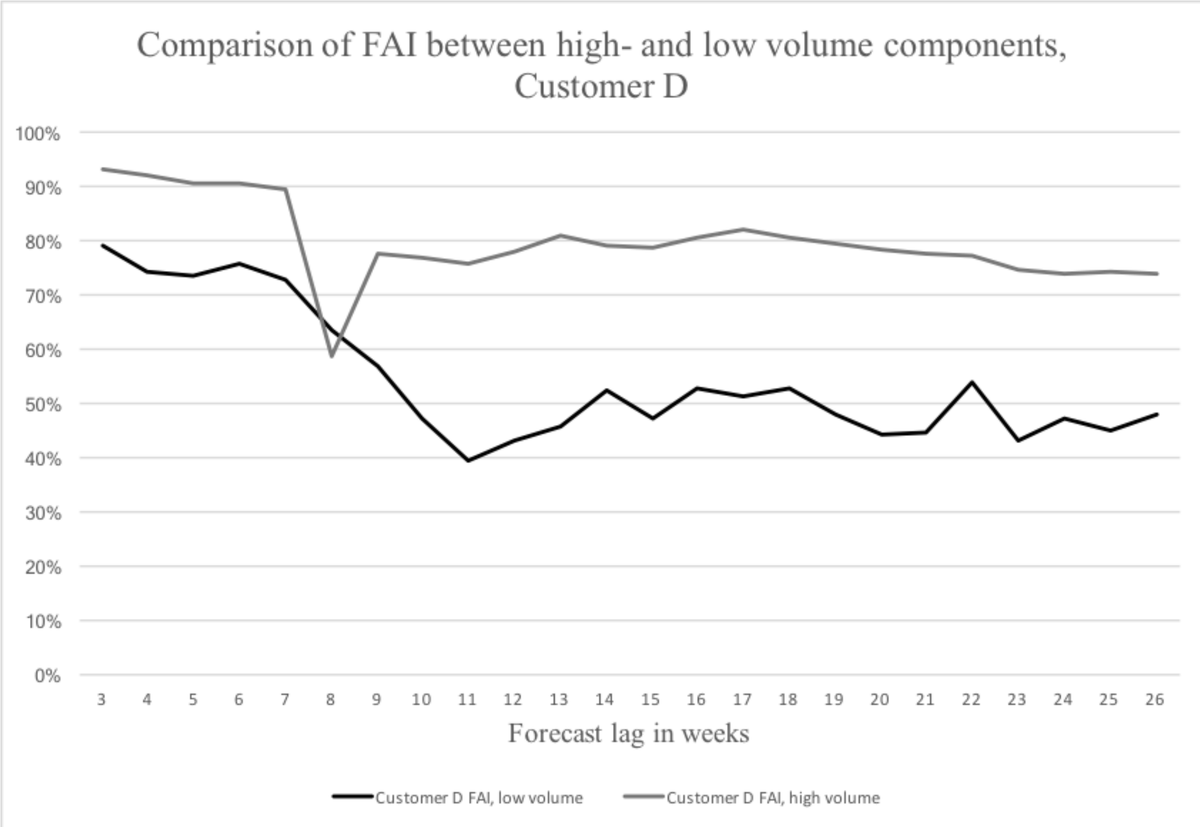

Figure 27. Comparison between high- and low volume components for Customer D.

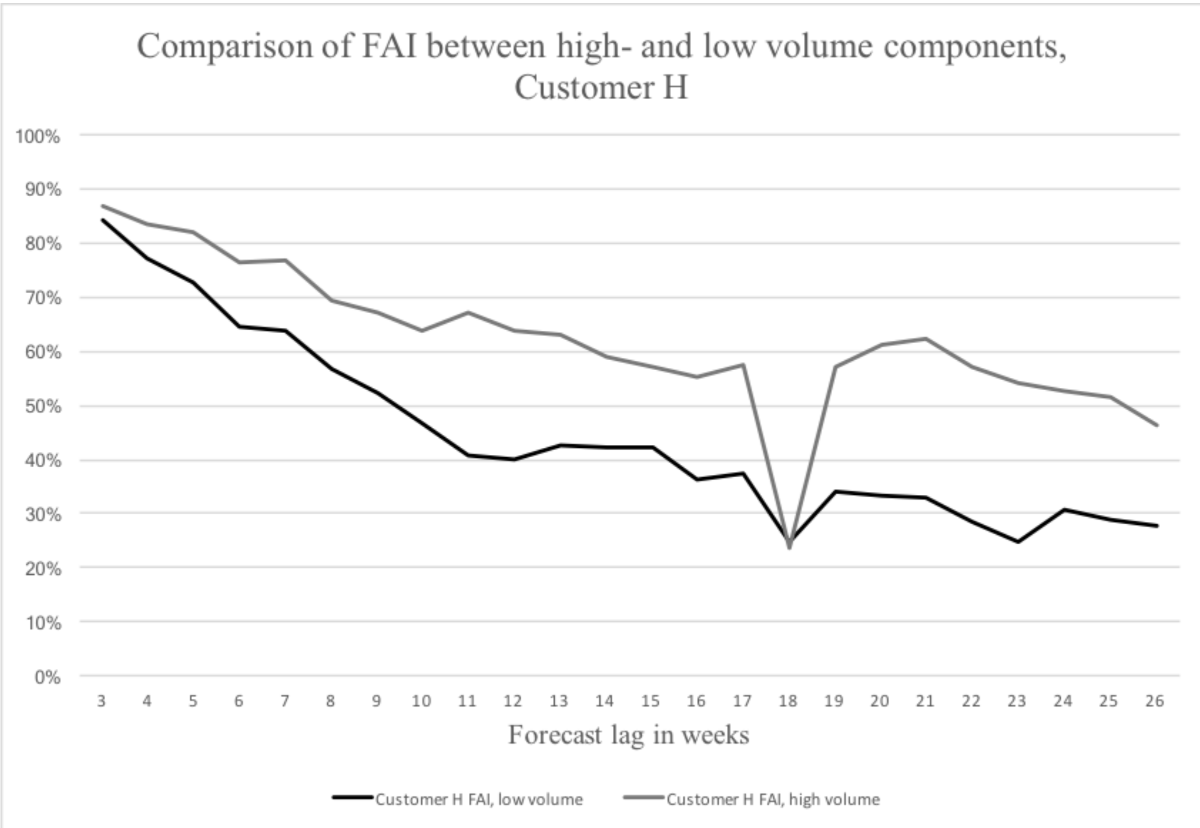

Figure 28. Comparison between high- and low volume components for Customer H.

