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IMPROVING DEMAND FORECASTING PRACTICES IN THE INDUSTRIAL CONTEXT

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ABSTRACT

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Demand forecasting is one of the fundamental managerial tasks. Most companies do not know their future demands, so they have to make plans based on demand forecasts. The literature offers many methods and approaches for producing forecasts. When selecting the forecasting approach, companies need to estimate the benefits provided by particular methods, as well as the resources that applying the methods call for. Former literature points out that even though many forecasting methods are available, selecting a suitable approach and implementing and managing it is a complex cross-functional matter. However, research that focuses on the managerial side of forecasting is relatively rare.

This thesis explores the managerial problems that are involved when demand forecasting methods are applied in a context where a company produces products for other manufacturing companies. Industrial companies have some characteristics that differ from consumer companies, e.g. typically a lower number of customers and closer relationships with customers than in consumer companies. The research questions of this thesis are:

1. What kind of challenges are there in organizing an adequate forecasting process in the industrial context?

2. What kind of tools of analysis can be utilized to support the improvement of the forecasting process?

The main methodological approach in this study is design science, where the main objective is to develop tentative solutions to real-life problems. The research data has been collected from two organizations. Managerial problems in organizing demand forecasting can be found in four interlinked areas: 1. defining the operational environment for forecasting, 2. defining the forecasting methods, 3. defining the organizational responsibilities, and 4. defining the forecasting performance measurement process. In all these areas, examples of managerial problems are described, and approaches for mitigating these problems are outlined.

Keywords: supply chain management, organizational development, demand information, demand forecasting

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PART II: PUBLICATIONS

LIST OF PUBLICATIONS AND AUTHOR'S CONTRIBUTION

Publication 1

Kerkkänen A. "Determining semi-finished products to be stocked when changing the MTS-MTO Policy: Case of a steel mill", International Journal of Production Economics, Vol. 108, issues 1-2, 2007, pp. 111-118.

The author is the sole author of this publication.

Publication 2

Kerkkänen A, Huiskonen J, Korpela J. "Selecting an approach for making aggregate demand forecasts – a case study", 15th International Working Seminar on Production Economics, Innsbruck, Austria, 3.-7.3.2008 – revised version

The author is responsible for presenting the research question, planning the collection of the research data, and writing a major part of the paper. The co-authors participated in the data collection and provided comments on the written report.

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Kerkkänen A, Huiskonen J. "The role of contextual information in demand forecasting", Accepted for publication in International Journal of Production Economics (2009)

The author is responsible for presenting the research question, planning of the collection of the research data, and writing a major part of the paper. The co-authors participated in data collection and provided comments on the written report.

Publication 4

Kerkkänen A, Korpela J, Huiskonen J. "Demand forecasting errors in industrial context: Measurement and impacts", International Journal of Production Economics, Vol. 118, Issue 1, 2009, pp. 43-48.

The author is responsible for presenting the research question, planning the collection of the research data, and writing a major part of the paper. The co-authors participated in the data collection and provided comments on the written report.

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Publication 6

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PART I

Overview of the dissertation

1 Introduction

1.1 Background of the research topic

Forecasting is one of the oldest management activities. Forecasting means estimating a future event or condition which is outside an organization's control and provides a basis for managerial planning. Many companies do not know their future demands and have to rely on demand forecasts to make decisions in production planning, sourcing and inventory management both in long and short term.

In principle, forecasting offers several benefits, when the forecast improves the quality of the plans based on it. If capacity plans, production plans, and sourcing and inventory plans can be made well in advance, the resources can be used more efficiently, stockouts reduced, and operating with lower inventory levels enabled.

However, there are some limitations to forecasting. There is always some uncertainty in demand, and all future events that have impacts on demand cannot be reliably predicted. The further into the future the forecasts are made, the less reliable they are. Forecasts are less reliable on the detailed level than on a general level. That is, forecasts are less reliable for single customers than for customer groups, and on the daily level the forecasts are less reliable than on the weekly level etc. Forecasts are most accurate in situations where the demand is continuous and smooth, although accurate forecasts would be especially welcomed in opposite situations, where there are significant and fast changes in demand patterns.

It is challenging to define the level of predictability and the level of demand uncertainty that a company has to adapt to. This task requires ongoing work. In addition, in recent years there have been some environmental changes that pose challenges to forecasting. The demand uncertainty has increased (Bartezzaghi et al. 1999, Miragliotta & Staudacher 2004, Kalchschmidt et al. 2006), and globalization has caused many companies to become more decentralized (McCarthy et al., 2006). At the same time, the technical ability to manage and share information with trading partners has increased (Waters, 2003), and there is pressure to remain in the pace of technological development.

The main focus of forecasting research has been on the development of forecasting methods (Wacker & Lummus, 2002, Moon et al. 2003). Forecasting techniques range from simple to complex, and include the use of executive judgment, surveys, time-series analysis, correlation methods and market tests. The literature is focused especially on statistical methods (Fildes & Goodwin 2007, McCarthy et al. 2006). The widest selection of forecasting methods exist in the category of time series techniques, which are techniques that extrapolate demand history into the future with mathematical formulas. Less attention has been paid to the application side of forecasting. Also, in practice, organizing the forecasting process is often left with little attention, whereas selecting the forecasting software is considered as the most important decision related to demand forecasting (Mentzer & Moon, 2005 p. 316-317).

Even though many sophisticated forecasting methods have been developed, surveys concerning the use of forecasting methods report that simple forecasting methods are preferred over complicated ones, and qualitative forecasting methods have a strong role (Dalrympe, 1987, Tokle & Krumwilde, 2006). Though more sophisticated forecasting methods have been developed and the technical prerequisites for forecasting have improved, the satisfaction with forecasting processes has not increased in recent decades (McCarthy et al., 2006).

Since there is an imbalance between forecasting research and forecasting practice, and advances in forecasting techniques have not in general led to improved forecasting performance, it has been frequently suggested that more focus should be put on the practical side of forecasting, especially on organizational issues. Forecasting methods are just a single component of the forecasting process, and it is reasonable to study the process as a whole, instead of single components. However, the studies considering this aspect are still relatively rare.

There are a few studies that approach the organizational issues in forecasting by identifying the problems that occur when forecasting methods are applied in practical contexts. In an extensive literature review, Winklhofer et al. (1996) summarize studies that investigate forecasting problems and forecast improvement. Some authors consider low accuracy as a problem, and report that the most important factors limiting the forecast accuracy is outside of the control of management (McHugh & Sparkes 1983, Sanders & Manrodt, 1994). According to Wotruba and Turlow (1976), overoptimistic salespeople, lack of information about company plans, and lack of knowledge and understanding as to how the economy affects the firm's customers and territory cause forecast errors in salespeoples' estimates. Peterson (1990) reports that expert opinion forecasters seem to lack information, forecast training, experience and time, and suffer from too tight deadlines.

All authors do not only aim at explaining low accuracy, but point out typical problems or disadvantageous behavior in forecasting. Moon and Mentzer (1999) focus on salesforce forecasting, and in nearly all of the 33 companies that they studied, they found resistance from salespeople concerning their forecasting responsibilities. Many salespeople simply felt that it was not their job to forecast. Hughes (2001), studied the difficulties encountered in demand forecasting in three case companies. The conclusion is that the main difficulty was that the forecasters were unaware of the potential for improving decision making by using formal forecasting techniques. Fildes and Goodwin (2007) have conducted a survey of 149 forecasters and four case studies in order to investigate the use of managerial judgment in demand forecasting. Their conclusion is that companies rely too heavily on unstructured judgment and insufficiently on statistical methods, and often blur forecasting with their decisions.

Some authors aim at identifying issues that are critical to successful forecasting. Davis and Mentzer (2007) report the results of a large interview study, where 516 practitioners at 18 global manufacturing firms were interviewed. The study aimed at providing a rich and detailed description about the forecasting attitudes and formal and informal practices. The findings imply that attempts to strengthen a firm's forecasting capability may meet with limited success when the firm has a negative sales forecasting climate. Secondly, the managers reported that building a shared interpretation of the sales forecasting information is more important to a strong sales forecasting capability than managing the information logistics of sales forecasting. Third, linking the sales forecasting performance to the business performance was reported to be critical to evaluating and improving the firm's sales forecasting capability and sales forecasting climate.

Suggestions for improving the forecasting task have been given in the literature. Some authors offer general suggestions, e.g. Hughes (2001, p.148) suggests "rethinking the whole organizational structure", and Sanders (1992) and Sanders and Manrodt (1994) suggest that forecasting performance could be improved with better data, greater management support and better training. A book called "Principles of Forecasting" (Armstrong, 2001), presents 139 general principles on how to apply forecasting correctly.

The most recent stream of literature aims at putting good forecasting principles into practice by offering tools for the management. Moon et al. (2003) suggest a methodology for conducting a sales forecasting audit, the goal of which is to help a company understand the status of its sales forecasting process and identify ways to improve it. Some approaches have aiming at focusing the forecasting resources by categorizing customers or products have been presented (e.g. Småros & Hellström, 2004, Caniato et al. 2005).

As a summary, it can be said that there is growing interest in organizational issues in demand forecasting. Even though some normative studies exist, there is still work to be done in bridging the gap between forecasting research and practice: implementing good forecasting principles and understanding the diversity of the managerial reality.

1.2 Focus and aim of the study

In this study, demand forecasting is studied from the perspective of demand management. In such a perspective, forecasting is not seen as an isolated task, but interaction with other managerial tasks is the point of interest. This approach is in contrast with the mainstream of forecasting studies, which consider forecasting as an isolated task, and focus on forecasting techniques and accuracy. The focus is on what kind of problems managers face in organizing the forecasting process in a practical setting, and how managers can be supported in mitigating those problems.

In practice, one of the most fundamental questions is whether improving the forecasting process is of value for the company or not. To be able to answer this question, it is essential to know the context in which forecasting is applied. The forecasting process should fit to the special characteristics of the environment, and to the forecasting needs of the company. Much of the practical work of forecasting depends on the context where forecasting methods are applied. In different contexts, forecasts can be used for different purposes, and the information that the forecasts base on come from different sources. Therefore, it is reasonable to focus on a certain kind of environment at a time. This study focuses on the industrial context. The term "industrial context" means a situation where a company produces physical products for other manufacturing companies. The industrial context has some special characteristics that pose challenges for forecasting.

A majority of the forecasting literature focuses on forecasting independent demand. Many forecasting methods operate best in situations where the demand is continuous, smooth, or following repeated patterns. However, there are many situations where the demand environment is significantly different. This is the case in the industrial context, which this study focuses on. The demand is dependent on the customers' demand, and therefore more unpredictable than independent demand. The contact with the customers is typically close, so there is usually some information available about the customers' future demand. The information is of varying reliability and exists in varying formats, so one of the problems is linking this, so called "contextual information", with the forecasting process. The customer base is typically heterogeneous, so that one forecasting method does not usually fit for all situations. If production is made to order, forecast errors do not have easily measurable impacts, and so it is difficult to link the forecasting performance to the business performance.

It is noted in the literature that support from management is important in implementing efficient forecasting practices. However, it is not defined how a manager can, in practice, efficiently support the improving of forecasting practices. Managers face questions that do not necessarily have easy answers. To support forecasting, managers need to be able to assess the current state of the forecasting process, diagnose the problems, point out areas of improvement, and define development actions. In complex environments, it is important to create a cross-organizationally shared view of the demand environment and of the ways of reacting to it. These are the challenges that managers face, but the forecasting literature does not directly provide answers to them. However, it is possible to develop analysis tools that help in this kind of tasks.

The aim of this study is to enhance the understanding of the challenges in organizing a forecasting process in the industrial context. This includes outlining the analysis tools that can be used in mitigating the problems observed.

1.3 Outline of the thesis

This thesis consists of two main parts: an introductory part and six research publications. The purpose of the first part is to provide an overview of the research topic. The first part is organized as follows. In the second chapter, the research area is defined, the theoretical background introduced, and research motivation for the study presented. The third chapter discusses methodology and research design, including details of the conducted case studies. The fourth chapter presents a framework that the individual research publications form, and the content and contribution of the publications are reviewed. The fifth chapter contains discussion of the results and conclusions.

2 Managing the demand forecasting process in the industrial context

This chapter describes the topics necessary for the positioning of the study in its context. Before reviewing the basic issues of demand forecasting, the special characteristics of industrial companies are discussed.

After that, an overview of basic issues and concepts of demand forecasting is presented, including

- the role and typical uses of forecasts
- forecasting methods and their popularity
- forecasting performance measures
- organizational issues in forecasting
- demand forecasting process models.

Finally, a summary of the forecasting literature is made, pointing out the research needs in the area of forecasting practices in the industrial context.

2.1 Special characteristics of industrial companies

This thesis focuses on problems that managers face in organizing the forecasting process in the industrial context. In this section, it is discussed how the industrial context differs from other contexts in terms of demand forecasting management.

2.1.1 Definition of an industrial company

According to Kotler (1997), the industrial markets consist of all the individuals and organizations that acquire goods and services to be used in the production of other products or services that are sold, rented or supplied to others. Industrial customers produce their own products with the help of purchased products, or use these products as parts of their own products, which are offered forward.

Industrial markets have characteristics that differ significantly from the characteristics of consumer markets. Some typical characteristics of the industrial markets are

- derived demand
- fewer and larger buyers
- close supplier-customer relationships

The demand that an industrial company meets is derived demand, which is more volatile than independent demand. Forecasting dependent demand with time series methods leads to great forecast errors. Instead, it is reasonable to consider closer collaboration with customers and exploiting knowledge about the customer's future demand in the forecasting process. These issues are discussed below.

2.1.2 Managing dependent demand

The demand for industrial products is derived from the demand for the company's customers' products, and finally the end-user demand. In most companies, forecasting and demand estimation are based on historical order or delivery information, but the actual end-customer demand may be very different from the order stream. Each member of the supply chain observes the demand patterns of its direct customer (1st tier customers) and in turn produces a set of demands to its suppliers. The decisions made in forecasting, setting inventory targets, lot sizing and purchasing transform (or distort) the demand picture. The further upstream a company is in the supply chain (that is, the further it is from the end customers), the more distorted is the order stream relative to consumer demand (e.g. Gattorna, 1998). This phenomenon is also known as the *bullwhip effect* or the *Forrester effect*. This effect occurs when there is uncertainty in the supply chain based on the use of forecasts, and that uncertainty is then exaggerated by lead-time effects and differences in lot sizes when material moves through the supply chain.

Several actions have been suggested to mitigate the effects of the bullwhip effect. The approaches include managing visibility of data (information flow) in the supply chain and building flexibility and agility across the supply chain. Lee et al. (1997) categorize the proposed remedies under three coordination mechanisms:

- information sharing
- operational efficiency
- channel alignment

With *information sharing*, demand information at a downstream site is transmitted upstream in a timely fashion. In this context, the concept of *demand planning* is used. It means the coordinated flow of derived and dependent demand through companies in the supply chain. Rather than even attempting to forecast demand, each member of the supply chain receives point-of-sale (POS) demand information from the retailer, and the retailer's planned ordering is based upon this demand. However, there is a paradox in demand planning in any supply chain – the companies that are most needed to implement supply chain planning, that is, the downstream players, have least economical motivation (i.e. inventory reduction) to cooperate. (Mentzer & Moon, 2005).

Operational efficiency refers to activities that improve performance, such as reduced costs and lead time. Lee et al. (1997) suggest that large orders contribute to the bullwhip effect companies need to devise strategies that lead to smaller batches or more frequent resupply. One reason that order batches are large or order frequencies low is the relatively high cost of placing an order and replenishing it. Another reason for large order batches is the cost of transportation. Electronic data interchange and use of third-party logistics have been suggested to improve operational efficiency.

Channel alignment is the coordination of pricing, transportation, inventory planning, and ownership between the upstream and downstream sites in a supply chain. Even if the multiple organizations in a supply chain have access to end-customer demand history, the differences in forecasting methods and buying practices can still lead to unnecessary fluctuations in the order data placed with the upstream site. In a more radical approach, the upstream site could control resupply from upstream to downstream. The upstream site would have access to the demand and inventory information at the downstream site, and update the necessary forecasts and resupply for the downstream site. The downstream site, in turn, would become a passive partner in the supply chain. For example, in the consumer products industry, this practice is known as Vendor Managed Inventory (VMI) or a Continuous Replenishment Program (CRP). (Lee et al. 1997)

2.1.3 Concepts for supply chain collaboration

It is widely accepted that creating a seamless, synchronized supply chain leads to responsiveness and lower inventory costs. Several concepts have been developed for supply chain collaboration. Examples of such concepts are Efficient Consumer Response (ECR) in the fast moving consumer goods sector, or Vendor Managed Inventory (VMI) and Collaborative Planning, Forecasting and Replenishment (CPFR).

Efficient consumer response
ECR is a strategy developed by the grocery industry for streamlining the grocery supply chain. The strategy is a result of the work of a specifically-formed industry project guided by a mission statement of reducing channel costs and improving inventory controls within, and between, all levels of the grocery distribution channel, while simultaneously improving customer satisfaction (Joint Industry Project for Efficient Consumer Response, 1994). The resulting strategy, ECR, requires the supply chain participants to study and implement methods that will enable them to work together to meet the mission of grocery industry. (Viskari, 2008)

ECR is a strategy in which the grocery retailer, distributor, and supplier trading partners work closely together to eliminate excess costs from the supply chain. The ECR strategy focuses particularly on four major opportunities to improve efficiency:
(1) Optimizing store assortments and space allocations to increase category sales per square foot and inventory turnover.
(2) Streamlining the distribution of goods from the point of manufacture to the retail shelf.
(3) Reducing the cost of trade and consumer promotion.
(4) Reducing the cost of developing and introducing new products. (Viskari, 2008)

Vendor managed inventory
The basic idea in *VMI* is that the supplier manages the inventory on behalf of the customer, including stock replenishment. In VMI, the vendor is given access to its

customer's inventory and demand information (Pohlen & Goldspy, 2003; Småros et al., 2003). Implementing a VMI solution requires that there is an established and trusted business relationship with the partners, and the material flow is substantial and continuous.

In the VMI model, the customer does not place purchasing orders to the seller, even though the purchase orders may be triggered by the IT systems for legal and archiving reasons (Pohlen & Goldsby, 2003). The main tool used to operate the VMI is a demand estimate or forecast. The customer is responsible for giving the estimate for a period of time and use the goods according to the estimate within agreed tolerances. The customer is invoiced according to the real usage or even pays according to the usage without being invoiced. The supplier is responsible for maintaining an agreed level of inventory also within certain tolerances.