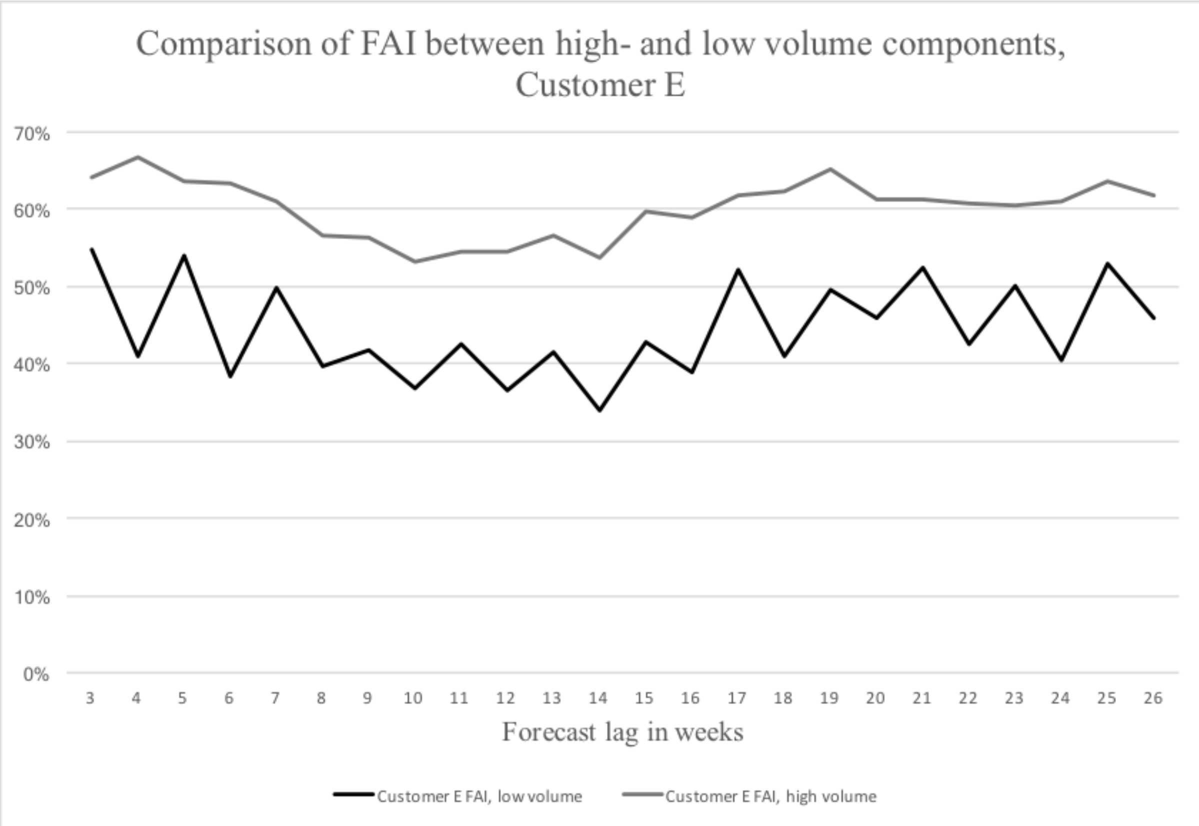

Figure 29. comparison between high- and low volume components for Customer E.

For all three customers, forecasting accuracy for low volume components was significantly lower when compared to high-volume components. While the majority of the total volumes of each of the customers studied come from the high-volume components, many of the customers order significantly smaller volumes in total, and their most frequently ordered components may account for smaller volumes than the low volume components for the major customers. In total, infrequent or low volume components still account for a sizeable portion of the total volume, which contributes to a lowered forecasting accuracy performance. With material lead times at the Supplier being roughly 1 week, and freeze times for Customers being shorter in most cases, the Supplier always needs to maintain inventory either in the form of materials or finished components to meet any sudden orders.

It is difficult to do anything about unit loads creating variations for low volume components, and these components will inherently have larger variations compared to the high-volume components. This will make them harder to forecast, however the low volume components have worse FAI even for very short horizons, where volumes are hardly a forecast, but more of a preliminary order. For Customer H the difference between high and low volume components are insignificant for horizons below 5 weeks, where the order book at OEM 1 is filled or close to filled. Customer D also has order books that are filled for this horizon, yet low volume components have much lower FAI. This difference in FAI cannot reasonably be attributed to not knowing the demand for the low volume components as well as the demand for the high-volume components.

MRP nervousness and volatility

Based on the improvements made to the accuracy of short term demand information between Customer E and the Supplier an attempt was made to quantify the benefits to provide a basis for evaluating potential future initiatives to improve forecasting accuracy. The prolongation of the freeze period for delivery schedules was expected to lower both planning and replanning costs for the Supplier, while also allowing lower inventory levels for the main components in this flow. The planner at the Supplier expressed that planning had been made easier, at least in the short term. However, he also highlighted a potential issue in that variations previously occurring in the final two weeks before delivery instead would appear as long term variations. If the customer cannot change plans they would tend to order with a margin resulting in an accumulation of components in their inventory over time. This would then lead to them lowering their demand for a period while they reduce their inventory. Demand would then show a pattern similar to seasonal variation, albeit not connected to any external events or time of year, instead of semi-random spikes in demand short term. The planner was however satisfied with the changes overall, and felt that it was a definite improvement for them. As for inventory levels, this data was not available far enough back in time for an analysis of potential changes due to the reduced short term volatility to be made. This could highlight a general issue in that enough data to make an in-depth business case for these types of changes to be made. With information unavailable, however, analysis of de facto cost savings cannot be made. We will show that theoretically, this allows a reduction of inventory levels and through that cost savings for the Supplier. For future calculations of ROI for business cases to make investments in improving forecasting accuracy, more extensive and reliable information on inventory levels and costs of replanning needs to be available if the business case is to give a realistic picture of the costs and benefits of investing.