In VMI relationships, increased visibility will allow the supplier a larger time window for replenishment, if reliable forecasts can be used in combination with customer allocation data (Kaipia et al., 2002). However, there are a number of different ways to configure VMI systems, and there are system configurations that will limit the supplier's possibility to utilize the information made available through VMI. The customer may e.g. limit the replenishment or shipment decisions (Elvander et al., 2007).

Collaborative planning, forecasting and replenishment

The Consumer Packaged Goods (CPG) sector has published an initiative called Collaborative planning, Forecasting and Replenishment, which describes the basic structure of managing the demand chain collaboratively. The organization behind CPFR is called Voluntary Inter-industry Commerce Solutions (VICS), whose mission is to engage communities of interest in joint forums, targeting a world with seamless and efficient supply chains. The mission of the CPFR Committee is to develop business guidelines and roadmaps for various collaborative scenarios, including upstream suppliers, suppliers of finished goods and retailers, which integrate demand and supply planning and execution. The real power of CPFR is that, for the first time, demand and supply planning have been coordinated under a joint business-planning umbrella. CPFR can be regarded as an evolutionary step from VMI and Continuous Replenishment (CR), covering a more comprehensive area of supply chain activities. (Viskari, 2008)

Current state of implementations of collaborative incentives

Some recent studies have questioned the benefits of demand visibility, and in particular, the benefits of information sharing. While individual successful implementations of the latter have already been reported, there has not yet been the widespread adoption that was originally hoped for. (Holweg et al., 2005)

However well thought out in theoretical/simulation models, in practice the issue of how to benefit from external collaboration and use demand visibility to improve capacity utilization and inventory turnover is still not well understood. Collaborative forecasting is frequently advertised as a key objective in the implementation of VMI, but is less frequently applied. The reason is that the customer often does not have a forecasting and planning process in place that can provide the supplier with information on the level of detail required, and at the right moment in time. Linking the customer's and supplier's planning processes on a sufficiently detailed level is also a cornerstone towards implementing the CPFR strategy. Based on field studies, it can be generalized that supply chain players do not know how to use the available information, and therefore collaboration in VMI solutions is limited to collaborating on replenishment. (Holweg et al., 2005)

In principle, only independent demand should be forecasted. However, in real life settings, due to the difficulties in linking planning processes with customers, companies end up in forecasting also dependent demand. Increasing demand visibility and exploiting the information are difficult to implement. In practice, the need to forecast is not totally eliminated with collaboration. However, even though it might be difficult to gain access to fully reliable information about customers' demand, there is usually access to some sort of customer information. This issue is discussed below.

2.1.4 Contextual information

In a company operating in a B2B environment, the relationship with customers is typically closer than in consumer markets. Being so, it is possible that future demand information is available in different formats and from different sources, such as:

- contracts
- inquiries
- preliminary orders
- customers inventory levels and production plans
- customers' own forecasts
- customers' oral estimations about their future demand

To describe the context-dependent demand information, many authors use the concept of "contextual knowledge" or "contextual information", but the definition of it is not very precise. According to Sanders & Ritzman (2004), contextual knowledge is information gained through experience on the job with the specific time series and products being forecasted. According to Webby and O'Connor (1996), contextual information is information, other than the time series and general experience, which helps the explanation, interpretation and anticipation of time series behavior.

Several similar concepts are used in the literature, e.g. "causal knowledge", which pertains to an understanding of the cause-effect relationships involved (Webby & O'Connor 1996), product knowledge (Edmundson et al., 1988) and extra-model knowledge (Pankratz, 1989). Experience of similar forecasting cases can be also seen as contextual information. Using such information, that is, analogies, in forecasting has been studied e.g. by Hoch and Schkade (1996), Green& Armstrong (2007), and Lee et al. (2007).
Fildes and Goodwin (2007) mention information about special events, such as new sales-promotion campaigns, international conflicts or strikes as examples of contextual

information. Sanders and Ritzman (2004) mention rumors of competitor launching a promotion, a planned consolidation between competitors, or a sudden shift in consumer preferences due to changes in technology and causal information, such as relationship between snow shovels and snow fall, or temperature and ice cream sales. Lawrence et al. (2000) mention new marketing initiatives, promotion plans, actions of competitors, and industry developments as examples of contextual information that is actually discussed in forecasting meetings of manufacturing companies. In addition to these pieces of information, customers own forecasts can be considered as contextual information. According to a survey reported by Forslund and Jonsson (2007), 87% of suppliers received forecast information from their customers. However, customer forecasts suffer from quality problems. The authors define forecast information quality with four variables. Forecast information is of good quality if it is (1) in time, (2) accurate, (3) convenient to access and (4) reliable. Forslund and Jonsson (ibid.) found out in a survey that forecast information quality is lower further upstream in the supply chain, and the greatest quality deficiency of the forecast is that it is considered unreliable. Therefore, it is not self-evident which information sources should be selected for the basis of forecasts.

In the industrial context, the role of contextual information is emphasized, and linking contextual information to forecasts requires using judgemental forecasting methods. However, judgemental forecasting methods are known to be time-consuming, and prone to biases and inefficiency. Therefore, in the industrial context the challenge is to find a resource-efficient forecasting approach, where the role of salespeople is well defined and focused.

Publication (3) focuses on the concept of contextual information. Problems in managing contextual information are discussed, and the role of contextual information is analyzed with probability calculations.

2.2 The role of demand forecasting in a company

Forecasting as a function does not have a similar role in all companies. Even companies operating in similar environments may pay a different amount of attention to forecasting. In this section it is described, how demand forecasting is linked to other managerial activities, why forecasts are usually made, and what are the alternatives to forecasting in managing demand uncertainty.

2.2.1 Demand management

The term "demand management" is defined in the APICS dictionary (Cox et al., 1995) in the following way: "The function of recognizing all demands for products and services to support the marketplace. It involves doing what is required to help make the demand happen and priorizing demand when supply is lacking. Proper demand management facilitates the planning and use of resources for profitable business results. It encompasses the activities of forecasting, order entry, order promising, and determining branch warehouse requirements, interplant orders, and service parts requirements."

Mentzer and Moon (2005) have defined the role of demand forecasting within demand management. The traditional demand creation role of marketing is tempered in demand management by a desire to coordinate the flow of demand across the supply chain (*demand planning*) and creating incentives for supply chain partners to help manage those flows (*supply chain relationship management*). Demand planning is concerned with the coordination across the supply chain of derived and independent demand. *Sales forecasting management* is concerned with independent demand that occurs in any supply chain.

2.2.2 Forecasting needs

Companies need forecasts for developing plans of any kind. Forecasts have to be done for the strategic business plan, the production plan, and the master production schedule. The planning horizons and level of detail vary for each type of plan.

Arnold et al. (2008) list typical uses of demand forecasts in planning. The strategic business plan is concerned with overall markets and the direction of the economy over the next 2 to 10 years or more. Its purpose is to provide time to plan for those things that take long to change. For production, the strategic business plan should provide sufficient time for resource planning: plant expansion, capital equipment purchase, and anything requiring a long lead time to purchase. The level of detail is not high, and forecasts are usually made for sales units, sales value, or capacity. The forecasts and planning will probably be reviewed quarterly or yearly.

Production planning is concerned with the manufacturing activity for the next one to three years. For manufacturing, it means forecasting the items needed for production planning, such as budgets, labor planning, long lead time, procurement items, and overall inventory levels. Forecasts are made for groups or families of products rather than specific items. The forecasts and plans will probably be reviewed monthly.

Master production scheduling in concerned with production activity from the present to a few months ahead. Forecasts are made for individual items, as found on a master production schedule, individual item inventory levels, raw materials and component parts, labor planning, and so forth. The forecasts and plans will probably be reviewed weekly.

One common problem is that when there are many needs for forecasts, different functions end up making their own forecasts that may lead to inconsistent plans. This phenomenon is called "island of analysis" and it has been described e.g. by Mentzer & Moon (2005, p.320). "Islands of analysis" means that distinct areas within the firm perform similar functions, in this case sales forecasting. It is a common finding in case studies, and is due to lack of interfunctional communication between units.

2.2.3 Strategies for reducing the impacts of demand uncertainty

Because of inherent error in forecasts, companies that rely on them can run into a variety of problems. Fore example, goods are not in the right place with the right timing. There are some strategies for reducing the impacts of demand uncertainty. E.g. Arnold et al. (2008) use the concept of P/D ratio to introduce these strategies.

"P" or production lead time is the stacked lead time for a product. It includes the time for purchasing and arrival of raw materials, manufacturing, assembly, delivery, and sometimes the design of the product.

"D" or demand lead time is the customer's lead time. It is the time from when the customer places an order until the goods are delivered. It can be very short, as in a make-to-stock environment, or very long, as in an engineer-to-order company. The traditional way to guard against inherent error in forecasting is to include safety stock in the inventory. There is an added expense to the extra inventory carried "just in case". Another way is to make more accurate predictions. There are five ways to move in this direction.

1) Reduce P time. The longer the P time, the more chance there is for error. Ideally, P will be less than D.
2) Force a match between P and D. Moving into this direction can be done in two ways:
   a) Make the customer's D time equal to your P time. This is common with custom products when the manufacturer makes the product according to the customer's specification.
   b) Sell what you forecast. This will happen when you control the market. One good example is the automobile market. It is common to offer special inducements toward the end of automotive year in order to sell what the manufacturers have predicted.
3) Simplify the product line. The more variety in the product line, the more room for error.
4) Standardize products and processes. This means that "customization" occurs close to final assembly. The basic components are identical, or similar, for all components.
5) Forecast more accurately. Make forecasts using a well-thought-out, well-controlled process.

One option for reducing the impact of demand uncertainty is to operate on the make-to-order (MTO) basis instead of make-to-stock (MTS). To distinguish MTS and MTO operations, the concept of "customer order decoupling point" has been presented (Figure 1). The term "decoupling point" was first introduced by Sharman (1984). Later, the concept has been discussed e.g. by Olhager (2003), who uses the term OPP (Order Penetration Point) and Hoekstra & Romme (1992) and Van Donk (2001), who use the term CODP (Customer Order Decoupling Point).

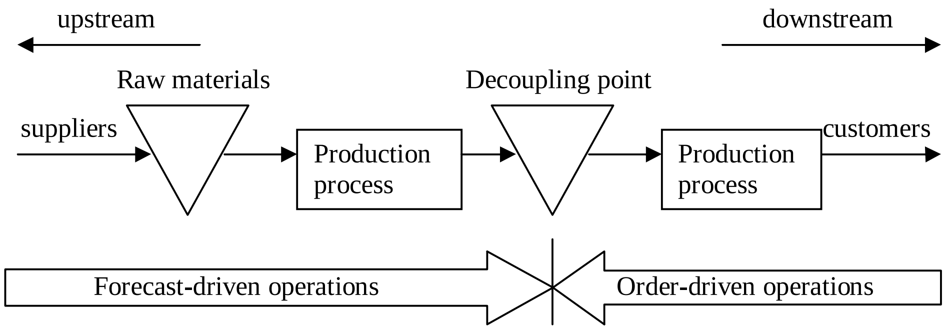

Figure 1: Customer order decoupling point (adopted from Hoekstra & Romme, 1992)

Selecting the position of the customer order decoupling point is a multi-criteria decision. According to some authors, the main factor in determining the position of OPP is the P/D ratio (Andries & Geldres, 1995). Others (e.g. Olhager 2003) see that positioning the CODP depends on three factors: 1) market characteristics, including e.g. volatility of demand, delivery lead-time requirements and product customization requirements; 2) product characteristics, including modular product design and customization opportunities and; 3) production characteristics including e.g. production lead-time, number of planning points and flexibility of the production process.

Even though positioning the OPP has gained academic interest, there are still only a few articles that deal with the positioning problem in a practical setting. Paper number 1 in this thesis discusses the problem of selecting the location of the order decoupling point in a steel factory.

Even though a great amount of production is made to order, some part of planning still needs to be made on the basis of forecasts. For example, sourcing materials with long lead times and capacity allocation require forecasts. However, the ultimate goal of demand forecasting is to match supply with demand. When the aim is to improve the forecasting, the costs of improvement can be compared with the costs of reducing the need to forecast. In that sense, investing in forecasting is a strategic decision.

2.3 Forecasting methods

The literature focuses on providing new forecasting methods, and there is an abundance of demand forecasting methods available today. This study focuses on the application of forecasting methods, and does not suggest any new methods. However, studying the application of methods requires basic knowledge about the available methods. Therefore, the main categories of forecasting methods are reviewed in this section.

2.3.1 Classification of methods

The range of existing forecasting methods can be described by considering several frameworks suggested for their classification. Makridakis & Wheelwright (1979) suggest two criteria for the classification of methods. The first criterion is the type of information available (quantitative or qualitative), and the other is basic assumptions about the type of demand pattern (history repeats itself or external patters determine events). It is also common to divide forecasting methods in two main groups; *qualitative* and *quantitative* methods (e.g. Mentzer & Moon 2005). After that, quantitative methods can be divided to the ones that are based on demand history and the ones that are based on external factors.

2.3.2 Qualitative methods

Qualitative techniques are projections based on judgment, intuition, and informed opinions, and they are subjective by nature. The term *judgemental* forecasting method is also used almost as a synonym with qualitative forecasting methods. All forecasting involves judgment, in selecting the forecasting method or formulating a forecasting model. Even sophisticated statistical methods rely heavily on judgment, e.g. in the model identification phase or in the selection of independent variables. More commonly, however, the term "judgemental forecasting" is associated with forecasts made wholly on the basis of judgment, or with judgemental adjustments to statistical forecasts (Wright & Goodwin 1998).

When attempting to forecast the demand for a new product, there is no history on which to base the forecast. In some cases, if there are considerable changes in the circumstances, demand history is not considered relevant or sufficient for forecasting future demand. In these cases, qualitative techniques come into question. One of the qualitative methods that is widely applied is using expert opinions. The experts may be *internal* experts, such as executives or the sales force, or *external,* meaning an industry survey (Armstrong, 2001).

There is a wide range of qualitative methods, and it is difficult to make a simple categorization of them. While the simplest qualitative methods mean entering forecasts based fully on intuition, some of the methods are more like team work methods. Some methods are special forms of market research, and some aim at modeling, structuring or facilitating the decision-making of a single expert.

2.3.3 Causal methods

Causal methods (also called *extrinsic or explanatory* methods) are quantitative methods that are projections based on external indicators related to the demand for a company's products. Examples of such data would be housing starts, birth rates, and disposable income. The theory is that the demand for a product group is directly proportional, or correlates to activity in another field. (Arnold et al., 2008)

The problem is to find an indicator that correlates with demand and one that perfectly leads demand, i.e. occurs before demand. For example, the number of construction contracts made in one period may determine the building material sold in the next period. When it is not possible to find a leading indicator, it may be possible to use a non-leading indicator for which the government or an organization forecasts. In a sense, it is basing a forecast on a forecast. Extrinsic forecasting is most useful in forecasting the total demand for a firm's products or the demand for families of products. As such, it is used most often in business and production planning rather than the forecasting of individual end items (Arnold et al., 2008).

2.3.4 Time series methods

Time series methods, also called *intrinsic* or *extrapolation methods/techniques*, use historical data to forecast. The data are usually recorded in the company and are readily available. Time series techniques are based on the assumption that what happened in the past will happen in the future. Historical demand is projected into future with a mathematical formula. (Arnold et al., 2008)

Time-series methods vary from simple to complex. The simplest technique is to use the sales history of the previous period as a forecast. This method is usually referred as the *naïve* forecast. Other simple techniques are e.g. moving averages and simple exponential smoothing. More complex techniques use more complicated formulas with more variables, concerning trend and seasonality in demand. Example of a sophisticated time series method is the Box-Jenkins method, which focuses on finding the most suitable formula for making the forecast. There are at least 70 different time-series techniques available (Mentzer & Moon, 2005).

2.3.5 Integrating forecasting methods

There has been debate about the superiority of qualitative and quantitative forecasting methods, but the only conclusion is that the performance of the method depends on the circumstances (e.g. Lawrence et al., 2006). To take advantage of the strengths of both time series and judgemental methods, combining these methods has been suggested. Integrating statistical and judgemental forecasts generally improves forecasts when the experts have domain knowledge and when significant trends are involved (Webby & O'Connor, 1996). At least four integration methods have been presented (e.g. Goodwin, 2000, Sanders & Ritzman, 2004):

- *Correcting:* the methods involve the use of regression to forecast errors in judgemental forecasts. Each judgemental forecast is then corrected by removing its expected error.

- *Combining:* Forecast is obtained by calculating a simple or weighted average of independent judgemental and statistical forecasts.
- *Judgemental adjustment*: Statistical forecast is adjusted according to contextual information.
- *Judgment as input to model building:* Judgment is used to select variables, specifying model structure, and set parameters.

2.4 Selecting the forecasting approach

There are many forecasting methods available, but the managerial problem is how to select a forecasting approach that is suitable for the needs of a specific company. There are many factors that need to be considered in choosing the forecasting method. In this section, different approaches for selecting forecasting methods are presented. After that, the popularity of different methods in real life is discussed.

2.4.1 Criteria for selecting forecasting methods

The overriding consideration in choosing a forecasting method is that the results must facilitate the decision-making process of the organization's managers. The essential requirement is that the chosen method should produce a forecast that is accurate, timely, and understood by the management, so that the forecast can help produce better decisions. Also, the use of the forecasting procedure must produce benefit that is in excess of the cost associated with its use (Hanke et al., 2001).

In the forecasting literature, forecast accuracy is a popular criterion when different forecasting methods are compared (Yokum & Armstrong, 1995). However, it has been noticed that in a practical setting, forecast accuracy as a single criterion is insufficient for selecting the forecasting method. Other factors to be noticed are for example cost, data availability, variability and consistency of data etc. (Georgoff and Murdick, 1986). Yokum & Armstrong (1995) found out in their survey research that managers rated such criteria as "flexibility", "ease of implementation" and "ease of use" almost as important as forecast accuracy in selecting a forecast method.

Armstrong (2001) examines six ways to select forecasting methods: (1) convenience, (2) market popularity, (3) structured judgment, (4) statistical criteria, (5) relative track records, and (6) guidelines from prior research. The author states that methods should not be selected based on convenience (that is using methods that are already familiar) or market popularity (that is using what other companies are using). Using statistical criteria, such as distribution of errors, or statistical significance of relationships can be useful in some situations, but the approach is not appropriate for making comparisons between substantially different methods. Furthermore, some statistical criteria are irrelevant or misleading, and may lead the analyst to overlook relevant criteria. When great changes are expected and errors have serious consequences, the track record of leading forecasting methods can be assessed. While useful and convincing, comparing the accuracy of various methods is expensive and time consuming. Approaches that the author recommends are structured judgment and following the guidelines from prior research.