A calculation of safety stock levels based on the SERV2 formula, which is as follows:

$$Safety\ stock = Service\ factor * standard\ deviation\ of\ demand * \sqrt{Lead\ time}$$

A SERV2 calculation was made for the total demand from Customer E. Lead times for components and service factors were kept constant for both cases studied, resulting in the standard deviation of demand being a direct determinant of demand. Assumptions made for this calculation was that only the final two weeks were relevant to determining the safety stock. No variations outside of this period were considered as relevant to the safety stock. While this is in line with the situation as perceived by planners at the Supplier as they maintained that changes outside of this period were generally manageable by increasing order volumes to suppliers or ordering extra shifts resulting in variations having limited effect on inventory levels. In reality these factors can have an effect on desired safety stock levels. While calculating the safety stock it was discovered that the change had resulted in improvements for the Supplier not only in terms of their effective lead time, but also in the standard deviation of demand. There was no significant change to the average weekly volumes, but the standard deviation decreased from .44 of weekly demand prior to the change to .31 of weekly demand after. The standard deviation as a fraction of average demand for each of the periods (before and after the change) was calculated using weekly reference demand for each component.

The examined components were randomly selected from components with varying volumes, both high and low. All components are included in delivery schedules covering a whole year. Components are sorted from A to G, based on average weekly quantity, with A having the largest average quantity and G having the lowest. The average volume for each period (before or after) is also presented as a fraction of the average demand for both periods combined. This was done as higher average volumes is expected to give increased stability, as fewer weeks will have a reference demand of 0 and rounding to unit loads will be less significant. This is also reflected in the patterns for standard deviation of each component, with higher volume components having lower standard deviation. For all components except for component D, changes in average volumes were small enough to not be expected to have had significant impact on differences in standard deviation between the two periods. Figure 30 presents an overview of standard deviations in the weekly demand of each of the components A to G.

Component	Average volume before	Average volume after	σ (weekly demand) before	σ (weekly demand) after	F tests, p-value
A	0.95	1.05	0.39	0.76(0.28)	0.000(0.349)
B	1.01	0.99	0.44	0.31	0.035
C	0.97	1.03	0.57	0.33	0.026
D	0.87	1.15	0.56	0.45	0.762
E	0.99	1.01	0.76	0.5	0.062
F	0.94	1.07	0.78	0.55	0.300
G	1.01	0.98	1.07	0.95	0.499

Figure 30. Standard deviation in weekly reference quantities.

For all components studied apart from component A, the standard deviation in weekly demand is lower after the change. In the case of component A, there were a few extreme outliers, with one week having an order equal to roughly four week's average demand, with the following three orders having no orders of this component. The number in parenthesis is the standard deviation for this period, with the 4 outlier weeks excluded. The reason behind the outliers is unknown, however, if they are excluded this component also follows the same pattern of lowered standard deviation.

While only 2 individual components have a change in standard deviation that is statistically significant, $p<.05$, the small sample size needs to be considered. For each component, there are 27 observations before and 23 after (weeks 1 and 52 excluded due to no order activity on any component around Christmas and New Year's Eve). Such a small sample makes it difficult to find statistically significant correlations. However, while most individual components do not have statistically significant changes, the changes are all reductions in standard deviation. An additional concern is that the patterns sought is for standard deviation compared to the average of each sample, whereas f-tests compare the absolute variance of each sample. Changes in average volumes could change the absolute variance while the relative deviations remain the same, or vice versa. This could also affect the results of the f-tests for components with changes in average volume between the two periods.

The effects on standard deviation indicates that the prolongation of the freeze time has had an effect not only on lead times and variations with short notice, but also on the long-term predictability of demand, by making weekly quantities more stable. As this change does not change the end customer demand or how it is forecasted, it must have had an effect on the internal processes processing this data to achieve this effect. As the underlying logic for ordering remained unchanged in terms of batching, unit loads and logic for safety stock calculations it seems likely that the effect is on the MRP calculation. The MRP will continuously make changes based on available data until it is told that it cannot make any more changes. This point changed from 1 week before to 2 weeks before delivery and had a significant effect on the stability of order quantities.

Patterns in order quantities are similar for components A to G. One week there is an order significantly above the average quantity, followed by a quantity significantly below average quantity the next week. This pattern repeats itself, creating a zig-zag pattern if plotted over time. Figure 31 shows the weekly order volumes over time for component C. Note that component C was chosen for the clarity of the pattern as well as a relatively stable average volume over the course of the year. The patterns are less obvious albeit still visible for most of the components.

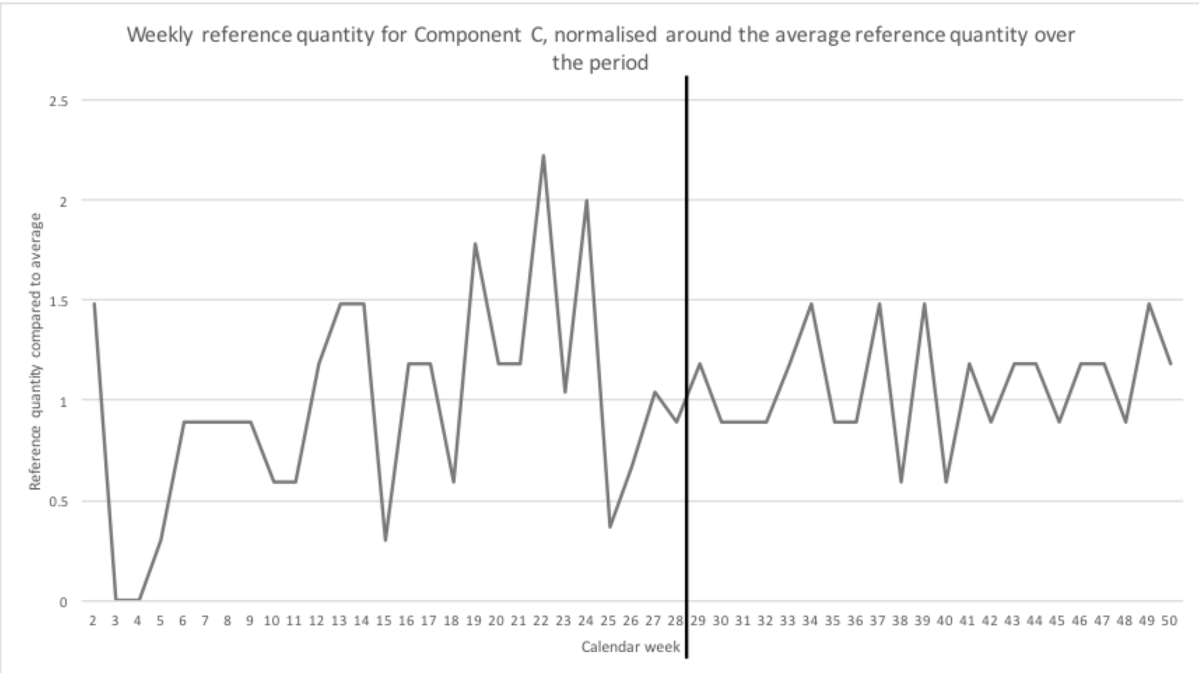

Figure 31. Weekly reference quantities compared to the average reference quantity for the period for component C delivered to Customer E. The vertical black line indicates the point in time where freeze times were prolonged.

While the pattern of alternating high and low quantities remains unchanged after freeze times were prolonged, the magnitude of variations was significantly smaller.

A possible explanation is that the MRP creates the additional variation seen before on its own. In general, the variations seen in the demand information from Customer E is that the volumes are steady for the majority of the time. However, sometimes there is a large increase in volume for one week followed by a large decrease for the following week. Before freeze times were prolonged, these sequences of increased and decreased weekly volumes were slightly more frequent, but more importantly the changes were larger. Before the change, some weekly were close to double that of the previous week, with the following week being close to zero. After the change, there are almost no changes of this magnitude. It would seem that before freeze times were prolonged, the MRP overestimated the risk of material shortage, resulting in large orders. Once the materials were delivered the MRP lowered orders as inventory levels were high. After freeze times were prolonged, the MRP has not been overestimating the risk of material shortage to the same degree resulting in fewer instances of over-ordering of materials. A potential explanation is that with the prolonged freeze time there are larger volumes of materials in confirmed orders that the MRP can see as available or on the way. This results in larger buffers in the calculations made by the MRP, and subsequently fewer instances of the MRP over-ordering for a fear of material shortage.

To test whether the increased stability in demand quantities was visible in longer term prognoses, the accuracy of forecasts 4 weeks and 6 weeks ahead of time were compared before and after the prolongation of freeze times. The average accuracy of 4 week forecasts increased from 47% to 55%, and the accuracy of 6 week forecasts increased from 40% to 51%. This indicates that the stabilisation of weekly demand has improved predictability within both organisations potentially making planning more accurate.

Variations in quantities of end customer demand can be assumed to remain the same, as the change made should have no bearing on it. Regardless, the variations in quantities found in orders from Customer E to the Supplier have been significantly reduced. This indicates that Customer E currently manages more of the variations in end customer demand internally, or at the very least do not amplify them as much. Prolonging freeze times will have impacted the flexibility of Customer E negatively when it comes to component acquisition, however the Supplier will have been given more flexibility. As Tsay (1999) showed, there is an optimum that maximises system profit for QF contracts with regard to customer flexibility in changing volumes. Both having no flexibility and having full flexibility for the customer results in sub-optimal system profits. As such there should, for each system, be an optimal level of commitment to forecasted volumes that maximises system profit. While freeze times are not explicitly discussed in the component, they could be seen as one of the determinants for customer flexibility. Depending on the structure of the system, considering production lead times, current distribution of inventories among other factors, there should be a freeze time that optimises total system profit. Regardless of whether there is a true optimum in terms of the length of freeze times, changing the freeze times appear to have changed the system in a multitude of ways in this case. The Supplier has been given some additional flexibility by having longer periods of firm demand, while simultaneously having a demand profile that is more stable over time. This would allow them to lower their safety stock and general inventory levels for these components. On the other hand, Customer E has increased their inventory levels to cover for the lower flexibility. While it may be possible that optimal freeze times exist that maximise total system profits, they are likely complex to find and subject to the attributes of each individual product.

However, longer freeze times appear to reduce variations in weekly quantities, in addition to giving suppliers longer time to react. This would be preferable to the suppliers, but disadvantageous to the customers as they give up their flexibility. A potential solution could be to maintain freeze times for deliveries, but move the "earliest changeable date" forward in the MRP system. This would achieve the same calming effect on the MRP as prolonging freeze times, while still retaining the right for customers to make changes. We would expect this to stabilise volumes significantly at the cost of some manual labour for monitoring MRP warning signals and potentially a slightly larger risk of stockout at the customer. This would likely prove too time consuming and risky for critical components, however could provide a way to significantly reduce volume variations for low quantity and non-critical components.