In using structured judgment, the forecaster first develops explicit criteria and then rates various methods against them. Evidence that structured judgments are superior to unstructured judgments has been found in many types of selection problems. Especially applicability and understandability of the method are important criteria. When rating different methods according to selected criteria, unbiased experts should be asked to rate the potential methods.

As a conclusion from prior research, Armstrong (2001) presents a selection tree for forecasting methods (Figure 2). Using this selection tree requires answering some apparently simple questions about the forecasting environment. However, it is not explicitly stated how the answers to these questions can be found.

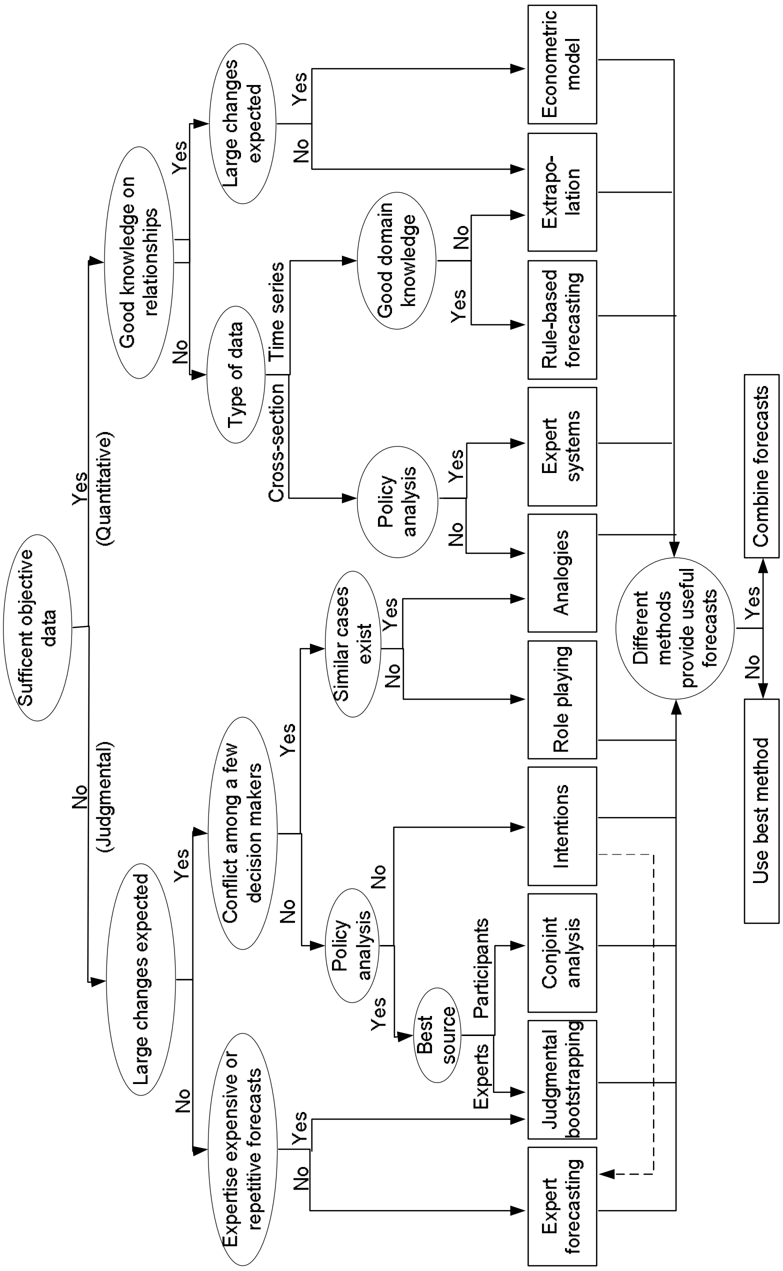

Figure 2: Selection tree for forecasting methods (Armstrong, 2001 p. 376)

2.4.2 Popularity of different forecasting methods

There are many surveys that focus on finding out which forecasting methods are actually used in companies. Below, some examples of such surveys are given. Dalrympe (1987), using a mail survey, obtained information about the use of forecasting methods at 134 companies in the United States. Kahn & Mentzer's survey (1995) obtained information about 99 consumer market companies and 60 industrial market companies. Tokle and Krumwilde (2006) report the results of a survey administrated by the Global Manufacturing Research Group, where the sample size was 235 companies.

As the surveys have different phrasing of questions, the results are not easily comparable. However, some comparisons are made in table 1. There is a great variation in the survey results. For example, Dalrympe (1987) reports that only slightly over 10% of the companies studied used exponential smoothing, whereas Kahn & Mentzer (1995) report that almost all the studied companies used that method on some time horizon. However, a general message that the surveys give is that simple methods are more popular than complex methods, and qualitative forecasting methods are widely used. Especially in industrial context, judgemental forecasting methods are common (Mentzer & Moon, 2005).

Table 1: Use of some forecasting methods according to three different surveys

Study	Dalrympe, 1987	Kahn & Mentzer, 1995			Tokle & Krumwilde, 2006
Time horizon	Not specified	Less than 3 mo.	3 mo. to 2 yr.	Greater than 2 yr.	Not speficied
Qualitative methods					3.9 on a scale from 1 to 7
Sales force opinion	44.8 %	-	-	-	-
Executive opinion (specific name in the study)	37.3 % (Expert opinions – executives)	2% (Jury of exec. opinion)	65% (Jury of exec. opinion)	45% (Jury of exec. opinion)	5.3 on a scale from 1 to 7 (Management opinion)
Quantitative methods					3.6 on a scale from 1 to 7
Naïve	30.6 %	-	-	-	-
Moving average	20.9%	5%	42%	15%	-
Exponential smoothing	11.2 %	3%	98%	12%	-
Box-Jenkins	3.7 %	0	32%	8%	-

The empirical studies show the focus of forecasting literature is not on the methods that are the most popular in practice. A majority of forecasting literature focuses on quantitative methods, so it is reasonable to ask why judgemental methods are so popular in real life. One reason is that in real life, demand patterns are more irregular than assumed in theoretical examples. E.g. Sanders and Manrodt (2003) point out in a survey study that the company characteristics that correlate with the preference for judgemental methods are lack of relevant quantitative data, environmental uncertainty, and variability of associated data. Another reason for preferring judgemental methods is that qualitative information is considered more valuable than the available demand history. However, some case studies show that judgemental forecasts are not uniformly better than naïve forecasts (Lawrence et al., 2000). Arkes (2001) notes that overconfidence in judgemental forecasting is a typical finding in forecasting literature, and suggests that overconfidence should be reduced consciously.

The literature suggests that in practice, quantitative methods generally provide better forecast accuracy than judgemental methods (Sanders & Manrodt, 2003, Mentzer & Moon, 2005), but this is at least partially explained by the fact that quantitative forecasting methods are more commonly applied in situations where the demand is more predictable. To make an equal comparison, different methods should be compared against each other in specific contexts. The comparison must consider all the relevant dimensions of performance. In the next section, performance measures developed for forecasting are reviewed.

Publication 2 of this thesis discusses the selecting of the forecasting approach in the industrial context. The selection approach is based on relative track records using multiple criteria. According to Armstrong (2001), only a few studies exist that assess the use of relative track records in selecting the forecasting approach, and this should be a fertile area for further research.

2.5 Forecasting performance measurement

Several authors emphasize the importance of performance measurement in managing the forecasting process (e.g. Mentzer & Moon, 2005, Holmström, 1998, Croxton et al., 2002). In this section, different performance measures are reviewed, and some problems of performance measurement are pointed out. This section is organized according to the three dimensions of performance measurement presented by Mentzer & Moon (2005): 1) Accuracy, 2) Costs, 3) Customer Satisfaction

2.5.1 Accuracy measures

According to Chopra & Meindl (2001), measuring forecast accuracy serves two main purposes: Firstly, managers can use error analysis to determine whether the current forecasting method predicts the systematic component of demand accurately. For example, if a forecasting method consistently results in a positive error, the manager can assume that the forecasting method is overpredicting the systematic component and take appropriate corrective action. Secondly, managers estimate forecast error because any contingency plan must account for such an error.

There are several different error measures. Mentzer & Moon (2005) divide these into three groups:

- Actual measures
- Measures relative to a perfect forecast
- Measures relative to a perfect forecasting technique

All *actual measures* are based on the simple calculation of:

$\text{Error}_t = E_t = \text{Forecast}_t - \text{Sales}_t$

where t: the time period in which the sales occurred.

One example of actual measures is the Mean Error.

Mean Error = ME $\sum E / N$

where: N= the number of periods where the error has been tracked.

Other absolute error measures are e.g. mean absolute deviation, mean absolute error, sum of squared errors and mean squared error.

Measures relative to a perfect forecast are error measures that relate the forecast errors with actual demand. These measures are also called relative measures. Of these error measures, the Mean Absolute Percentage Error (MAPE) is probably the most common measure used in practice.

One example of *accuracy measures relative to perfect forecasting techniques* is Theil's U. This statistic simply calculates the ratio of the accuracy of the technique that is used to the naïve forecast's accuracy. Naïve forecast is the sales of the previous period, e.g. month. If the U statistic is grater than 1.0, the technique used is worse than the naïve forecast and should be discarded. If the statistic is less than 1.0, the technique is better than the naïve technique. The same idea can be accomplished by using a simple ratio of the MAPE of the forecast, divided by the MAPE of the naive forecast. (Mentzer & Moon, 2005)

One problem with accuracy measurement is that it is often difficult to receive information about the actual demand. Demand is often manipulated with such things as price discounts, so that the actual sales do not represent the actual demand. In a business-to-business environment, it is more common that prices and delivery dates are negotiated, so there is more room for demand manipulation than in the consumer markets. Another problem is the lack of suitable reference values (Bunn & Taylor, 2001).

However, sales forecasting accuracy is widely accepted as an appropriate standard for evaluating sales forecasting performance. A 20-year longitudinal study of forecasting practice reported that U.S.-based firms consistently ranked accuracy as a top criterion for evaluating sales forecasting performance (McCarthy et al., 2006).

2.5.2 Costs of forecasting and customer satisfaction

Costs of forecasting include the software, personnel, training and time taken from other activities (Mentzer & Moon, 2005). Inaccurate forecasts may create changes in schedules, high inbound materials costs, excess transportation costs, and excess inventories. Mentzer and Moon (ibid.) state that any metric of sales forecasting performance should address the production and logistics costs of inaccurate forecasts. They suggest that a first step in doing this is to match monthly or quarterly production overrun costs, raw material and finished goods excess inventory costs, and finished goods transshipment costs with forecasting error in the same periods. By correlating these costs with forecasting error, a clear picture is provided of the impact of forecasting accuracy on operation costs.

However, numerous studies demonstrate that the impact of forecast errors is not constant, but varies according to organizational characteristics (Sanders & Ritzman, 2004, Zotteri & Kalchschmidt, 2007). According to Zotteri and Kalchschmidt, forecasting has an impact on company performance, but the impact depends on what the forecasting is used for.

The marketing costs of inaccurate forecasting include not only trade promotions but also the costs of ineffective advertising, product development of new products without adequate demand, pricing at the level that does not maximize profit contribution and inappropriate sales quotas. Low service levels caused by inaccurate forecasts may cause losing sales, losing old customers, or even losing potential customers.

The difficulty of defining the costs of forecasting is emphasized if production is made to order. Forecasts do not necessarily have direct impact on inventory levels or customer satisfaction, so performance measurement is more complicated on all the dimensions of performance. Wacker and Lummus (2002) note that there is a lack of error measures that relate the forecast accuracy with the actual use of the forecasts.

2.5.3 Selecting suitable performance measures

According to Crandon and Merchant (2006), useful performance measures are decision-based, reflect major dimensions of performance, and distinguish between controllable and uncontrollable factors. Davis and Mentzer (2007) note that in the absence of useful measures that link sales forecasting performance with business performance, managers do not have the information that is needed to diagnose problems effectively and to motivate changed behavior, which are necessary for achieving different performance outcomes.

Publications (4) and (5) focus especially on performance measurement in industrial context. The papers discuss the problems of performance measurement in detail and present some approaches for overcoming these problems. The aim in these papers is to develop performance measurement so that it is possible to give more constructive feedback to the forecasters and to specify potential corrective actions.

2.6 Organizational issues in forecasting

In order to implement any forecasting process successfully, the organizational roles and responsibilities need to be adequately defined. Applying forecasting methods include e.g. defining the type of forecast required, the resources committed and the data sources used, selecting the forecasting methods, reviewing the forecast, and measuring the forecast performance. This thesis emphasizes the need to see forecasting as an organizational, rather than a technical issue. In this section, the grounds for this point of view are presented, and it is reviewed how organizational issues have been approached in former research.

2.6.1 Call for organizational research

Already in 1979, Makridakis and Wheelwright stated: "Practical application may derive from theory, but they (the forecasting methods) require considerable modifications before they can be used. Strong bridges are required to connect theory and practice, and many problems must be solved before forecasting methods can be used efficiently and effectively in management situations." (Makridakis & Wheelwright, 1979, p.15) One reason for the role of organizational issues to have been emphasized recently is that globalization has caused many companies to become more decentralized (McCarthy et al., 2006).

Despite the fact that it has for long been suggested that organizational factors in sales forecasting management should gain more interest in research, organizational issued in sales forecasting management continue to be relatively neglected. In a 25-year review of forecasting literature, Winklhofer et al. (1996) identified only 35 surveys and six case studies that explored sales forecasting management, and they were mostly descriptive by nature. The authors point out that questions concerning the utilization of forecasting methods have attracted a lot of study, but such issues as the role and level of forecasting have been relatively neglected. While such variables as company size and industry type have been systematically linked to some aspects of forecasting practice (e.g. resources available and forecast accuracy), such linkages have been left unexplored for other aspects (e.g. data sources utilized).

Later studies, e.g. Zotteri & Kalchschmidt (2007), show that organizational issues are dominant, but still understudied area in forecasting. Based on survey results, the authors note that a company's aims and organization play a major role in designing how forecasting is conducted. The authors suggest that more normative research is needed on how companies should organize their forecasting processes.

2.6.2 Challenges in applying forecasting methods

Even though organizational responsibilities in forecasting have not been extensively studied, there are some studies that explore the problems in implementing forecasting methods. These problems are mostly organizational by nature.

Hughes (2001) has used a mail survey to examine the forecasting practices in the electronics manufacturing sector and financial services sector in Scotland. The survey investigated reasons for the non-use of forecasting techniques. The results are summarized in table 2. Other barriers inhibiting the use of forecasting (not mentioned in the table) were the lack of importance attached to forecasting by senior management, lack of knowledge of the potential of forecasting, and lack of knowledge of how to carry out the function, and in particular, the difficulty of convincing colleagues and senior executives of the validity of forecasts.

Table 2: Barriers to forecasting (Hughes, 2001)

Barrier	% of respondents
Insufficient time due to other work	41
Insufficient resources	28
Limited historical database	24
Insufficient training	23
Lack of computer resources/skills	20

Some other research findings imply that similar issues appear in companies that do apply forecasting. In a large interview study by Davis and Mentzer (2007), the authors noticed that the nature of "forecasting climate" seems to be linked to the forecasting capability. The "forecasting climate" consists of leadership support, credibility of sales forecasting and reward alignment. The more negative the forecasting climate, the more detrimental it is for the forecasting capability. In an in-depth study of the sales-forecasting management practices of 33 companies, Moon and Mentzer (1999) found some resistance from the salespeople concerning their forecasting responsibilities in almost all the studied companies, and the forecasters seldom got any feedback of their forecasts.

2.6.3 Challenges in applying judgemental forecasting methods

There are challenges in implementing forecasting methods in general, but some special challenges exist in implementing especially judgemental forecasting methods. The salespeople are closest to the customer, so they are assumed to have the best access to customer information, and it is common that the salespeople participate in the forecasting process. However, judgemental forecasts, especially when produced by salespeople, are known to be prone to bias and inefficiency (Mentzer & Moon, 2005).

One explanation for the weakness of the forecasts made by salespeople is the conflict between the roles of selling and forecasting. Sales quotas are often set according to forecasts (Davis & Mentzer, 2007), and therefore it is reasonable for a salesperson to underestimate the future sales. On the other hand, salespeople sometimes need to secure capacity, and that leads to over-forecasting. Forecasting takes time from the actual work of the forecasters, selling, so it decreases the motivation to forecast. A general conclusion is that in general, sales people make relatively poor forecasts (Moon & Mentzer, 1999).

Moon and Mentzer (1999) offer some suggestions for enhancing salespeople's commitment to forecasting:

- It is important to make forecasting accuracy an important outcome for salespeople. This means stating the forecasting responsibility clearly in job descriptions, offering incentives for high performance in forecasting, and offering adequate feedback and training.

- Forecasts should be disengaged from quotas, for example by using different units in forecasts and sales quotas, or by using different time horizons in sales forecasts and sales quotas.

- The work of the forecasters should be kept as simple as possible. It is preferable to ask salespeople to adjust statistically generated baseline forecasts instead of producing forecasts from scratch. Salespeople can truly contribute value to the forecasting process when they have insights as to how the future will not follow the same patterns as in the past. Another way that companies can "keep it simple" for salespeople is to provide them with adequate tools that enable them to complete their forecasting work as efficiently as possible.

- The final key to improving the effectiveness of salespeople's' forecasts is to keep them focused only on those forecasts where they can make significant contribution to the company's overall forecasting effectiveness. This focus comes by asking the salespeople to concern themselves only with those combinations of customers and products that are truly important to forecast accurately, and where they can provide real insight.

There is some research evidence implying that judgemental forecasting is a cognitively challenging task in general. Some psychological experiments have been carried out to examine how people behave in decision making situations. There are some inherent problems when demand information is collected from more than one source. Judgemental forecasters carry out voluntary integration of statistical methods and judgemental forecasts inefficiently (Goodwin, 2000). The forecasters tend to ignore cues, especially if there are several available, and people tend to be irrational when it comes to dealing with probabilities (Wright & Goodwin, 1998). Lim and O'Connor (1996) found out in their laboratory study that people often selected less reliable information when there were many types of information available to a forecaster. These findings support the conclusion that it is important to provide clear instructions on how to produce the forecasts in a simple way.