Order logic

The different customers studied utilise different logic in their MRP systems for triggering new orders to the Supplier. Customer E utilises a "traditional" MRP process, where orders are triggered based on current inventory levels including safety stocks, forecasted volumes for incoming demand, EOQ and lead times. This leads to batching of orders with the goal of optimising cost efficiency in logistics. A side effect of this is that order intervals and order sizes to suppliers are not directly connected to end customer orders. While end customer demand and orders will lead to replenishment orders from suppliers being triggered, the MRP works around inventory levels and expected rate of usage from the inventory. Logically orders are placed to refill the inventory in this case.

On the other hand, orders from Customer D and Customer H are based on a 1-to-1 relationships with end customer orders, either firm or forecasted. End customer orders are broken down into components and the exact number of components needed for each day is used to generate the daily order. The only batching that occurs is rounding to unit loads. Existing inventories are only seen as buffers and are not considered in the order process. This 1-to-1 connection between end customer demand and supplier orders creates weekly reference quantities at the Supplier that follow end customer demand more closely. Here, orders are not placed to refill inventories, but rather to fulfil end customer orders.

Figure 32 shows weekly reference quantities for a high-volume component ordered by Customer D, normalised in the same way as component C for Customer E in figure 30. Order quantities for the component from Customer D are significantly more stable across the year compared to component B, especially when the fact that weeks 18, and 19, which are lower in quantities, each contain a bank holiday, weeks 29 through 32 were the industrial vacation period and week 52 is around Christmas and New Year's Eve. Across all weeks with normal operations order quantities remain stable from Customer D, whereas for Customer E they are not. We believe this to be due to the order quantities of Customer D being solely determined by end customer orders, whereas Customer E also incorporates inventories and logistics factors in their order logic.

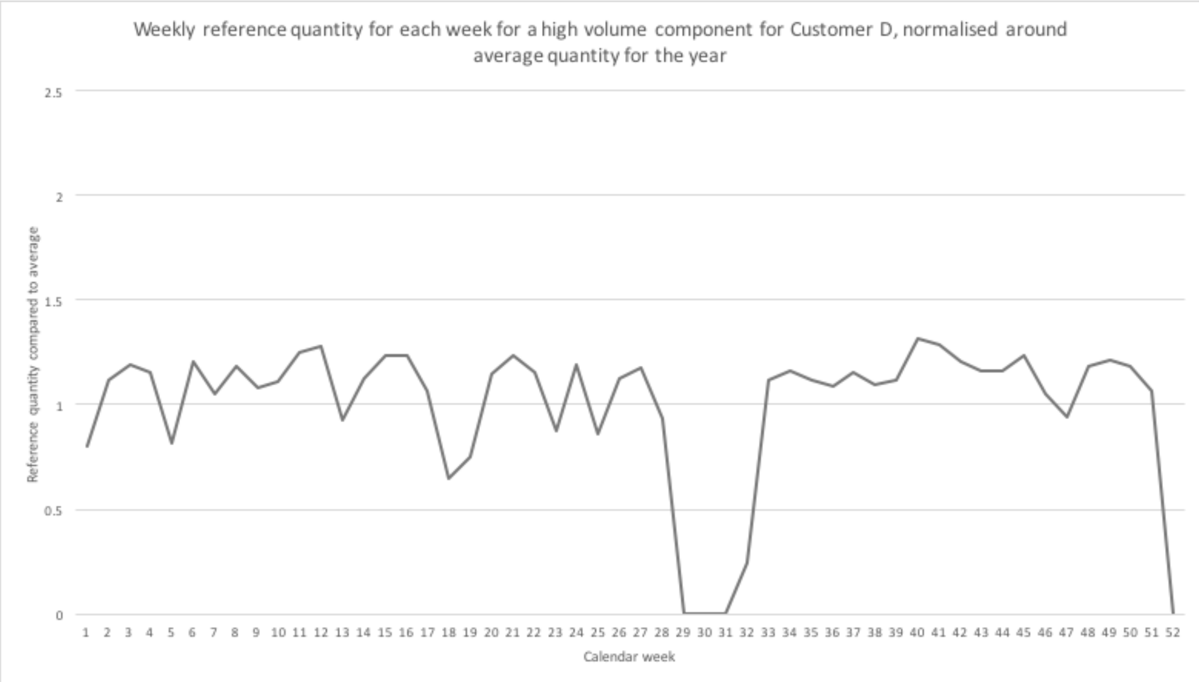

Figure 32. weekly reference quantities compared to the average reference quantity for the period for a high-volume component delivered to Customer D.

Decoupling inventories and buffers from the order process and letting orders to suppliers follow actual end customer orders directly appears to create stability in the system with a smoother flow compared to the situation where significant volumes are held in inventory and released in bulk quantities. For high-volume supply chains where high truck fill rates can be achieved without batching this would seem to be a preferable solution as the flow becomes more stable without significant sacrifices to logistics efficiency.

Figure 33. Weekly reference quantities compared to the average reference quantity for the period for a high-volume component delivered to Customer H.

Figure 33 shows the same information as figures 31 & 32, but for a high-volume component delivered to Customer H. Customer D and OEM 1 (orders visible through Customer H) use the same general order logic, using only end customer orders when generating orders to their suppliers. Component orders are generated specifically to fulfil existing end customer orders. The main difference is that OEM 1 has some incoming orders that are batched. They deliver some products as “lego boxes”, with half assembled vehicles being assembled elsewhere. This is done for some geographical markets, and can be seen in orders as sudden spikes up in quantities throughout the year. Having incoming customer orders that are batched could potentially cause problems for a system that is not built on the premise of batching, but rather a 1-to-1 relationship between customer order quantities and supplier order quantities. However, it does not seem to cause a cascade of replanning throughout the supply chain, but is absorbed by the buffers without resulting in stockouts or drops in delivery precision in or out.

6.3 Effects on the Supplier as a result of unforeseen variations

When there are variations in demanded volumes that were not predicted in demand forecasts, the Supplier needs to manage them in some way to maintain delivery precision. We identified several ways in which a supplier could manage unforeseen variations: Additional inventory, express or premium transport solutions, overtime in production and built in over-capacity in production. Based on interviews at the Supplier, inventories were the main tool used in managing unforeseen variations. Additional materials and components were kept on-hand to ensure that orders could be filled, and safety stock was then refilled with the next production batch or materials delivery. Based on financial data from annual reports the Supplier had an inventory turnover rate of 12.2 for between January 2016 and Mars 2017, and a turnover rate of 15.9 between April 2017 and December 2017 (Annual reports did not follow the calendar year due to ownership changes). At the time of the interviews, inventory turnover rates were 10.4 for component group D10 and 13.7 for component group H10. Compared to previous studies that placed average turnover rates for suppliers steel and metal components within the automotive industry at 6.1 for years 2006 - 2008 (Lind et al., 2012), and roughly 7.5 for transportation equipment manufacturing in the U.S. during 2017 based on total shipment values and inventories as estimated by the United States Census Bureau (industry code 336). Figure 34 shows the inventory turn rate for a selection of the largest automotive industry component suppliers by revenue, as well as the Supplier.

Company	Inventory turn rate	Main market (by share of revenue)	Year
Gestamp Automoción	18.02	Europe (61.9%)	2018
Lear Corporation	17.67	North America (40.9%)	2018
Aisin Seiki Group	14.11	Japan (58.8%)	2018
Hyundai Mobis	13.31	Republic of Korea (36.2%)	2017
Faurecia	12.25	Europe (50.5%)	2018
The Supplier	**12.2**	**Sweden (68.9%)**	**2017**
Magna International	12.00	North America (50.3%)	2018
Autoliv	11.45	Asia (36.8%)	2018
Aptiv	11.3	United States (37.3%)	2018
Valeo SA	10.03	Europe & Africa (48.5%)	2018
Plastic Omnium	9.83	Europe & Africa (54.4%)	2018
Continental	9.82	Europe (49.3%)	2018
ZF Friedrichshafen	9.43	Europe (47.1%)	2018
Denso Corporation	9.28	Japan (41.9%)	2018

Figure 34. Inventory turn rates of major automotive component suppliers compared to the Supplier. Note that not all companies had released annual reports for FY 2018 at the time of the study.

The Supplier ranks slightly above the median turn rate and almost exactly the average turn rate (12.19), indicating that their inventories are in line with current practices in the industry. However, all companies had turn rates significantly above the turn rates a decade ago. Inventories and buffers are significantly smaller compared to a decade ago, potentially making them more sensitive to disruptions and unforeseen events. As reliance on retroactive risk management through inventories has reduced, the ability to act proactively in relation to risks and variation is of increased value. Part of the necessities for proactive action to manage risk and variations is forecasting. With the reduction of inventories, correct forecasts become more important if the supply chain is to function optimally.

Based on these benchmarks, inventory levels in the supply chain segments studied are comparatively low. Considering that inventories are seen as the primary tool to manage unforeseen variations, and the comparatively low inventory levels, the system is sensitive to unforeseen variations. This emphasises the importance of accurate demand forecasts in ensuring the stability and functionality of the supply chain segments studied. However, the Supplier still has comparatively high inventory levels compared to the best in class. Improvements to forecasting accuracy are expected to allow for reductions in inventory levels. To reach the same inventory turn rate as the top performers, the Supplier would need to lower inventory levels by roughly 30%, and if improved forecasts could make this possible savings would be large. And if the multitude of Suppliers serving each of the major OEMs, and the number of subcontractors behind each of them, all dependent on demand forecast information from the OEM, the potential effects and potential savings become magnitudes larger.

While the FAI scores of most customers are poor, and none of the customers reach the target in forecasting accuracy set by the VDA, this is not seen as a big problem operationally at the

Supplier. At the same time, inventories at the Supplier which are the main tool used to manage unforeseen variations, are roughly equal to the industry average for component suppliers which indicates that the Supplier is not having bigger problems managing variations compared to similar companies. FAI does not perfectly capture the nature of variations and inaccuracies, and the FAI score may not accurately reflect the impact variations has on a supplier. Consider the following scenario: There is a forecast for 1000 units each week for a specific period. This forecast is changed late, after the supplier has made their production decision, with the following three different scenarios for the final demand. Figure 35 describes a forecast given for five weeks, and figures 36, 37 and 38 describe three different scenarios of possible changes from the forecast to the final orders.

	Week 1	Week 2	Week 3	Week 4	Week 5
Forecast	1000	1000	1000	1000	1000

Figure 35. Example of forecasted demand.

In Scenario 1, the delivery scheduled for Week 2 is delayed and instead sent along with the normal delivery on Week 3. The rest of the weeks remain unchanged.

	Week 1	Week 2	Week 3	Week 4	Week 5
Scenario 1	1000	0	2000	1000	1000

Figure 36. Change scenario 1: Demand is moved to a later week.

In Scenario 2, an additional 1000 units are added to the Week 3 delivery and the other days remain unchanged.

	Week 1	Week 2	Week 3	Week 4	Week 5
Scenario 2	1000	1000	2000	1000	1000

Figure 37. Change scenario 2: Increase in demand from forecast.

In Scenario 3, the delivery scheduled for Tuesday is cancelled and the rest of the days remain unchanged.

	Week 1	Week 2	Week 3	Week 4	Week 5
Scenario 3	1000	0	1000	1000	1000

Figure 38. Change scenario 3: Reduction in demand from forecast.

Calculating the FAI for these two scenarios yields the following results. For Scenario 1 FAI is 60% using unweighted average or if weighting by final volumes. For Scenario 2 FAI is 80% if using unweighted average and 66.7% if weighted by final volumes. Regardless of calculation method Scenario 2 is viewed as a more accurate compared to the forecast. For Scenario 3 FAI is 80% using unweighted average and 100% if weighting by final volumes. Operationally Scenario 1 would likely be the easiest to deal with (especially if the transport is owned by the customer). Since the production decision is already made, the Week 2 delivery need only be kept in inventory for an extra few days. For Scenario 2 the supplier needs to deliver 1000 units more than what they planned to when taking the production decision or they will be unable to deliver to their customer. For Scenario 3, the Supplier ends up over-producing resulting in additional inventory. This inventory will likely be possible to use to reduce production for the next period, so the effect is not very significant other than additional inventory for a short period of time and replanning of production for the following period.