Some research has been conducted on reducing the forecasting efforts by clustering customers or items. E.g. Holmström (1998) has presented an approach called 'assortment forecasting'. The approach focuses on reducing the time spent on forecasting by working with an entire assortment at a time, instead of producing a forecast for each product individually. The approach has been tested by Småros and Hellström (2004) with a case company that provides supermarkets, video rentals and the like with pick-and-mix sweets. Categorizing customers or products to reduce forecasting efforts has been studied also e.g. by Caniato et al. (2005), Thomassey & Fiordaliso (2006), and Fliedner (1999).

2.6.4 Organizational learning in the forecasting process

The forecasting process may offer some benefits that go beyond the forecast accuracy. During the forecasting process, the people responsible for capacity or production planning gain information about potential future events that cause changes in load rates, and salespeople gain information about the capacity situation. During a well-functioning forecasting process, a cross-organizational consensus is received, which results in aligned plans in the organization. This aspect may be more essential than the forecast accuracy itself.

Some case studies (e.g. Lawrence et al., 2000) show that in practice, the aim of forecasting is not necessarily to produce as accurate forecasts as possible. In some cases judgemental forecasting methods are applied even though the accuracy received is not uniformly better than naïve forecasts. One reason for this may be that in some cases, qualitative methods offer a better basis for cross-organizational discussion and learning. In a large interview study conducted by Davis and Mentzer (2007), it was found out that managers reported that building a shared interpretation of the sales forecasting information was more important to a strong forecasting capability than managing the information logistics of sales forecasting. That means that the dialogue over the sales forecast may be more important than the forecast. The informants claimed that having an opportunity to address questions regarding assumptions, market issues and other factors driving estimates is the most valuable aspect of sales forecasting (Davis & Mentzer, 2007). Lawrence et al. (2000) noted in a case study that in forecasting meetings of manufacturing companies, the managers discussed such things as new marketing initiatives, promotion plans, actions of competitors and industry developments.

Davis and Menzer (2007) suggest that conceptualizing sales forecasting management as an organizational learning process opens up a promising area for further research. In line with this suggestion, a new direction in forecasting research could be taken. Instead of focusing only on techniques and forecasting accuracy, the new focus could be facilitating the cross-organizational dialogue needed in the sales forecasting process.

2.7 Demand forecasting process models

Since demand forecasting is a combination of technical and organizational issues that involve several parties and several tasks, it is natural to describe demand forecasting as a process. In this section, models for describing a forecasting process, as well as auditing and improving the forecasting process are discussed.

2.7.1 Models for describing the demand forecasting process

There is no single established way to describe the forecasting process. Some authors have presented models for that purpose, e.g. Mentzer and Moon (2005), Holmström (1998), and Croxton et al. (2002). These are generic thought models that list issues related to forecasting. They are used for structuring the contents of a specific publication rather than attempting to provide a general tool for modeling the forecasting processes of companies.

One kind of a forecasting process model is presented as a framework of this study (Figure 6). The aim of this model is similar to other forecasting process models: it structures the content of this thesis, describing the areas of focus. As such, the model is also a generic model. It describes the issues that need to be defined to make the forecasting process a structured one.

2.7.2 Approaches for improving the sales forecasting process

It is generally assumed that a structured forecasting process is more efficient than an unstructured one (Armstrong 2001, Mentzer & Moon 2005). Wright and Goodwin (1998) state that in integrating judgemental and statistical forecasts, structure helps. The more structured the inputs and the more structured the integration procedures, the more accurate the forecasts. However, only a few authors have presented frameworks to serve as standards with which forecasting processes can be compared.

In the *Principles of Forecasting* by Armstrong (2001), 139 "principles of forecasting" are listed. They cover formulating a problem, obtaining information about it, selecting and applying methods, evaluating methods, and using forecasts. Each principle is described along with its purpose, by the conditions under which it is relevant, and the strength and sources of evidence. A checklist is provided in auditing the forecasting process.

Moon et al. (2003) present a four-dimensional framework based partly on former theoretical frameworks and partly on empirical research. They propose that, in order to adequately understand the overall management of the forecasting process in a company, that process must be investigated along the following four dimensions: (1) *Functional integration*, concerned with the role of collaboration, communication, and coordination of forecasting management with other business functional areas of marketing, sales, finance, production, and logistics; (2) *Approach*, concerned witch products and services that are forecast, the forecasting techniques used, and the relationship between forecasting and planning; (3) *Systems*, addressing the evaluation and selection of hardware and software combinations to support the sales forecasting function as well as the integration of forecasting systems with other planning and management systems in the organization; and (4) *Performance measurement*, considering the metrics used to measure the effectiveness of sales forecasting and its impact on business operations. In addition to identifying these four dimensions of forecasting management, Mentzer and Moon (2005) include four stages of effectiveness within each dimension. The article provides a description of the characteristics that can be found at each of the four stages of effectiveness within each of the four dimensions.

Fildes and Goodwin (2007) focus on judgemental forecasting, and list eleven principles that show how forecasters should use judgment and assess its effectiveness. These 11 principles have been identified from the *Principles of Forecasting* by Armstrong, 2001. Fildes and Goodwin (2007) found out that many companies do not follow the principles.

The models and suggestion lists divide the forecasting process into smaller tasks, and then provide suggestions on how these tasks should be performed. Some of the suggestions are very practical, and some are not. Some of the suggestions are based on theoretical reasoning, and some on experience. Examples of different suggestions are e.g. the following:

- More functional integration in forecasting is better than less (Mentzer & Moon, 2005).
- A developed information system is better than a simple system (Mentzer & Moon, 2005).
- Requiring the judgemental forecasters to justify their judgemental adjustments in writing reduces bias in forecasts (Arkes, 2001).
- Performance measurement should relate the forecast accuracy with the cost impacts of error (Mentzer & Moon, 2005).

However, the operational environments of companies are different, which implies that forecasting may not be of equal importance in all companies. Armstrong agrees that all the 139 principles of forecasting presented in the "*Principles of forecasting*" are not needed in one situation. From a point of view of this thesis it is interesting to study what are the most critical principles in the industrial context.

Publication (6) focuses on improving the existing forecasting process. The emphasis is on finding out the issues that are critical or important to the specific company in question and bring consensus in the forecasting process.

2.8 Demand forecasting practices in industrial context: research needs

In this section it is summarized, what kind of research needs exist in the forecasting literature concerning demand forecasting practice. After that, an agenda for answering those needs is presented.

2.8.1 Conclusions from the literature

1) *Organizational issues are still relatively neglected in forecasting research.*

Even though it has for long been emphasized that organizational issues are critical in implementing efficient forecasting practices, still quite little attention has been paid to organizational issues in the forecasting literature. However, some studies suggest that there are some common problems in implementing efficient forecasting practices. Therefore, it is possible that organizations could learn from the experiences of other organizations. Models that help pay attention to right things can facilitate decision making processes. To gain deep enough understanding in this area, more studies on implementing and improving forecasting practices are needed, for example case studies.

In the literature it is noticed that it is fundamental to focus the efforts of salespeople to the products and customers where the salespeople's' insight on changing demand patterns is truly important. However, there is a lack of descriptions on how this principle can be put in practice.

2) *The special characteristics of the industrial context are not well noted in research concerning forecasting practice.*

Most of the studies that deal with forecasting practices are conducted with surveys. Only in a few surveys, industrial companies are distinguished from consumer companies. Most of the surveys provide information on which forecasting methods are used, but not on why or how they are used. Industrial markets have some special characteristics compared to consumer markets. For example, the number of customers is typically lower and the relationship with the customers closer. It can be expected that also the problems in managing the demand forecasting process in the industrial context have some special characteristics that can be studied more deeply.

3) *More attention should be paid on the contexts in which forecasting is applied.*

The forecasting literature dealing with method selection provides clear solutions for clear situations. For example, if there is sufficient demand history available and no changes are expected, time-series methods can be applied, and if large changes in demand are expected and only qualitative information is available, some judgemental methods can be suggested. In practice, it is possible that the situation is such that there is some historical data available and some contextual information available, but it is not clear how reliable these pieces of information are. Typically, in the industrial context the customer base is heterogeneous, so selecting methods is not that straightforward. Thus, a possible area for research is finding out how the method selection situations are really like, how well the environment is known, and how the analyzing of the environment can be facilitated.

The literature emphasizes quantitative methods, but qualitative forecasting methods are preferred in real life. The former literature points out that the right choice between qualitative and quantitative methods depends on the circumstances, and often some kind of combination of judgemental and quantitative methods is necessary. More attention could be paid to the different environments where forecasting is applied. It could be examined, how quantitative data can in practice get connected into demand forecasting processes in different contexts.

4) *There is room for development in forecasting performance measurement*

Performance measurement has been noticed to be a critical factor in demand forecasting management. Performance measurement should provide feedback for the forecasters, so that they are able to make the forecasts more efficiently. Efficiency in demand forecasting means that the benefits received from forecasting are greater than the effort put in forecasting. This means that not only forecast accuracy, but also the forecasting efforts need to be considered. Especially in the industrial context, forecast accuracy as a single measure of performance is insufficient.

However, in many practical settings forecasting performance measurement focuses on measuring forecast accuracy. If only forecast accuracy is provided as a feedback, the forecaster becomes penalized for irreducible demand uncertainty. Therefore, there is room for research that aims at developing performance measurement practices that support the improvement of forecasting practices better.

5) *More attention could be paid to facilitating the cross-functional dialogue needed in forecasting.*

A majority of forecasting literature focuses on forecasting techniques and on the accuracy that is received. However, some research results imply that achieving as accurate forecasts as possible is not the only aim of the forecasting process. Another relevant aim is achieving a cross-organizationally shared view of the demand environment and about the ways to react to it. Therefore, a potential area for forecasting research is facilitating the cross-functional dialogue that is needed in producing the forecasts and in improving the forecasting practices.

2.8.2 Agenda for answering the research needs

In the previous section, some research needs in demand forecasting practice were addressed. In this section it is described how those research needs can be answered. The focal areas of this thesis can be divided to four interlinked areas (see figure 3): 1) defining the operational environment for forecasting, 2) defining the forecasting methods, 3) defining the organizational responsibilities, and 4) defining the performance measurement process.

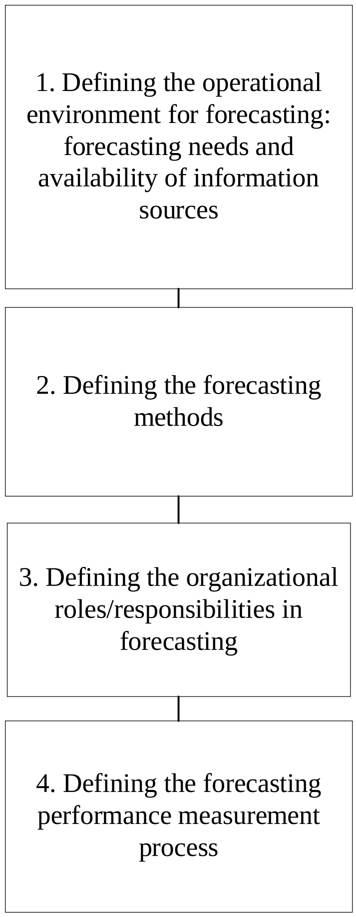

Figure 3: Areas of focus in this study

Defining the operational environment for forecasting means exploring what the environments in which forecasting is applied are really like. For an outside facilitator or a consultant aiming at improving the forecasting practices, it is important to gain a view of the environment, as in different environments it is reasonable to focus the forecasting efforts on different issues. For that purpose, approaches for analyzing the demand environment are welcomed. The industrial context has received little attention in the forecasting literature, though forecasting methods are applied also in industrial contexts. Therefore, it is of value to focus on the industrial context.

Defining the forecasting methods means selecting the forecasting methods and defining the level of detail on which the forecasts are to be produced. The context where forecasting is applied impacts the applicability of the forecasting methods. A relevant question is what the situations, where forecasting methods need to be compared or selected are really like, and what kind of tools are needed in the selection process.

Defining the organizational responsibilities means defining who does what in the forecasting process. Former research points out that forecasting effort should be focused on the most important customers and products, and cross-functional dialogue in forecasting process is considered important. A relevant question is what the situations which call for focusing resources or improving cross-functional communication are really like, and what kind of tools can be used to support these tasks.

Defining the performance measurement process means selecting the performance measures and linking those measures into the planning processes. Former literature points out that performance measures should support improving the forecasting process. A relevant question is what kind of performance measures are needed in practice, and how the performance measures can be linked to the planning processes in specific settings.

As a summary, supporting the improvement of forecasting practices requires pointing out the problems that occur in the improvement, and suggesting cures for those problems. Improving forecasting practices can be directed to single phases of the forecasting process, or the process as a whole.

The research questions of this thesis are:

> *1. What kind of challenges are there in organizing an adequate forecasting process in the industrial context?*
>
> *2. What kind of tools of analysis can be utilized to support the improvement of the forecasting process?*

3 Research strategy

This chapter concerns the methodology and research design of the study. In this chapter, the methodological choices of the study are explained. First, the research paradigm is presented. After that, case study as a method and its different forms are discussed. Finally, the details of collecting and analyzing the data are presented.

3.1 The research paradigm of this study

The foundation of scientific thinking is usually expressed in the form of a research *paradigm*. Briefly, paradigms can be defined as the worldviews or belief systems that guide researchers (Tashakkori, 1998). The paradigm of this thesis is very close to the paradigm of Design Sciences. This section discusses the paradigm of design science, as well as the foundations of scientific thinking behind this thesis.

According to Van Aken (2004), it has been remarked that the business world ignores the research coming from Business Schools. He states that the relevance problem of the academic management theory is not only caused by poor presentation but also by its nature, as most academic research in management is based on the notion that the mission of all science is to understand, i.e. to describe, explain and possibly predict. However, in management one needs research also in order to develop research products which can be used in designing solutions for management problems. Van Aken states that a major inhibition for adopting the academic management theory for instrumental use lies in the nature of the theory, and this theory is strongly influenced by the paradigm used for developing the theory.

Van Aken (2004) defines the research paradigm as combination of research questions asked, the research methodologies allowed to answer them and the nature of the pursued research products. He distinguishes three categories of scientific disciplines (Table 3).

Table 3: Three categories of scientific disciplines According to Van Aken (2004)

	Formal sciences	**Explanatory sciences**	**Design sciences**
Examples	Philosophy, mathematics	Natural sciences, major section of social sciences	Engineering sciences, medical science, modern psychotherapy
Mission	To build systems of propositions whose main test is their internal logical consistency	To describe, explain and possibly predict observable phenomena within its field.	To develop knowledge for the design and realization of artefacts, i.e. to solve *construction problems,* or to be used in the improvement of the performance of existing entities, i.e. to solve *improvement problems.*

In this thesis, the mission is definitely solving “construction problems” and “improvement problems”, as analysis tools are planned to help improve the forecasting process. However, the thesis is also partly descriptive, as the problems need to be described before actions can be planned to solve them.

Every time a professional sets out to solve a unique and specific problem for a client or in conjunction with a client, he or she does so by using the *problem solving cycle* (Figure 4). This study focuses mostly on the two first phases of the problem solving cycle: defining the problem and planning an intervention. The two second phases, applying the intervention and evaluating the intervention are performed only with limited sample data sets. This could be compared to a laboratory test, where an intervention is tested in a limited scale before its actual use.

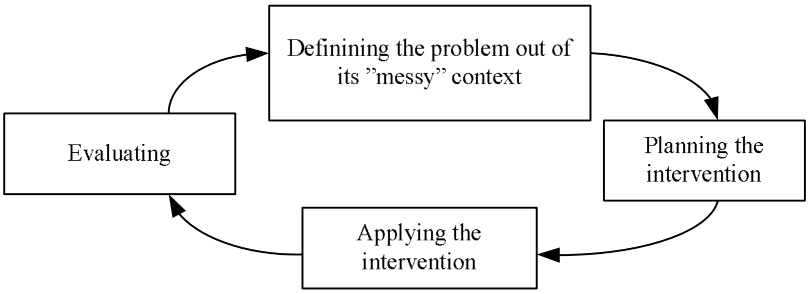

Figure 4: Problem solving cycle (Van Aken, 2004)

3.2 Case study research

Practically, the design science paradigm leads to case studies. As a research strategy, the case study is used in many situations to contribute to our knowledge of individual, group, organizational, social, political, and related phenomena. In all situations, the distinctive need for case studies arises out of the desire to understand complex social phenomena. In brief, the case study method allows investigators to retain the holistic and meaningful characteristics of real-life events, such as organizational and managerial processes (Yin, 2009). Case studies are considered as an appropriate research strategy particularly for new types of research areas where qualitative data is needed in the creation of proper understanding of the studied phenomena (Gummesson, 2000). Case study can be either a single case study or a multiple case study. The present study is a series of single case studies, since each case has different research questions.

Case studies can be divided into intervention-oriented and non-intervention-oriented ones. In intervention-oriented case study, the researcher seeks to influence the research object. In non-intervention-oriented case study, the researcher avoids influencing the research object.

Stake (1995) sees case study as non-interventive, which means that the researcher does not try to disturb the ordinary activity of the case, not to test, not even to interview, if the information can be gained by discrete observation or examination of records. "For all their intrusion into habitats and personal affairs, qualitative researchers are noninterventionists. They try to see what would have happened had they not been there. During field-work, they try not to draw attention to themselves or their work. Other than positioning themselves, they try to avoid creating situations to test their hypotheses." (Stake, 1995 p. 44)

According to van Aken (2004), there are two types of multiple-case studies in management theory: *extracting* and *developing* multiple case-study. Extracting multiple case-study is a kind of best-practice research and is aimed at uncovering technological rules as already used in practice. In the developing multiple case-study, technological rules are developed and tested by researcher(s) in close collaboration with the people in the field.

One form of case study, in which interventions play a crucial role, is action research. Action research (AR) is an approach that aims both at taking action and creating knowledge about action. Several authors characterize action research as:

- research in action, rather than research about action
- participative
- concurrent with action
- a sequence of events and an approach to problem solving.

Action research works through a cyclical 4-step process consciously and deliberately: planning, taking action and evaluating the action, leading to planning, and so on. The goal is to make action more effective while simultaneously building up a body of scientific knowledge (Coughlan & Coghlan, 2002). Validation of the results is experimental. Action research is fundamental about change, and one of the quality criterions, according to Reason and Bradbury (2001) is if AR results in new and enduring infrastructures, in other words, if sustainable change comes out of the project.

Since the use of interventions is in some sense a controversial issue, it is worthwhile to describe the role of interventions in this research. The aim was not to avoid interventions, but the interventions do not have as strong a role as in action research. The interventions made during this research can be divided into two groups.

1) interventions that were made in order to gather data
2) interventions that are considered to be results of the study.