These scenarios help explain some of the aspects of demand variations that cannot be captured fully by FAI. The scenario with the lowest FAI regardless of calculation method probably has the smallest effect on the supplier operationally, whereas the scenario with the largest operational effect is not seen very clearly in FAI scores unless volume weighting is used. However, if weighted by volume, cancellation of orders is not seen as an inaccuracy at all. In a normal supply chain variations of the same types as all three of these scenarios occur, which can make it difficult to fully understand the impact of forecasting accuracy on the supplier based on FAI scores alone. Perhaps, supplementary measures that help understand to what degree different types of changes and variations contribute to the FAI score. WTS can help understand this to some extent, but not fully.

	Scenario 1	Scenario 2	Scenario 3
WTS	0	-1	1

Figure 39. Summary of WTS scores for the 3 described scenarios

WTS can give some idea on whether variations tend to be increases or decreases in volume compared to forecasts, but can do little to quantify the effect from the inaccuracies on the suppliers. For example, the frequency and magnitude of changes and inaccuracies remains unknown. For the supplier, 1 change of magnitude 4 is likely more difficult to handle than 4 changes of magnitude 1. Additionally, FAI and WTS only capture inaccuracies in forecasts which are one source of variations and uncertainty. But just because a change in demand is known in advance, it does not mean that it cannot be problematic for the supplier. More accurate forecasting methods and fewer systematic variations introduced between the sales forecasts will result in less uncertainty and fewer variations in quantity for the supplier, but there are limits to how much can be done through forecasting alone. Nevertheless, forecasting is an important supporting function to production and measures should be taken to ensure that forecasting supports production as effectively as possible.

7. Conclusions

In this section, a summary of the conclusions will be provided for each of the research questions.

7.1 Research question 1

Based on the quantitative data, current forecasting accuracy performance was deemed to be poor. No companies were able to achieve what the VDA had set as a target for 'good' forecasting performance. Assuming the VDA was realistic when setting the targets, there is plenty to be done in terms of improving forecasting accuracy. In general, high-volume customers were better than low-volume customers in terms of FAI. There were no obvious seasonal patterns concerning forecasting accuracy. On an aggregated level, forecasts tended to be overestimations rather than underestimations, showing positive WTS scores. For most individual companies WTS was also positive, however a few companies had negative WTS scores close to delivery. Customers of the Suppliers are a mix of OEMs, aftermarket organisations and systems suppliers doing pre-assembly for OEMs. The only major customers showing notable negative WTS were systems suppliers.

7.2 Research question 2

Based on the finding that major customers outperformed other customers in research question 1, is was assumed that this was due to the higher volumes resulting in a more stable flow. This was further supported by comparisons of high- and low-volume components for major customers, where high-volume components consistently had higher FAI scores.

There were however differences in the forecasting accuracy of the major customers. For all of the three studied customers, sales forecasts were the primary data used for long term production planning, and subsequently demand forecasts sent to suppliers. There were differences in the sales forecasting process, with an indication that moving away from time series based data could help improve forecasting accuracy. Integrating macroeconomic measures more closely with the sales forecasting process may improve long term forecast accuracy for manufacturing customers. Aftermarket organisations could look into measurements such as current product population, age of product population, service intervals and take rate of spare parts to improve accuracy in forecast. While conclusions regarding the comparative value of artificial neural networks are mixed in academia, a majority of covered literature conclude that artificial neural networks are better or situationally better compared to traditional statistical methods, in particular one article identified ANNs outperforming traditional statistical methods when forecasting seasonal or trend patterns, as well as when small amounts of data was available; a scenario such as a new product launch. Both of these types of circumstances apply to the automotive industry to some extent, and as such ANNs could likely prove to perform better than traditional statistical methods in the industry. As a conclusion, there are likely possibilities to improve forecasting accuracy through closer integration of other data than historical sales or production, but also through ANNs potentially providing a more accurate forecast based on the historical data.

The study also found that internal processes between the generation of the sales forecast and the demand forecast can mutate the data in such a way where additional variation in quantity and uncertainty is created. These effects were primarily found to be connected to the MRP, with different order logic generating different effects. A "traditional" MRP process focused around batching to achieve inventory and logistics efficiency was found to likely cause variation and unpredictability. This effect could be reduced by increasing freeze times in the MRP to reduce its nervousness. Prolonging the period where the MRP cannot make changes (while still retaining rights to make manual changes towards the suppliers) for low-volume or non-critical components should reduce variations due to MRP nervousness at minimal cost and risk to the customer. Doing the same for high-volume components would likely prove too risky.

Furthermore, companies that utilised an MRP logic where supplier orders are connected directly to incoming customer orders were found to have lower variations in weekly demand, resulting in a more stable component flow and potentially improved forecasting accuracy. This should be relatively easy for organisations with incoming demand that is relatively stable demand to transition to.

7.3 Research question 3

Effects of unforeseen variations on the Supplier was found to mainly be in the form of inventories being kept to manage these variations. Express or premium transports were seldom used and production was almost never re-planned on short notice to meet late changes to orders. Despite inventories being the main tool used to manage late variations, the inventory turnover rate of the Supplier was found to have an inventory turn rate in line with other suppliers, yet significantly higher than industry benchmarks from the last decade. Additionally, the inventory turnover rates of the major customers were even higher. This indicates a high reliance on quick response to changes and minimal occurrences of major changes to orders or addition of new orders close to the delivery date, as the system becomes sensitive to sudden changes. This requires good knowledge of incoming demand and a forecasting process that consistently delivers accurate forecasts. To achieve this it is imperative that manufacturers continuously work on improving their forecasting processes and how the data from these processes are managed and used. This study has identified some areas where most of the inaccuracies in demand forecasts to suppliers appear to originate, and some potential areas to work on achieving improvements in.