Developing the ways of action was a starting point in this study. Case company 2 impacted on the selecting of the specific research questions in articles 2 – 6. Data about past sales and past demand forecasts were collected from company information systems via a key informant. It is known that paying attention (in research) to a certain theme or target may have an impact on it. However, in this study, the impact of this intervention was not assumed to be very strong, since the need to improve the forecasting process was already apparent in the case company.

In all the articles, some kind of tool or approach is presented, but the tools are of different nature. Publications 4 and 5 present numerical analysis tools. The tools gained some acceptance from managers, but the approaches were not implemented in their original form (that is, like presented in the articles). Publication 3 presents an approach that was not presented for the case company, as it is a rather theoretical approach that needs more data before results can be presented. The data analysis presented in publication 2 was presented to the management, and the management ended up in similar conclusions as the ones in the paper, but it cannot be estimated what was the actual reason for the management's actions. The nature of intervention in publication 1 is similar to that in publication 2. The results of analysis presented in publication 1 were presented in the company, but in this case it did not lead to any direct changes in ways of action. One reason for this can be that the analysis results showed some potential savings that could be achieved from changing the way of behavior, but the savings did not seem considerably attractive in the current situation. In publication 6 an approach has been designed that aims to be useful for the management, but the approach has not been tested yet.

When interventions are in question, assessing their impacts is of interest. As the aim of each tool in this study is to help point out areas of development and potential actions, it is assessed how well the tool succeeds in these aims. Is it able to point out potential areas of development? Does it bring about information that is new and useful for managers? This assessment is performed in the articles with limited data sets.

The ultimate aim of the tools is to help find resource-efficient practices. Succeeding in this aim is more difficult to measure, and as mentioned above, all the tools were not implemented yet. Some of them were implemented, but not in their original form. Even if it is assumed that the tools have impacts on such things as the use of resources or forecast accuracy, in practice it is difficult to distinguish the impact of the intervention from the impacts of other interventions and changes that take place at the same time. As the causality between the tools and company performance is complex, no statistical analysis has been considered relevant.

3.3 Description of the data gathering and analysis methods employed in the study

According to Stuart et al. (2002), the research and publication process of a case study can be broken down into five critical stages, as illustrated in figure 5. The *first step* of the research process involves defining the research question. Invariably, this involves contributing to building a body of knowledge and developing theory. The *second step* is the development of the research instrument and selection of appropriate field sites. Having defined the research question, the case-based investigator needs to develop measurement instruments to capture the data for future analysis. The *third step* is gathering data, which are usually written and taped records of interviews, documents that the company is willing to provide, and the researcher’s observations. The *fourth step* is analyzing the data, which includes determining what has been learned and how to present it. The *fifth* and final step is disseminating the research findings. This step includes responding to the criticism that case studies are often subject to. In this section, it is discussed how these steps were realized in this study.

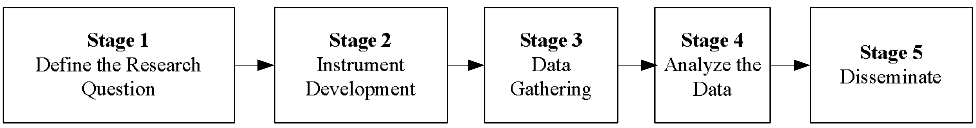

Figure 5: A five-stage research process model (Stuart et al. 2002)

As the thesis consists of several research articles, it is natural that the different process stages overlap. Figure 6 shows how the research processes of individual research articles can be placed on a timeline. The earlier studies have impacted on selecting the research questions of the later articles. Each research paper concerns an individual research problem, and follows the process presented in figure 5.

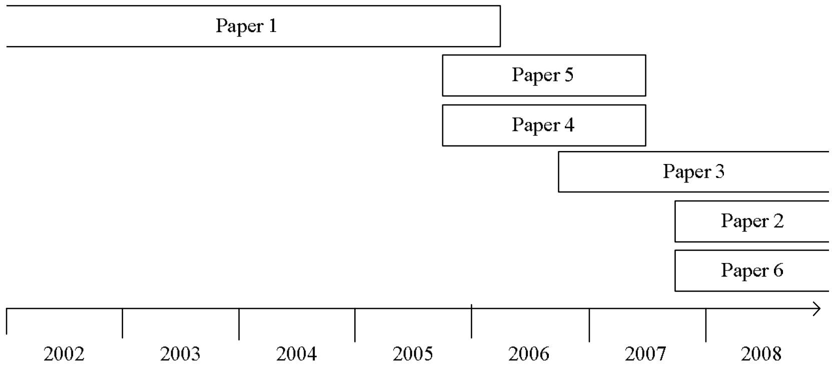

Figure 6: Positioning the thesis on a timeline, from the start to the acceptance of the research articles.

Defining the research questions

The first stage of the research process involves defining the research question. Yin (2009) suggests that case studies are particularly appropriate when the research question centers on "why" observed phenomena occur, when there is no control over behavioral events, and when the focus is on contemporary events. According to Stuart et al. (2002), a well-conducted case study may point out some patterns in implementation problems with a particular technology.

This study deals with implementation problems in demand forecasting. The most important thing that had an impact on selecting the research questions was that the research should fit the interests of the case companies. Being so, the research goal was selected to fit the cases. The problems dealt with are planning problems. In each article, a managerial problem is described, and an approach is suggested to mitigate it.

According to Eisenhardt (1989), the research questions are tentative and may shift during the research. In an ideal situation, in the beginning of theory building research there should be no theory under consideration and no assumptions to test, in order not to bias or limit the findings by preordained theoretical perspectives. The investigators should formulate a research problem and possibly specify some potentially important variables with some reference to existing literature. However, they should avoid thinking about specific relationships between variables and theories as much as possible, especially at the outset of the process. (Eisenhardt, 1989)

This study is not fully free of a priori assumptions. For example, in the second case company the personnel had some assumptions of the sources of forecast errors, for example that forecast errors would be reduced if the forecasts were updated more often.

Some of these assumptions were tested during the forecast. However, these assumptions were not used as research hypotheses.

In this research, the research questions of articles did not change much after they were selected. One observation was that in the when the case company was not very familiar, research questions were quite technical, focusing on forecast errors since it is easier to start with a narrow focus. When the understanding about the case company increased, the organizational issues emphasized more. That way, the overall focus of this thesis shifted from technical aspects of forecasting into organizational aspects of forecasting process.

Instrument development and site selection

Case studies typically combine different data collection methods, such as archives, interviews, questionnaires and observations (Eisenhardt, 1989). Case study research can involve qualitative data only, quantitative data only, or both (Yin, 2009). Qualitative data are useful for understanding the rationale of theory, the underlying relationships revealed in the quantitative data, or they may directly suggest theory which can then be strengthened by quantitative support (Eisenhardt, 1989).

Instrument development is closely related to selecting the cases. According to Yin (2009), theoretical sampling in single cases is straightforward. They are chosen because they are unusually revelatory, extreme exemplars, or opportunities for unusual research access. According to Stake (1995), it is not unusual for the choice of a case to be no "choice" at all. Case study research is not sampling research. A sample of one or a sample of just a few is unlikely to be a strong representation of others.

In this study, the empirical material has been collected from two case companies. The material for the first research article was collected from a Finnish steel producer. In the latter articles, the case company was a large international paper producer with headquarters in Finland. The first case company was selected because access to empirical material was available after a master's thesis. The second case company was chosen because it had recently implemented an information system for forecasting, but had some problems in achieving accuracy targets. The case provided a suitable environment for conducting this study, as there was motivation for development work. The case companies are process industry companies operating in a B2B environment. From a theoretical point of view, this is an atypical environment for demand forecasting, because observed demand is dependent and the manufacturing capacity is inflexible. It can be seen that the cases are "extreme examples" of forecast application.

The use of research instruments was quite restricted. For geographical reasons, direct observation or multiple in-depth interview studies were not possible in case company 2. Also confidentiality issues limited the access to company data. Usually, the problem in case research is that there is too much data, so in that sense there was unusually little data available. In this study, the data was collected mostly from the case companies' information systems via a key informant, and from discussions with the key informant and other personnel.

The data collection methods also included a Group Decision Support System (GDSS) session. GDSS or Group DSS is an interactive computer-based system that facilitates the solution of semi-structured or unstructured decision problems by several decision makers who work as a group. In a narrow sense, the term GDSS is used to describe a network of computers in a face-to-face environment, such as a conference room, and the software which enables a group to exchange written comments and votes. In the GDSS session, the aim was to collect information about the managers' views on the performance of the forecasting process, and on the issues that needed improvement in the process. In the session, the participants also voted for the most important development targets. It would have been possible to guide the managers to a certain direction, but the manipulation was kept to the minimum. It is possible that the participants impacted on each other during the session, but such impacts were not assessed. To orient the participants to the GDSS session, a short survey was used.

The narrowness of the empirical basis can be seen as a weakness of this study. On the basis of the empirical material, it cannot be concluded how general the observed problems are, how widely the presented tools can be applied, or what would their impacts be in the long run. Eisenhardt (1989) notes that when empirical material is limited, connecting with former literature becomes more important. In this study, former literature has been used to evaluate if the studied managerial problems are relevant in general.

On the other hand, the demand for efficient use of resources is not unusual in industrial companies. When designing analysis tools, they have to be such that their use does not consume too much company resources. From this point of view, the narrowness of empirical data can be seen also as the strength of this research. If development targets can be pointed out with analyzing a small amount of easy-access data, it can be more beneficial than if the same conclusions have been made from more extensive data that is time-consuming to gather.

Data collection

According to Eisenhardt (1989), a striking feature of research to build theory from case studies is the frequent overlap of data analysis with data collection. It is legitimate to alter and even add data collection methods during the study. Flexibility is controlled opportunism in which the researchers take advantage of the uniqueness of a specific case and the emergence of new themes to improve resulting theory. The main data sources used in individual research articles are presented in table 4.

Data from the information systems of case company 2 was collected during the study. In the beginning, one problem in collecting the data was that there was no information on exactly what kind of data existed. The data was obtained through request, so part of the problem was specifying the requests. In this stage, free access or familiarity with the company's information system would have facilitated the data collection.

During the spring 2008, it became possible to plan an all-day GDSS-session on process development, so this opportunity was exploited. However, shortly before the session the session shrunk to a half-day one, so the data collection needed to adapt quickly to the changing situation.

Table 4: Main data sources in the publications of the study

	1	2	3	4	5	6
Title	Determining semi-finished products to be stocked when changing the MTS-MTO policy: Case of a steel mill	Selecting an approach for making aggregate demand forecasts – a case study	The role of contextual information in demand forecasting	Demand forecast errors in industrial context: Measurement and impacts	Analysing inaccurate judgmental sales forecasts	Assessing demand forecasting practices in the B2B Environment
Main data sources	Demand data Product data Participative observations	Literature Demand data Forecast data	Observations Literature	Literature Demand data Forecast data	Literature Demand data Forecast data	Literature Survey Group panel data

Data analysis

According to Eisenhardt (1989), analyzing the data is the heart of building theory from case studies, but it is both the most difficult and the least codified part of the process. One key step is within-case analysis, which typically involves detailed case-study write-ups for each site. However, there is no standard format for such analysis. The overall idea is to become intimately familiar with each case as a stand-alone entity. The next step is cross-case analysis, but as this study is not a multiple case study, this step was not relevant for this study.

Shaping hypotheses in theory building research involves measuring constructs and verifying relationships. These processes are similar to traditional hypothesis testing research. However, the processes are more judgemental in theory-building research, because the researchers cannot apply statistical tests, such as an F statistic. The research team may judge the strength and consistency of relationships within and across cases, and also fully display the evidence and procedures when the findings are published, so that the readers may apply their own standards.

An essential feature of theory building is comparison of the emergent concepts, theory, or hypotheses with existing literature. This involves asking what they are similar to, what do they contradict, and why. Comparison with conflicting literature increases the confidence in the findings and builds internal validity, whereas comparison with similar literature enables wider generalisability and higher conceptual level. This stage is particularly important if the findings are based on a very limited number of cases (Eisenhardt, 1989).

The mechanism by which different types of data was converted into results in this research, was simply the following:

- ***Discussions*** and ***observations*** guided the selection of specific research problems.
- ***Literature*** was used for verifying the relevance of the research problems.
- ***Company data*** such as ***product data***, ***demand data*** and ***forecast data*** were used for testing and illustrating the use of the designed tools.

All the studies included in this thesis are at least partly descriptive. The descriptive part of the papers describes the research problem as it exists in the case company. The research problems are not given from the outside, but defining them is a part of the problems solving cycle (Figure 4). In all the papers, some kind of tool or approach is presented for the selected problem. The approaches presented in papers 2, 4 and 5 have been tested with a sample data set, as the tools in these papers are analysis tools to be used for numeric data. The approaches presented in papers 1, 3 and 6 have not been tested in that way, as these tools combine qualitative and quantitative data, and same kind of criteria for their evaluation is not possible.

4 Summary of the publications and review of the results

In this section it is described how the individual publications are related to each other. The contents and contribution of each paper is reviewed. After that, it is summarized how the publications contribute to answering the research questions.

4.1 Links between the individual publications and the framework of the study

Figure 7 presents the linkage between the individual publications. There are four interlinked areas of focus in this thesis. Some publications are more closely related to a specific area of focus, and some publications concern the whole forecasting process.

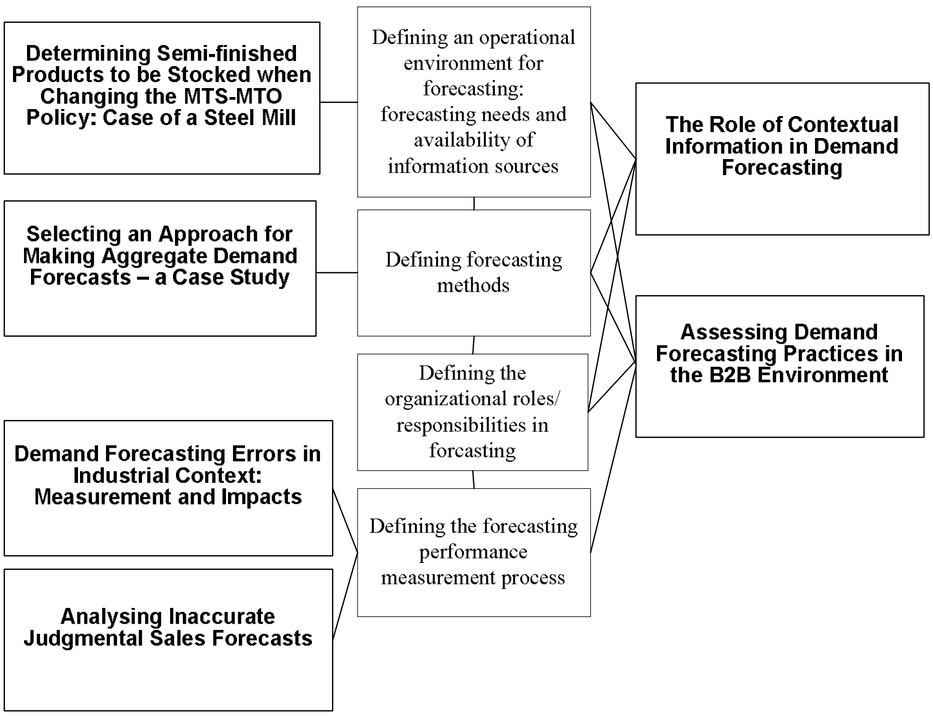

Figure 7: Areas of focus of the study, and their links to individual publications

4.2 Overview of the publications

1. Determining Semi-finishedPproducts to be Stocked when Changing the MTS-MTO Policy: Case of a Steel Mill

This paper considers the problem of selecting between make-to-stock (MTS) and make-to-order (MTO). The case company is a small MTO steel mill planning to move towards a hybrid MTS/MTO-system. In the decision process, determining the semi-finished items to be stocked plays a critical role. Demand predictability and estimates about future demand are an important factor in the decision. The complexity of the problem is illustrated with examples.

The publication presents a model for the decision making process. The idea is that the complex problem is divided into phases that are simpler to deal with. The idea is to find a potential pilot product, for which the hybrid MTS/MTO system could be tested with. In each phase of the decision process, potential pilots are sorted out so that the number of candidates is reduced in each phase of the decision process.

The main contribution of the paper is that it points out that with categorization it is possible to simplify the complex decision of selecting the production mode. The paper illustrates how demand forecasts are needed in this type of strategic decisions.

2. Selecting an Approach for Making Aggregate Demand Forecasts – a Case Study

This paper deals with selecting between judgemental and quantitative forecasting approaches in a situation where the forecasts are used for capacity allocation. This is a typical situation in the industrial context, where the production runs on the MTO basis. In the beginning of the study, the case company made forecasts by aggregating the forecasts that the salespeople had made for each customer separately.

Three different approaches for creating aggregate forecasts are evaluated in this paper. Forecast accuracy and the effort needed for creating the forecast are used as evaluation criteria. Examples and sales and forecast data from a large process industry company are used to illustrate the evaluation. The analysis points out that, different forecasting approaches can be suggested for different product/customer categories. Even though the forecast accuracy of salespeople's forecasts is better on the detailed level, there is less difference in the performance of different forecasting methods when the performance is assessed on the aggregate level. The main contribution of the paper is that it presents a framework to help in selecting between forecasting approaches.

3. The Role of Contextual Information in Demand Forecasting

The paper deals with clarifying the role of contextual information in demand forecasting. It is often noted that combining judgemental forecasting methods with statistical methods is needed to provide accurate forecasts. However, it has remained unclear when contextual information is useful and when it is not.

The paper provides some guidelines for how to evaluate the value of contextual information with probability calculations. It has been pointed out in former literature that people tend to be irrational when dealing with probabilities, so the aim is to provide a more objective view about the value of contextual information, and thereby to avoid setting unrealistic targets for forecast accuracy.

The main contribution of this paper is that the role of contextual information in forecasting should and could be expressed more clearly. The paper also points out that demand information that is seemingly relevant, cannot always improve forecast accuracy. If such a situation occurs, it should be noticed in the performance measurement. If such demand information exists that is necessary for planning, but not for forecasting, this may explain why forecasting is often mixed with planning in real life.

4. Demand Forecast Errors in Industrial Context: Measurement and Impacts

This paper discusses the dilemma that all forecast errors are not equally harmful. Often forecast accuracy is measured, but it is not identified what the impacts of forecast errors are.