The measurements of FAI and WTS may not perfectly explain if inaccuracies and variations in demand are a problem for a supplier. Types of variations with large operational effects on suppliers could appear insignificant in FAI and vice versa. For FAI to give a better picture of how forecasting inaccuracies and variations affect suppliers, and complementary measurements are likely necessary to better capture how these inaccuracies translate into effects on the supplier. For example, tracking frequency and magnitude of changes in addition to the “total volume” of changes could help in better understanding effects on supplier.

8. Recommendations

Based on the findings of this study, we make the following recommendations for practitioners and researchers.

Practitioners

Firstly, we recommend OEM practitioners to evaluate their current sales forecasting methods and the possibility to have a closer incorporation of data that are not historical sales figures in the sales forecasting process. Having a closer integration of complementary data was found to improve forecasting accuracy, due to the explanatory value of for example GDP for long term sales development. Additionally, the process of integrating complementary data in the forecast may increase understanding of the context of the forecast and lead to better forecasts due to questioning and re-evaluating the forecasts.

Furthermore, a review of literature regarding Artificial Neural Networks indicated that the methods used to evaluate historical data could be improved for better forecasts. Concurrent research within the FFI project also reached preliminary results indicating that machine learning could be applied in this context to improve forecast accuracy. We therefore recommend further research and investigation on this topic to evaluate and quantify the potential benefits and the value of implementation of new methods for forecasting based on historical sales data.

While we see an increase to the overall forecasting accuracy as an important step in improving the ability of manufacturers and suppliers to make accurate planning for the future, due to the complexity of the products and the number of different components, we deem a blanket approach to not be feasible. Trying to understand the end customer demand variations for each component would be too large of a task, and require immense amounts of resources. We do however, recommend companies to invest in understanding the underlying reasons for demand variations for the most critical and high-volume components. This would provide the best value for money by limiting efforts to the most impactful components, while still likely giving some carryover effects for the low-volume components as well.

In combination with the effort to improve forecasting accuracy for the high-volume components, manufacturers are also encouraged to evaluate current MRP practices. The MRP was found to create variations in addition to the “natural” incoming variations, in particular if the MRP employed some form of batching of deliveries. This was found to be reduced by either unbatching deliveries, or by prolonging the MRP freeze times to reduce nervousness. Practitioners are encouraged to unbatch deliveries if consistent with organisational requirements. If this is not possible, practitioners are encouraged to restrict the authority of the MRP to automatically make changes for low-volume and non-critical components. A potential approach that we recommend that would help stabilise the MRP without sacrificing much flexibility would be to increase the freeze time parameter in the MRP system, while maintaining the current commercial freeze times to retain the right to make manual changes if there is an urgent need to do so.

As inventories were found to be the primary tool used to deal with unforeseen variations in demand, suppliers are encouraged to evaluate their current inventories. Under-dimensioned inventories jeopardise the stability of the supply chain if there is a limited ability to deal with variations in other ways. However, if inventory levels are not routinely checked and adjusted suppliers also risk having over-dimensioned inventories carrying extra costs. This is of particular importance as for the benefits of improved forecasting accuracy to be realised, the inventory levels will have to be adjusted accordingly.

On a concluding note, while FAI was found to be relatively low for most customers, unforeseen variations were not seen as a major problem by the interviewees at the Supplier. FAI captures all variations, which may result in FAI not accurately reflecting issues connected to forecasts in the supply chain. We encourage practitioners and researchers to evaluate complementary measures that better reflect changes and misestimates that are operationally significant. For example, this could be changes from forecast to order that exceed a certain tolerance threshold or changes made after procurement/production decision was made by the supplier.

Researchers

We recommend that further research builds on the potential improvements to forecasting accuracy, mainly in the areas of machine learning and MRP practices. There is limited literature regarding the potential to implement machine learning for forecasting demand in a production supply chain, and more knowledge is needed to motivate a large-scale implementation in the industry. We also experience a lack of detailed literature regarding the interplay of forecasts and the MRP considering different contexts and parameters such as freeze times. There is general literature regarding MRP nervousness and how it can create a bullwhip effect, but not regarding MRP nervousness in the context of rolling horizon forecasts.

Additionally, we urge researchers to deepen the understanding of the specific effects of variations and changes to orders on the actors in a supply chain. There is abundant literature on the general effect, but this paper found that not all types of variations were equally significant operationally speaking. More research on what types of variations and changes create what types on effects would help in targeting the most harmful variations with organisational changes and improvement.

Appendix 1: Mathematical definitions

$$\alpha = weighting, \alpha_i \geq 0 \text{ where } \sum_{i=1}^{n} \alpha_i = 1$$

$d_0 = reference\ demand$

$l_i = forecast\ demand\ at\ lag\ i$

$\Delta_i = l_i - d_0$

FAI

FAI shows the (weighted) average deviation from the reference demand for a number of previous forecasts ("lags")

if: $d_0 \neq 0$

$$FAI := \sum_{i=1}^{n} \alpha_i \cdot max\left\{0; 1 - \frac{|\Delta_i|}{d_0}\right\}$$

if: $d_0 = 0$

$$FAI := \sum_{i=1}^{n} \alpha_i \quad where\ I_n = \{i|\Delta_i = 0;\ i = 1, \ldots, n\}$$

$for\ I = \emptyset,$ FAI:=0

WTS

WTS is used to determine whether previous forecasts (lags) were too high or low in relation to the reference demand.

$$if: \sum_{i=1}^{n} \alpha_i \cdot |\Delta_i| \neq 0$$

$$WTS := \frac{\sum_{i=1}^{n} \alpha_i \cdot \Delta_i}{\sum_{i=1}^{n} \alpha_i \cdot |\Delta_i|}$$

$$if: \sum_{i=1}^{n} \alpha_i \cdot |\Delta_i| \neq 0$$

$$WTS := 0$$

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