The paper contains a case study about assessing the impacts of sales forecast errors. The analysis steps include defining the planning flow and the role of sales forecasts in production planning and inventory management, and analyzing the characteristics of the sales forecasting errors in a company. It is suggested that the sources of forecast errors should be identified, even though the impacts of forecast errors cannot be implicitly measured.

The main contribution of the paper is that it points out the problems that industrial companies run into when measuring forecasting performance. One is the problem of timing errors that exists when sales occur close to the change of the forecast period (e.g. month). A filter is suggested for sorting out this type of errors. The filter is not mathematically perfect, but it provides a sufficient reference value, and using it may help in focusing on more fundamental issues.

5. Analysing Inaccurate Judgemental Sales Forecasts

This paper discusses the problem of finding out the reasons for forecast errors. If the reasons behind forecast errors could be pointed out, it would be easier to select approaches for reducing them, and it would enhance understanding about the nature of demand in general. However, finding out the causes for forecast errors should not consume so much resources that it exceeds the benefits.

A model for categorizing errors that exist in judgemental sales forecasts is presented in the paper. The framework includes analyzing demand profiles of customers and the continuity of under-/over-forecast errors. The error types are named as random error, positive bidirectional error, negative bidirectional error, systematic under/over estimation error, and unforecasted sales. Categorizing the forecast errors does not directly reveal the root causes behind them, but it serves as a first step in finding out the reasons. The potential actions for reducing each type of error are discussed.

The main contribution of the paper is that it points out that with proper categorization it is possible to get a detailed view of the error profiles in different sales units in a relatively short time. The error profiling enables benchmarking and giving more constructive feedback to the forecasters.

6. Assessing Demand Forecasting Practices in the B2B Environment

This paper deals with evaluating forecasting practices. Forecasting techniques have developed in recent years, but there is evidence that forecasting practices in companies have not changed accordingly. It has been suggested that more attention should be paid to the implementation of forecasting. The implementation includes sufficient instructions, training and feedback.

A model aiming at assessing demand forecasting practices in companies operating in the business-to-business environment is presented in the paper. The model aims at finding out if there are conflicting views inside the company about the performance of the forecasting process. If conflicting views exist about an issue, it is a potential area for development. The development actions may include creating rules, finding out fact through data analysis, and illustrating the state of the forecasting process in an objective way. The main contribution of the paper is that it notices consensus as a potential target of measurement.

4.3 Summary of the findings

The aim of this study was to enhance understanding about the challenges that there are in organizing a forecasting process in industrial context. This included outlining the analysis tools that can be used in mitigating the problems observed. This aim was put in form of two research questions:

> *1. What kind of challenges are there in organizing an adequate forecasting process in the industrial context?*
>
> *2. What kind of tools of analysis can be utilized to support the improvement of the forecasting process?*

The industrial context means a situation where a company operates on industrial markets aka business to business environment, and produces physical goods. As the research questions are quite general, it is clear that they have not been completely and finally solved. Instead, sub-problems and solutions to these sub-problems have presented. The publications in the second part of the thesis provide insight on specific problems and ways to mitigate those problems. In table 5 it is presented briefly, how the publications contribute to answering the research questions.

Most of the suggestions made in the thesis, for example using several different error measures instead of one, and comparing different forecasting methods against each other, are not fundamentally new in the literature. However, in this thesis the suggestions have been put on a more concrete level, so that detailed, practical examples have been given.

Table 5: The contribution of the publications to answering the research questions

Publication	*1. What kind of challenges are there in organizing an adequate forecasting process in the industrial context?*	*2. What kind of tools of analysis can be utilized to support the improvement of the forecasting process?*
1 Determining semi-finished products to be stocked when changing the MTS-MTO policy: Case of a steel mill	Illustrates how demand forecasts serve as an input in the MTS/MTO-decision. Demand forecast is only one, though an important part in the process.	Suggests a systematic approach for making a MTS/MTO decision.
2 Selecting an approach for making aggregate demand forecasts – a case study	Presents a situation in which the issue of selecting between quantitative and qualitative forecasting methods is interlinked with the issue of forecast aggregation.	Suggests using a systematic procedure in selecting a resource-efficient forecasting approach for creating aggregate forecasts.
3 The role of contextual information in demand forecasting	Points out that there is a need to clarify the role of contextual information in order to avoid unrealistic accuracy targets and to be able to focus forecasting resources.	Suggests using a probability calculations-based approach in order to define the role of contextual information in demand forecasting.
4 Demand forecast errors in industrial context: Measurement and impacts	Points out that all forecasting errors are not equally harmful, and harmful errors should be distinguished from harmless ones.	Suggests using an alternative measure for forecast error in order to illustrate the share of minor timing errors in forecast errors.
5 Analyzing inaccurate judgemental sales forecasts	Points out that traditional error measures are deficient in pointing out the potential reasons behind forecast errors and potential actions to improve forecasts.	Suggests categorizing forecast errors according to demand profiles and continuity of bias. This enables more detailed benchmarking and feedback.
6 Assessing demand forecasting practices in the B2B environment	Suggests that conflicting views about the forecasting process inside a company hinders the improvement of the process.	Suggests using an audit process to assess organizational consensus in the forecasting process and to enhance organizational learning about the forecasting process.

The challenges or managerial problems dealt with in the articles are characteristic to industrial context. They are likely to occur in situations where customer base is heterogeneous, and relationship to customers is close so that contextual information plays a crucial role in forecasting.

However, the managerial problems presented in the articles are not the only managerial problems that may occur in industrial contexts. In some other companies, the problems are not necessarily the same, and even in the same company, the topicality of the problems may change over time. It could be studied more profoundly, what kind of issues are considered as managerial problems, and how they are dealt with. Such a study would require extensive field work. However, former literature supports the assumption that the problems noticed exist also in other companies.

This thesis provides means for mitigating the problems observed. Mostly, the tools focus on pointing out potential areas for development and potential actions to be taken. However, this study does not go further, to implementing the development actions. Improvement takes place only if the suggestions are successfully implemented. Thus, this thesis only serves the initial steps in improvement.

5 Discussion and conclusions

This section contains evaluation of the results and the conclusion of the study. Also some suggestions for further research are presented.

5.1 Theoretical contribution

The aim of academic research is to create new, valuable understanding and knowledge. Theoretical contribution is a contribution that is of use for researchers and further research. In this section it is discussed how the thesis as a whole is able to answer the research questions so that a theoretical contribution is achieved.

The first research question was:

- *What kind of challenges are there are in organizing an adequate forecasting process in the industrial context?*

This study focuses on the implementation of forecasting methodologies, which has been a relatively neglected subject in former research, a majority of forecasting research focusing on developing sophisticated statistical forecasting methods. In this study, forecasting methods are seen only as a part of the forecasting process.

This study divides the forecasting process into four phases. It is suggested that achieving a structured forecasting process requires managing all these phases. This includes 1) defining the operational environment, 2) defining the forecasting methods, 3) defining the organizational responsibilities, and 4) defining the performance measurement process. The case examples show that it is possible that managerial problems occur in all these phases.

All the managerial problems dealt with in the articles have one common denominator: the resources that can be used for forecasting process are limited. In the industrial context, it is common to apply judgemental forecasting methods. These methods are more time-consuming than time series methods, so if they are applied, the issue of focusing the resources gets emphasized.

The individual problems themselves are context-dependent, so that even though there are some general characteristics, the problems of individual companies are unique. Therefore, this study does not describe all the potential problems there are in organizing a forecasting process in the industrial context, and this limitation of the study is discussed in more detail later in this section.

The second research question was:

- *What kind of tools of analysis can be utilized to support the improvement of the forecasting process?*

This thesis introduces new types of methods and constructions designed to facilitate the solving of important problems and challenges in the demand information management of industrial business-to-business companies in particular. The thesis offers a framework which the tools can be linked to. This includes the tools developed in this study, as well as tools to be developed in the future.

The analysis tools presented in the articles aim at pointing out potential areas of development and actions of improvement. Resource efficiency is a common characteristic of the developed tools. This shows in two ways. Firstly, the tools aim at finding resource-efficient solutions in different phases of the forecasting process. Secondly, the presented analysis tools are simple, and can be applied by a external expert, so that using them does not consume too much resources of the workforce.

How to know whether the understanding and knowledge is valuable?
This thesis approaches demand forecasting from the managerial point of view, dealing with such questions as how to identify development targets in the forecasting process, and how to identify potential ways of action. Taking this kind of normative approach is important, as according to the "design science" paradigm, the aim of research is to provide solutions to managerial problems. Taking problems and decision situations of real companies as the starting point of a study confirms that the study has managerial relevance.

How to know whether the understanding and knowledge are new?
This study focuses on the industrial context, which has gained less attention in forecasting research than the customer context. For forecasting, the industrial context is a "grey area", where it is not always clear if forecasting should be applied at all. In the

industrial context, many forecasting methods operate inefficiently, and traditional error measures are inapt. However, for managers the question of whether forecasting should be applied and how it should be applied is a relevant one.

This thesis discusses demand forecasting process as a multifaceted issue. The study emphasizes the need to see forecasting as an organizational rather than a technical issue. An important aspect in the demand forecasting process is that it succeeds in providing a cross-functionally shared view of the demand environment and about the ways to react to it. The performance of the forecasting process is assessed by its resource efficiency, not only accuracy. This approach is in contrast with a majority of forecasting studies that focus on forecasting techniques and accuracy.

5.2 Managerial implications

Managerial implications are the contribution that is of use for practitioners. First of all, this study shows that it is important to see forecasting also as an organizational, not only as a technical issue. Secondly, the study has been carried out according to a paradigm which emphasizes the development of new solutions to problems faced in practical decision-making. The tools presented in this approach may help the manager in different ways, depending on the situation. In the following, some potential managerial contributions are introduced.

1. The thesis provides a view of managerial problems that occur in the demand forecasting process in the industrial context. Before investing in forecasting software, it is useful to notice that in some contexts, the main trouble in implementing the forecasting practices is defining the goals of forecasting, defining organizational responsibilities, and building feedback-oriented performance measurement practices. Paying attention to organizational issues early enough may help in avoiding unnecessary investments.

2. The thesis offers tools for mitigating some problems that occur in managing demand information in the industrial context. As a summary, it can be said that the tools focus on the following issues:
- Facilitating selection problems relating to forecasting
- Refining forecast error measurement
- Enhancing consensus in the forecasting process

Some features of the suggested tools have already been implemented, and tests carried out in case companies show that the tools can work in practice. The tools are not necessarily applied as such, as they are examples of solutions, not proven to be optimal. The main managerial contribution of the approaches is that when used correctly, they help in operating the forecasting process in a resource-efficient way. The managerial contribution of each single approach has been discussed in more detail in the publications.

3. The thesis offers a framework for assessing forecasting practices. The framework can be used as a basis for organizing the improvement work of forecasting practices.

5.3 Limitations of the study

In this study, case study was selected as the method in the first place to guarantee the practical relevance of the research problem. However, case study as a method is criticized particularly because of a small sample size that limits the generalization of the results. In this study, the sample size is extremely small, since it is a series of single case studies.

According to Gummesson (2000), local generalizations are possible in case study. It can be asked what kind of companies the results could be generalized to. The results cannot be generalized to all industrial companies operating in a B2B environment, because it cannot be presumed that the case companies represent typical, average or any category of industrial B2B companies. Both the managerial problems observed and the tools developed for mitigating them are presented as results, so the question of the generalizability of these two types of results can be considered separately.

This study presents some managerial problems observed in the case companies. Both case companies are industrial companies operating in a B2B environment and mostly on an MTO basis. The second case company, which provided empirical material for most of the articles, applied salesforce forecasting, discussed in several articles. The observed problems are most likely to occur in similar environments, but this study does not provide information on how typical they are. Making conclusions about the prevalence of the problems would require several more cases. Also survey is a typical research tool in finding out the frequency of a phenomenon. Yet, the generalizability of this issue is not a particularly important objective in this thesis. More important is enhancing the understanding about the managerial problems that occur in managing demand information in the industrial context. However, broader empirical material, e.g. several interviews would have helped to understand better how managers perceive the problems related to organizing a forecasting process.

Some approaches are provided for mitigating the managerial problems observed, but the impacts of applying the approaches are not measured statistically. Rather than trying to prove the efficiency of the tools in a wider use, the work done can be seen as a basic ground for guiding the way of thinking. If the approaches are adopted more widely, their potential can be assessed more thoroughly. The developed tools can be applied in similar situations where they were developed in the first place. That is, in situations where a described problem is observed. The developed tools focus on the early phases of development, so they are most applicable in situations where the forecasting practices are not very advanced.

5.4 Suggestions for further research

Suggestions for further research can be given from two perspectives. The first perspective is overcoming the limitations of this study. The relevance of the managerial problems noticed in this study could be assessed with a survey or a large interview study. Wider applicability of the developed tools could be tested with a wider range of case studies.

The other option is to present suggestions for future research based on research questions that have appeared during the study, but were not approached or fully answered. Davis and Mentzer (2007) suggest conceptualizing demand forecasting as an organizational learning process. This thesis is in line with this suggestion, as the tools presented in the research articles aim at facilitating the cross-functional dialogue needed in the forecasting process and in improving it. The role of a consultant or a facilitator in the learning process or demand forecasting could also be an interesting perspective for further studies. For example, identifying the learning needs in different environments is a relevant problem.

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PART II

Publications

Publication 1

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Determining semi-finished products to be stocked when changing the MTS-MTO policy: Case of a steel mill

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Abstract

A practical problem of make-to-stock (MTS) or make-to-order (MTO) is described. The case company is a small MTO steel mill planning to move towards a hybrid MTS/MTO-system. A decision process is presented, where determining the semi-finished items to be stocked plays a critical role. The complexity of the problem is illustrated with examples. The main features of an appropriate approach needed in this type of decision making context are presented.

Keywords: Make-to-stock; Make-to-order; Inventory policy; Steel industry

1. Introduction

Understanding customer requirements and their implications has for a long time been an important issue in forming a manufacturing strategy. Therefore, since the 1960s, many studies have dealt with the problem of deciding whether to make-to-order (MTO) or make-to–stock (MTS). Making to stock is typically more cost-efficient, but with making to order a wider variety of more customized products can be offered.

Few production systems are fully MTS or MTO, however. Some parts of the logistics activities are performed for a known customer, but due to long production lead times or large economical batch sizes, some activities have to be performed on a discretionary basis. A concept frequently used in distinguishing MTS operations from MTO operations is the customer order decoupling point (CODP) (Hoekstra and Romme, 1992; van Donk, 2001); also known as the order penetration point (OPP) (Olhager, 2003).

In practice, determining the CODP for specific products is a complex planning problem, where different kinds of factors need to be analyzed and compared. This paper concerns the planning problem of a small MTO steel mill that is considering whether it would be profitable and feasible to make some semi-finished products to stock.

A critical part of the decision process in the case company is determining the dimensions of the semi-finished items that are potentially MTS. If the inventory of semi-finished items is managed poorly, it will nullify the cost savings that were attempted to achieve. If no suitable semi-finished products can be found for MTS, it is better to stay with the MTO-system. The objective of this paper is to describe the decision problem of comparing the MTO-system with a hybrid MTS/MTO system, focusing mostly on determining the dimensions of potential

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semi-finished items that are MTS. This paper illustrates the surprisingly great need of communication and visualization of production planning problems that affect several parties in the organization.

2. Literature review

The MTS or MTO problem has been studied since the 1960s (Rajagopalan, 2002), and the topic has maintained its relevance (Soman et al., 2004). The problem of MTS/MTO gets more complex as the amount of product variation grows and the market conditions become more dominant. The need to divide items into MTS and MTO items may result from different reasons. Leveling the use of the production capacity or guaranteeing shorter delivery times for some products may be the motivation to vary the production policy between products.

Choosing between MTS and MTO is closely connected with the problem of scheduling the production. Scheduling production of multiple products on a single facility that incurs significant change-over costs or times is one of the classic problems in production research. Continuous time version of the problem is called stochastic economic lot scheduling problem (SELSP). (Sox et al., 1999)

The insufficiency of mathematical approaches in solving the MTS/MTO has been noticed (Soman et al., 2004), the main reasons being the difficulty of modeling the problem accurately. This is probably why the methods for analyzing the MTS/MTO problem are often more like frameworks. The concept that is generally used for analyzing the MTS or MTO problem, customer order decoupling point, CODP by Hoekstra and Romme (1992) or the order penetration point, OPP by Olhager (2003) is a point in a production process where MTS operations turn into MTO operations.

In some sources, the main factors determining the CODP is the P/D- ratio, P being the production lead time and D the demanded delivery time in addition to inventory costs (Andries and Gelders, 1995). However, in some sources the factors are grouped in a different way, taking into account production and market-related factors in more detail (Olhager, 2003; Hoekstra and Romme, 1992). The applicability of a set of general factors determining the CODP for a particular industry or a particular case is restricted, because different characteristics are emphasized in different industries. This raises the interesting question of how to refine the analysis to fit the needs of a particular company.

In the case company, a characteristic that needs extra attention due to its complexity is that we are dealing with semi-finished products, that are more specified than raw materials but less specified than final products. Managing the inventory of semi-finished products in the steel industry and similar process industries has been discussed in literature before. Denton et al. (2003) introduced an optimization model that is used as a decision support tool for choosing the design of make-to-stock slabs in a steel factory producing coils and bands. Balakrishnan and Brown (1996) have described the problem of choosing the sizes of semi-finished aluminum tubes (the bloom-sizing problem) from which tubes of different sizes can be drawn and finished to meet customer orders. These two and studies dealing with ingot design (Vasco et al., 1991; Vonderembse, 1984) are close to the problem discussed in this paper. Similar problems can be found also in other industries, like cardboard (Waders Henrico et al., 2004).

The most important fact that makes this paper different from the above-mentioned production and inventory management literature is that in this case the decision of moving from an MTO system towards a hybrid MTO/MTS system has not been made yet. Therefore, in this paper, the question is not about improving the inventory policy of the existing semi-finished items inventory, but about sketching a new inventory policy in order to enable a comparison between the existing MTO system and the potential hybrid MTO/MTS system.

This situation makes demands on the approach that is used for determining the semi-finished products that are made to stock. The economical importance of the issue is not yet fully known, and some parameters for the calculations are difficult to obtain, so the use of sophisticated optimization methods is restricted. It is more important to clarify and visualize the problem so that it can be communicated in the organization, and they can agree on the needed further steps.

In the next section, the steel-making process is described in order to provide sufficient understanding of the concepts and terminology used in this paper.

2.1. The steel-making process in the case company

Steel-making is a one-to-many industry; the product differentiation increases as the raw material proceeds on its journey toward a finished product.

The production process of the case company is described in Fig. 1. The case plant uses fully recycled scrap metal as raw material, which is then melted, cast, rolled and further processed according to customers' needs and specifications into round, square, flat and thread bars.

The scrap metal is melted electrically in an electric arc furnace. The cast size is 75 tons. The melt is alloyed and treated to obtain the required properties. In this part of the process the steel diverges into different grades of steel based on their metallurgical characteristics. The finished melt is cast into blooms with a continuous casting machine. Setup-costs occur when the grade of steel changes in the continuous caster. When the grade stays the same during successive meltings (75 tons), there is no need to discard steel between the casts, but when the grade changes, 7 tons of steel must be discarded to ensure the quality.

The blooms are charged in the bloom heating furnace and then rolled into billets and in some cases final products that are called profiles. This paper concentrates on the grades of steel that are made into billets. The quality of the billets is controlled, and the billets are transferred to the bar rolling mill. All the billets are stocked between the processes of heavy rolling and bar rolling. The billets are stocked outside, and there is no need to perform any action to shelter the steel.

An inventory of semi-finished items is much cheaper to carry than the stock of finished products, because less value has been added at that stage. Also, there is a greater flexibility in matching semi-finished items to orders than at later stages. That is why MTS is being considered only at the level of semi-finished products.

The billets are heated in the billet furnace and hot rolled to round, square or flat bars. Part of the bars are inspected and bundled for delivery to customers, part is transferred for further processing.

The mill has as its objective to maintain and further develop its position as a supplier of high quality and special steels. Specialization is a vital condition for this small a steel mill. Still, the fixed batch sizes, multiples of casts, bring about that sometimes it is economical to produce some billets to stock without customer orders. Hence, the production mode has not been purely MTO even in the past.

2.2. Description of the decision problem

Nowadays the trend is to move towards smaller production lot sizes, but in some industries the production setup costs are so substantial that lot size reduction is not a self-evident objective. In the case company, 7 tons of steel is wasted in a setup at the continuous caster. For a 75 ton lot, this is a

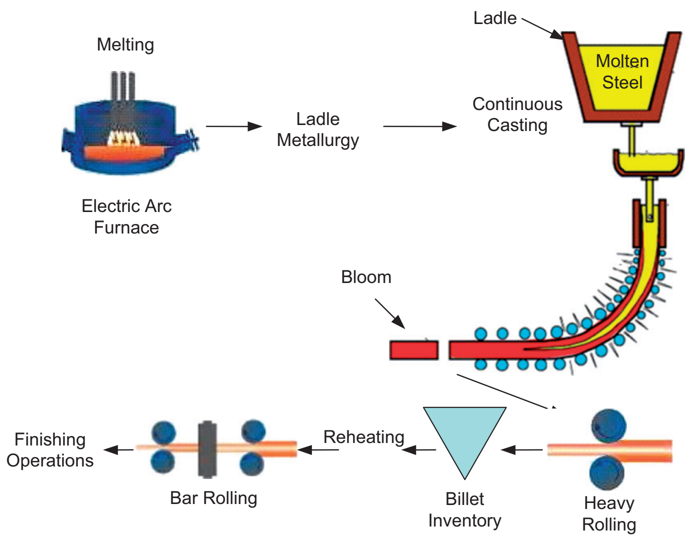

Fig. 1. The production process of a steel mill.

considerable amount. Therefore there is a need for a critical analysis of the production lot size. Some steel mills have lately moved from a purely MTO planning system towards a hybrid MTO/MTS planning system, which has also been reported in the literature (Potter et al., 2004) and it is interesting for the case company to analyze if that strategy would be profitable. One sign of this possibility is that when using the traditional economic order quantity (EOQ), the economic lot sizes end up being averagely over 20 casts, whereas the average realized production lot size at the continuous caster is around 1.8 casts.

There are several factors that affect the decision of whether to make to stock or not. The factors that are usually discussed in this context are the delivery times and/or the smoothing the use of the capacity. Though these factors are clearly important, they are quite general and strategic issues. The case company is not about to make a massive strategic change, however. That is why the possible changes are made only in a small scale, and that is why the MTS/MTO decisions are first made on the grades level. So, in this study the focus is on finding distinctive factors between the grades of steel, and not on analyzing the MTS/MTO issue at a strategic level. In addition, MTS is considered as an option only if it is possible within the limits of situational factors, like the current workload at the continuous caster.

The structure of the decision process, that was chosen to be followed, is presented in Fig. 2. The aim is to find the most potential pilot grades for moving towards an MTS system, and to assess the potential savings. Some costs are easy to determine, because some estimates have already been made in the case company. The numeric values of estimated costs presented in this paper are based on the accounting information of the case company. Some affecting factors are not in quantitative form, however. The calculations are simple, because the calculations cannot carry too much weight in the decision process. Deterministic demand is used in the early stages of the analysis, and the stochastic feature is catered for only if the saving potentials, etc. seem attractive enough to study the issue further.

In the first phase of the analysis, most of the customer-specific grades of steel are left out from the analysis. After this phase the focus is on grades that are made mostly to standard design billets. This means that only the length of the billet varies, and in principle there is a possibility for some form of standardization.

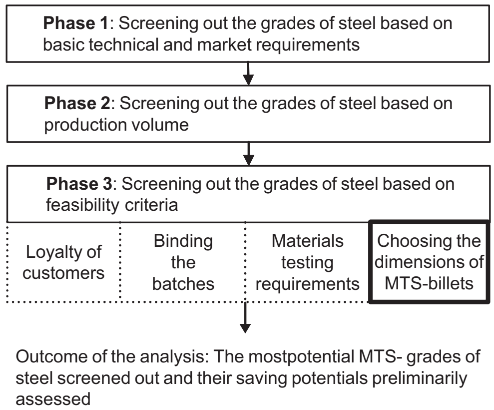

Fig. 2. The decision process and the focus of this paper.

In the second phase the trade-off between production setup-costs and inventory holding costs forms a quantitative basis for this analysis. The setup costs consist of material losses and capacity loss. Material cost is 7 tons of steel (that is scrapped) multiplied with the absorption cost at the billet level minus the cost of scrap metal. Capacity loss is calculated in the following way: The continuous caster casts one ton per minute, and the setup time is 15 min. This is multiplied with the absorption cost at the bloom level minus the cost of scrap metal. Altogether this equals 1660€ per setup. Capital costs of holding inventory are estimated to be 20% of the value of the inventory, 250€/t. When the number of setups at the continuous caster is reduced by making to stock, the inventory holding costs increase because the inventory levels increase. This means that the demand volume has to be high enough that the increase in inventory holding costs does not exceed the reduction in setup-costs.

The third phase collects the factors that are seen as obstacles for moving towards MTS in the organization. These are called "feasibility criteria" in Fig. 2. Common to these criteria is that their effect is unquantified and grade-specific. These are factors that do not cause problems in MTO production, only in MTS-production, if the billets that are made to stock do not fit the actual customer orders. Most of the customers are long-term customers, but some are short-term customers, so the marketing has to estimate the loyalty of the customers if some billets are made to stock. The dispersion of ordered lot sizes may cause extra work, if the bounded batches of billets do not fit the customer orders and they need to be rebound. Also, customers call for material tests that are now done at the heavy rolling phase. If billets are made to stock without customer orders, materials testing will cause extra work for some grades of steel. The above-mentioned factors, however, are not as complex to deal with as the factor that is described in the next section. Estimation of the material loss at bar rolling was chosen as the focus of this research paper because this part of the analysis was found to be the most disorganized, but still critical part of the analysis needed.

2.3. *Potential increases in material losses at the bar rolling if billets are made to stock*

Though similar analysis problems have been dealt with in the literature before, it still has not been defined how this kind of problems should be handled in the organization and how they should be integrated into development projects. This case example indicates that when dealing with this kind of problems there is a need for methods that facilitate the analysis and communication of these problems.

In an MTO planning system, the dimensions of the billet can be set to meet the particular customer orders, but in an MTS planning system this is not the case. Materials loss at the bar rolling occurs if the length of the rolled bar does not match the customer orders (Fig. 3). There is a technical limitation to the billet used (740 kg), and the heavier the rolled bars of customer order are, the greater the potential percentage of materials loss is.

As can be seen in Fig. 3, there is normally more than one billet that is suitable for a particular customer order. That is why the demand profile of semi-finished items is not as clear to see as the demand profile of finished items. Fig. 4 demonstrates the material loss of a particular order as a function of the billet. In MTO systems, it is economical to choose the heaviest suitable billet, because it loads the rolling capacity less than the lighter billets, as fewer billets are needed to produce the same amount of steel.

The complexity of the optimization increases, if the same billet is used for different kinds of customer orders. Fig. 5 shows how the figure changes if 50% of the stocked billets are used for a different order.

In this example the optimal billet for order 1 is 740 kg, the optimal billet for order 2 is 700 kg, but the average losses are at the minimum at 600 kg.

Which billets to stock?

If the demand profile is assumed to stay the same, 50% of the orders are like order 1 and 50% of the orders are like order 2. The annual demand volume is assumed to be 8 casts. In this case, there are 4 potential billets to stock. Here these options are compared below.

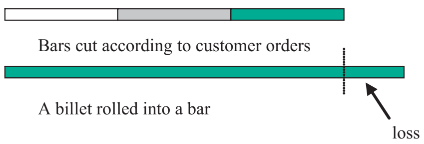

Fig. 3. How materials losses come about.

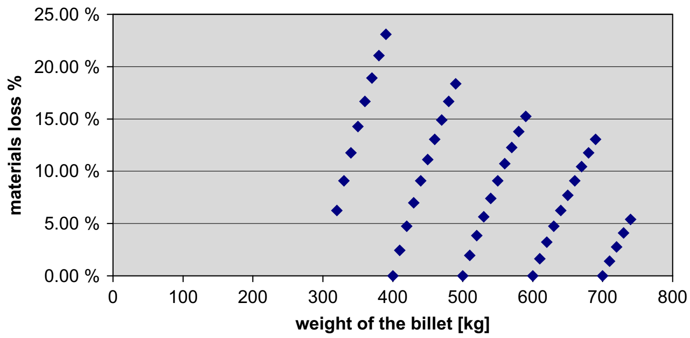

Fig. 4. Material losses as a function of the weight of the billet (the weight of the final product being 100 kg).

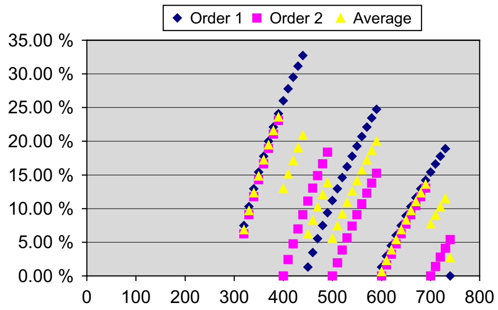

Fig. 5. Finding the optimal billet for two different kinds of orders (the weight of the final products being 148 and 100 kg).

Options within the numeric example:

1. Stock only 740
2. Stock only 700
3. Stock both 740 and 700
4. Stock 600

Comparison of materials losses

In Table 1 we see without any complicated analysis that if there is a billet that is best on average, the best option is to choose it for MTS production, at least if only materials losses are taken into account. The problem is that only billets that have been actually produced can be seen from historical data. The best suitable billet (600 kg) does not show in historical data. This is why this kind of visualization and examination is important.

Nevertheless, the visualization and examination described above do not guarantee that the one clearly best billet is immediately found. Then the case could be something like in Table 2.

Averagely, the material losses would end up at 5% if the billets in stock were used for every order. If the stocked billet is not used for all orders, the billets will stay in the stock longer, and the inventory holding costs increase. In a way, the inventory holding costs trade off with the materials losses. In many cases, the same billet cannot be used for all the orders. Therefore, a choice has to be made whether to allow some materials losses or none at all. Fig. 6 demonstrates this trade off. Fig. 6 shows when it is profitable to increase the lot size from 1 to 2 casts by making to stock, when the demand volume is 8 casts per year. The inventory holding costs are assumed to be 25% of the value of the inventory. The area below the line illustrates the cases when the inventory holding costs and materials losses are tolerable and the area above the cases shows when the sum of the increase in inventory holding costs and materials losses is intolerable.

Table 1
Potential MTS-billets and the material losses with different types of orders

	Order 1 (%)	Order 2 (%)
740	0	5.4
700	15.4	0
600	1.33	0

Table 2
Two potential MTS-billets and the materials losses with two types of orders

	Order 1 (%)	Order 2 (%)
740	0	10
700	10	0

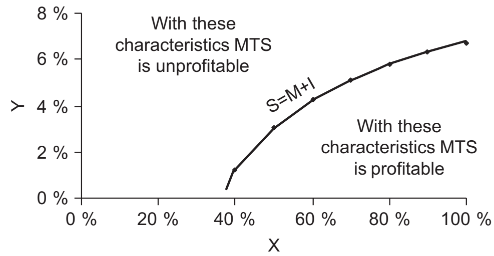

Fig. 6. The break-even curve between MTO and MTS, when demand volume is 8 casts/year.

If the billet cannot be used for all the orders, the actual demand volume is lower, and the inventory turnover decreases.

If the future demand can be accurately forecast, the approach for choosing the billets for MTS is different. The amounts and dimensions of stocked items are made to fit the particular customer orders that are the most likely to occur. But as a general rule, the decision maker should try to limit the number of different billets in stock, and to exploit the possible risk-pooling benefits.

2.4. Implications for making MTS/MTO policy changes

The decision maker who plans the billets does not need sophisticated analysis, but clear instructions how to pick the right billets that are made to stock. So, first of all, the decision maker has to know if any billets should be made to stock or not. After that he has to know which weight to choose. This decision can be made on the basis of former demand data, if there are no recent considerable changes in the demand data.

The best possible solution would be to find a billet that fits all the customer orders, without any material loss at the bar rolling. For most of the grades, the kind of billet could not be found in this case. The second best solution would be to find the kind of billets that can be used for most of the customer orders, with tolerable material losses. If no suitable billets for MTS production are found, it is better to stick with the MTO system.

If a suitable billet for MTS production is found and some billets are made to stock, follow-up data must be collected in order to determine the actual inventory turnover times and materialized materials losses in the bar rolling.

There are three main reasons why I suggest that visualization and examples are needed in the decision process:

1. *To provide basic understanding about the production process:*
   Actually, this approach is all about analyzing the demand profiles from a new point of view. It is a kind of what-if analysis, "what if some billets had been made–to–stock". The demand profile for billets can be used to demonstrate the suitability of the grade for MTS production, because it helps to compare the effect of choosing the billet. The decision making in the steel factory involves many people, and therefore this kind of simple demonstration is needed. Not everybody in the organization is aware of the production planning facts.
2. *To provide understanding about the gains of standardization:*
   One example of the need of visualization is that in some cases, customer demand can be guided to fit better to the semi-finished products that are stocked. Actual customer-specificity is not always as high as it seems in the demand data that is collected within an MTO planning system.
3. *To help to combine qualitative customer information with quantitative analysis*:
   In the case company, like in most of the similar companies, some customers are more important than others. It is difficult to quantify the importance of a customer, but visualizing the effects of losing a particular customer may provide some illustration.

Because the aim here is not to improve an existing inventory policy, but to draft totally new one, the approach is not very mathematical. Instead, it focuses on clarifying the decision process and demonstrating the effect with examples and visualization. Because there are so many intangible affecting factors, collecting and analyzing qualitative information and combining it with quantitative analysis is as important as a quantitative analysis itself.

In the case company, the approach helped to analyze a problem that was ambiguous in the beginning. The approach was considered useful and applicable, but due to the changes in the circumstances, including the development in some other areas of production planning, the approach was not implemented in its entirety and original form, so realized savings cannot be presented in this paper.

3. Conclusions

The main objective of this paper was to point out problems that are typical to production and inventory problems where the decisions have cross-functional effects. In this paper it was suggested that coping with these kinds of problems calls for approaches that are simple, illustrative and are able to guide the development resources.

Typical problems introduced in this paper were the following: the decisions or the sub-problems of decisions involve many parties, all of whom are not production and inventory management professionals. Also the needed sub-decisions are interrelated, and so the economic importance of the decisions is not well known. For these reasons, simplicity is needed in methods, both to spare the resources and to provide needed understanding about the decision on hand.

When a large amount of information that is needed for making the decision is in an intangible and qualitative form, organizational factors will dominate. Optimization in this case is not a sufficient method, but there is a need to combine qualitative and quantitative information and to enhance the needed communication about the critical issues.

The approach for production and inventory problems that involve many parties should provide understanding of the process to all involved by demonstrating the effects of the decisions, and this way it is possible to facilitate the needed communication and increase commitment. According to this case example, these are the main features needed in this type of decision-making context, though further research is needed.

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Publication 2

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“Selecting an approach for making aggregate demand forecasts – a case study”
15th International Working Seminar on Production Economics, Innsbruck, Austria, 3.-7.3-2008
– revised version

Selecting an Approach for Making Aggregate Demand Forecasts - A Case Study

Kerkkänen Annastiina, Huiskonen Janne, Korpela Jukka

Abstract

The paper deals with selecting an approach for making aggregate demand forecasts to be used in capacity planning. The paper presents a case study, where an industrial company uses salespeople's forecasts as an information source in making aggregate forecasts. The current approach is compared with two approaches that use demand history as the basis of information. The three approaches are compared for forecast accuracy and the effort needed in making the forecast. Real-life examples of the case company show that even though the salespeople's forecasts are on the detailed level more accurate than statistical forecasts in some cases, on the aggregate level the difference almost disappears. On the basis of the comparison procedure, different forecasting approaches can be suggested for different customer categories. The results suggest that systematic comparison of forecasting approaches can be beneficial when the aim is to improve the forecasting process in similar settings.

1. Introduction

Demand forecasting is a traditional subject in management literature, and the literature offers many methods for demand forecasting. The main focus of forecasting research has been on the development of forecasting methods, and relatively little research in forecasting has been done to aid in understanding the managerial side of forecasting (Wacker & Lummus, 2002, Moon & Mentzer 2003). Focusing on the managerial side of forecasting means focusing e.g. on such problems as method selection and on the use of forecasts in practical contexts. One of the common uses of demand forecasts is allocating the production capacity. This paper focuses on improving a forecasting approach that is used for capacity planning.

In capacity allocation, aggregate forecasts are needed, which means that forecasts are not made for individual products, but for product groups. There are several options for producing aggregate forecasts. The forecast can be made on the same aggregation level as the capacity plans, or the forecast can be aggregated from forecasts that are produced on a more detailed level. There are many methods available for making forecasts - time series methods, causal methods, judgmental methods and different combinations of these. The forecasting approach should be selected so that a sufficiently accurate forecast is produced without consuming too much resources. There is much research evidence that companies prefer simple methods over complex ones, and judgmental methods are widely used (e.g. Dalrympe, 1987, Kahn & Mentzer, 1995 Tokle & Krumwilde, 2006).

This research paper presents a case example that deals with comparing approaches for making aggregate forecasts in an industrial company. At the starting point, the company used the same forecasting approach for all product groups: forecasts were made separately for each individual customer by the salespeople, and these forecasts were then aggregated on a product group level. In this paper, the original approach is compared with two approaches that use demand history as a basis of forecasts. The comparison criteria include forecast accuracy and the time needed to accomplish the forecast. Also difficulties in applying the approaches are discussed. This comparison serves as one step in improving the forecasting process. The aim is to identify what are the potential actions in finding resource-efficient forecasting practices, and what kind of further analyses are needed.

The case results, based on a sample data set, show that even though judgmental forecasts are more accurate when reviewed on customer level, quantitative forecasts are approximately as accurate when reviewed on an aggregate level. There are differences between customer categories, so different forecasting approaches can be suggested for different customer categories. These results show that systematic comparison between forecasting methods can be beneficial in pointing out areas of improvement in the forecasting process.

2. Literature review

In this section, we review earlier studies dealing with judgmental forecasting methods and method selection. Forecast aggregation, which is typically discussed as a separate issue from forecast method selection, is discussed in the end of this section.

2.1 Judgmental forecasting methods

Many surveys point out that judgmental forecasting methods, such as the sales force composite method and executive judgement are popular in practice (McCarthy et al., 2006). Judgmental methods are commonly used in the business-to-business environment, and there has even been an increasing interest in judgmental methods in recent years (Mentzer & Moon, 2005, Lawrence et al., 2006). As the majority of forecasting literature focuses on quantitative methods (McCarthy et al., 2006, Fildes & Goodwin, 2007), it is relevant to ask why judgmental forecasting methods are so heavily preferred.

One reason for preferring judgmental methods is demand uncertainty. E.g. Sanders and Mandrot (2003) point out in a survey study that the company characteristics that correlate with the preference for judgmental methods are lack of relevant quantitative data, environmental uncertainty, and associated data variability. Several authors have found that in many industrial contexts, companies encounter increasingly uncertain and irregular demand (Kalchschmidt et al., 2006, Bartezzaghi et al., 1999, Miragliotta & Staudacher, 2004).

Another reason is that there is so called “contextual information” that is considered valuable for the forecasting process, and linking this contextual information into forecasts requires applying judgmental methods. According to Sanders & Ritzman (2004), contextual knowledge is information gained through experience on the job with the specific time series and products being forecasted. According to Webby and O’Connor (1996), contextual information is information, other than the time series and general experience, which helps the explanation, interpretation and anticipation of time series behaviour. Several closely similar concepts are used in the literature, e.g. “causal knowledge” (Webby & O’Connor, 1996), “product knowledge” (Edmundson et al., 1988) and “extra-model knowledge” (Pankratz, 1989).

The impact of judgment on demand forecasting has been studied both with laboratory research (Wright & Goodwin, 1998) and some field studies (Lawrence et al., 2000, Fildes, 1991). In general, judgements will outperform models when the forecasters have contextual information to help them comprehend discontinuities in series. Human judgment is most effective if "broken leg cues" are available (Webby & O’Connor, 1996). A broken-leg cue refers to an unusual important piece of information whose presence would dramatically alter the judgment compared to a model of that judgment.

The research evidence is mixed as regards the accuracy of judgmental forecasting in real life (Webby & O'Connor, 1996, Lawrence et al., 2006). Some results report successful judgmental forecasting examples (e.g. Fildes, 1991), but in some cases contextual information fails to influence the forecast accuracy (e.g. Lawrence, 2000). Arkes (2001) states that overconfidence in judgmental methods is a common finding in forecasting studies. It depends on the circumstances, whether judgment improves forecasts (Fildes & Goodwin, 2007).

The salespeople are closest to the customer, so they are assumed to have the best access to contextual information. However, judgmental forecasts, especially when created by salespeople, are known to be prone to bias and inefficiency (Mentzer & Moon, 2005). Without proper guidance, people tend to use their judgements inefficiently and even irrationally. For example, there is evidence that forecasters carry out voluntary integration of statistical methods and judgmental forecasts inefficiently (Goodwin, 2000), forecasters tend to ignore cues, especially if there are several available (Wright & Goodwin, 1998), and they sometimes make damaging adjustments to reliable statistical forecasts even when they do not anticipate special events (Goodwin & Fildes, 1999). Lawrence et al. (2006), after reviewing 200 studies about judgmental forecasting, state that much remains to be researched to develop improved methods for supporting judgmental forecasters, particularly in identifying when judgmental intervention is needed and when it is not needed.

To overcome the problems of judgmental forecasting, it is suggested that salespeople's efforts should be clearly focused on situations where the forecasts truly matter, and the forecasting task should be kept as simple as possible (Moon & Mentzer, 1999). Some approaches for focusing forecasting approaches have been presented (e.g. Holmström, 1998, Caniato et al., 2005). These approaches are based on categorizing products and/or customers.

2.2 Selecting a forecasting approach

In real life, forecasting approaches are not necessarily systematically selected. Armstrong (2001) identifies six strategies for selecting forecasting approaches: (1) convenience, (2) market popularity, (3) structured judgment, (4) statistical criteria, (5) relative track records, and (6) guidelines from prior research. The author states that methods should not be selected based on convenience (that is using methods that are already familiar) or market popularity (that is using what other companies are using).

Using statistical criteria, such as distribution of errors and statistical significance of relationships can be useful in some situations, but the approach is not appropriate for making comparisons between substantially different methods. When large changes are expected and errors have serious consequences, the track record of leading forecasting methods can be assessed, though comparing the accuracy of various methods is expensive and time consuming. In using structured judgment, the forecaster first develops explicit criteria and then rates various methods against them. Guidelines from prior research mean defining the forecasting situation and applying a method that has been seen to work in a similar situation.

The selection strategy that is used in this article is as a combination of relative track records and structured judgment. As the use of relative track records is known to be time-consuming, it is justified to apply it to a smaller scale as a part of a selection process. Using relative track records can be useful also in defining the forecast situation, which is needed if guidelines from prior research are to be applied.

In forecasting literature, forecast accuracy is a popular criterion when different forecasting methods are compared (Yokum & Armstrong, 1995). However, it has been noticed that in a practical setting, forecast accuracy as a single criterion is often insufficient for selecting forecasting methods. Other factors to be noticed are for example cost, data availability, variability, and the consistency of data (Georgoff and Murdick, 1986). Yokum & Armstrong (1995) found out in their survey research that managers rated such criteria as “flexibility”, “ease of implementation” and “ease of use” almost as important as forecast accuracy for selecting a forecast method.

One problem with using forecast accuracy as a selection criterion is the lack of reference values. Field studies have shown that in many companies it is not possible to measure the benefits of accurate forecasts in terms of their impacts on business performance (Mentzer & Moon, 2005). It has also been noticed that in real life, forecasting is often mixed with planning, and so in practice high accuracy is not always the target after all (Lawrence et al. 2000). In some cases, sales are manipulated to meet the target that was set (Lawrence et al. 2006). Bunn and Taylor (2001) state that cross-company comparisons have not generally been relevant or feasible in the area of setting the goals of forecasting quality.

2.3 The issue of forecast aggregation

The total workload of the forecasting process is significantly affected by the level of forecast aggregation. Other issue that affects the workload is the extent to which judgmental forecasting is applied. It is more time-consuming to use judgmental than quantitative methods. When searching a resource-efficient forecasting approach, in some cases these two issues need to be considered at the same time.

However, only a marginal number of studies deal with the issue of aggregation (Dekker, 2004, Zotteri & Kalchschmidt, 2007). The studies that are closest to the focus of this paper focus on selecting the proper level of aggregation in the forecasting process (Caniato et al., 2005 and Zotteri et al., 2005). Zotteri et al. (2005) point out that empirical evidence shows that many companies choose a level of aggregation of the forecasting process that differs from the level of aggregation of the forecasting problem. The term “forecasting problem” refers to the use of forecast, and the term “forecasting process” refers to the process of producing forecasts. The authors conclude that there is no “one best way” of defining the proper aggregation level, but the amount of information available and the heterogeneity of the market seem to play a crucial role.

Studies about forecast aggregation deal with different areas of aggregation, such as aggregation over time, over items, or over geographical locations. Our study focuses on aggregation across customers. In the case company, the question is if forecasts should be made for individual customers or if they should be made on a more aggregate level; that is on customer categories or on total demand of product groups.

3. Introduction to the case

The case company has several sales units and production units around the world. The company operates in business-to-business markets, serving as a materials producer for industrial customers that operate in different types of business. The purpose of the forecasts is to support capacity planning; therefore aggregate forecasts on the product group level are needed.

The customer base is heterogeneous, and the customers operate in distinct businesses: contractual markets and spot markets. On the latter markets, each order is competed for, so the predictability is considerably lower than in the contractual markets. From different customers, different pieces of information about demand are available in advance. In contractual markets, contracts are made for four months or twelve months ahead. In practice, these contracts define only the maximum volume the customer may receive during the given time period. In addition to this, some customers place preliminary orders before they place their actual order. In the spot markets, customers make inquiries, that indicate customers buying intentions, but inquiries are not as reliable indicators as contracts. Customers are not the end users of the products, so their demand depends on their own customers. Salespeople are usually aware in what kind of end-products the material ends up. However, the demand profiles of the end products vary, some end-products having regular demand and some having irregular demand.

The customers have been categorized into distinct categories. The categorization has been made for the marketing purposes, and authors have not participated in this categorization. The customer categories are determined by the type of customers business. For confidentiality reasons, detailed information about the customers is not given. The data sample used in this study is presented in table 1. Demand information from 43-month time period was available for five product groups. This limited data sample is used for illustration; the idea is to point out that some results and tentative suggestions can be found also when using limited data sets.

Table 1: Data sample used in the example

Product Group	Sales volume [units/a]	Number of customers during last 12 months
A	8700	8
B	10448	10
C	9330	22
D	7364	18
E	20826	19

In former literature, the problem of selecting forecasting methods is discussed separately from the problem of selecting an aggregation level. In this particular practical setting the issue of aggregation cannot be fully separated from the issue of method selection. This is because in current approach in the case company, the forecasts are needed on a more aggregate level as they are produced. The forecasts are made for each customer separately, since information about customer's future demand is available on customer level. When alternative approaches for forecasting are considered, it is natural to compare forecasting methods on the same aggregation level as the need of the forecasts is. For creating aggregate forecasts, there are different options. Both judgmental and statistical methods could be applied.

In this case company, contextual information obviously exists, but it is not clear what is its' role in forecasting. The managers that are responsible for leading the work of forecasters consider customer's predictions about future demand as important as demand history. Also contracts and preliminary orders are seen important in some cases.

3.1 Motivation for comparing forecasting approaches

The comparison presented in this paper can be seen as a part of a larger development project. In the case company, performance of the current forecasting system had been under examination for over a year. During this period, forecast accuracy has been examined, error types of forecasts analyzed, some errors have been explained and even reduced. Other steps in this development work are presented in articles by Kerkkänen & Huiskonen (2007) and Kerkkänen et al. (2009). In the beginning of the development work the aim was to reduce forecast errors, but after that the focus of the development work has shifted more on providing resource-efficient approaches for forecasting. The aim is to identify when it is possible to forecast accurately, and to distinguish reliable forecasts from less reliable ones.

The role of this comparison is to identify where the judgmental forecasts are of value, so that they provide better forecasts than the statistical methods, and where they are worse than simple statistical forecasts. If judgmental forecasts are of value, it implies that it implies that it may be reasonable to focus the efforts of the salespeople in this type of situations, and if the statistical forecasts are more accurate, there is need to better include the demand history in the forecasts in a way or another. However, these development acts call for managerial judgment, and this is where the role of this data analysis ends. Its role is to provide new information for the management in order to support the decisions of the following development actions. The result of this analysis is not providing optimal forecasting approaches for specific situations, but more like defining the area where the best solution is likely to be found.

This comparison has some similarity with statistic named Theil's U. The logic of Theil's U statistic is that a perfect forecasting technique is one that forecasts well and is easy to use. An easy way to make a forecast is to simply take sales from last month as a forecast for next month. This approach is usually referred as Naïve forecast. If any other technique cannot come up with a more accurate forecast, there is no reason to use it. Theil's U statistic calculates a ratio of the accuracy of the technique we are using to the naïve forecast's accuracy. If U statistic is greater that 1.0, the technique is worse than naïve forecast and should be discarded. (E.g. Mentzer & Moon, 2005 p. 55.)

The starting point is that the company is producing judgmental forecasts on a detailed level. This approach has not been selected by authors. It is less time consuming to use statistical methods, so they are compared with the current method. We prefer simple statistical methods instead of more sophisticated method for the same reason as in Theil's U, to emphasize the ease of use of forecasting techniques. We consider the ease of use as an important aspect, since this is a pragmatic study.

4. Three approaches to create aggregate forecasts in the industrial context

In this section, three approaches for creating aggregate forecasts are presented and analysed. Examples and sales and forecast data from a large process industry company are used to illustrate the differences of these three approaches. The approaches have been named in order to enhance the readability of this article, so we are not suggesting the naming practice for wider use.

<u>Aggregating details</u>
The first approach is called "aggregating details" (AD). In this approach, forecasts are created separately for individual customers. After the creation, the forecasts are aggregated, first over customers in each sales unit and then across sales units. In the beginning of this study, this approach was in use in the case company. The salespeople created forecasts for each product group and each customer separately. It was considered natural for the salespeople to create the forecasts on the same aggregation level as the orders arrived.

Aggregate forecasting

The second approach is "aggregate forecasting" (AF). In this approach, forecasts are created on the aggregate level. This approach was chosen to be analysed because when allocating the production capacity, it is more fundamental to know the aggregate demand of the product group, rather than the demand of individual customers. It seems to be a relevant option to create forecasts on the same aggregation level as they are used, and the overall forecasting burden of the forecasting process is assumed to be lower if the number of forecasts is lower.

Semi-aggregate forecasting

In the semi-aggregate forecasting approach (SAF), forecasts are first created for customer categories and then aggregated. The idea behind this approach is that the customer base is heterogeneous, and the uncertainty of end-demand varies between customer categories. Some customers operate on businesses where production is planned months ahead, whereas some customers operate on project business, where the end demand is discrete and uncertain. In the case company, the customers have already been categorized by sales-related factors by the marketing department. The advantage of this approach is that if the predictability of demand in some customer categories is very low and in some customer categories very high, separating these different categories provides a better view on the reliability of the aggregated forecast.

4.1 Information base for creating forecasts

In *AD*, forecasts for individual customers are created at sales units. In principle, this gives an opportunity to link the forecaster's knowledge and experience of customers into the forecasts. In practice, the information that the forecaster has about customers consists of basic knowledge about the customers' business, demand history, and early information about forthcoming orders. Some customers make preliminary orders that they are allowed to update until 2-6 weeks before the delivery date, depending on the capacity situation. Despite the knowledge about the customers, the forecaster's ability to create reliable forecasts is limited, as can be seen in the following examples;

With many customers, yearly or quarterly contracts are made, but these contracts define only the maximum volume the customer may order per year or a quarter of a year. If the forecasts are based only on yearly contracts, a possible way to translate the contract into a forecast is to divide the yearly maximum sales volume evenly for 12 months. This will show as slightly upwards-biased forecasts, and since the exact timing is not known, the forecast is inaccurate every month.

Many customers have a production break during midsummer, and this is reflected as a seasonal pattern in the aggregate sales. With an individual customer, the demand drop does not happen exactly the same month every year, so getting the timing right in detailed forecasts is fairly random. In addition, the customers are not the end users of the products, so their demand predictions depend on how reliable information is received from the end customers.

If *AF* is applied, the advantage is that on the aggregate level the demand is continuous, so it is possible to use time series methods in the forecasting. Figure 1 shows an example of the demand history of a product group in one of the sales units. The labels have been left out of the figure for confidentiality reasons. Even though there seems to be some seasonality in the demand pattern, the demand pikes and drops do not happen at the same time every year.

Therefore applying seasonal adjustment to the time series does not improve the forecast accuracy.

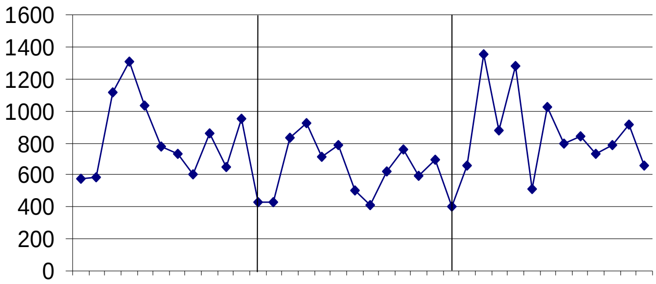

Figure 1: 3-year demand history of an example product group

In addition to the demand history, it is in principle possible to adjust the aggregate forecast judgmentally. Contextual information that could be used as a basis for judgmental adjustment are for example economic trends, the number of yearly contracts, or promotions.

If SAF is selected, the information sources that are used in the forecasting can be specified by customer category. The idea is that if the demand is smooth among a customer category, the forecasts may be based on demand history, but if the information received from the customers is truly valuable, i.e. the forecasts produced by the sales people beat the time series forecasts, judgmental forecasts are used. This way, the efforts of the salespeople can be focused on the customer categories, where the contextual information has true value. Basically, the performance of different forecasting methods can be tested in different customer categories, in order to select the most suitable method for each customer category.

4.2 Forecast accuracy

The order intervals of customers are typically one month or less, so when the demand of an individual customer is analysed on the monthly level, the demand seems intermittent. However, this does not apply to all customers. Even if the end demand of some customers is smooth, they have their own inventories, so they do not place orders continuously.

To compare the forecast errors of different forecasting approaches, a data sample was collected in the case company. The data sample comprises 5 different product groups in one sales unit, and it consists of forecasts and sales history. Customers without demand history and customers without demand forecasts were left out of the data sample. Cleaned this way, the data sample represents 90% of the actual sales.

Table 1 presents some examples of forecast errors. Since the demand of individual customers is often intermittent, meaning that in some months there are no sales, traditional error measures such as MAPE (mean absolute percentage error) are not very applicable. Instead, the following variation of the 12-month MAPE is used, indicated as MAPE*:

$$\text{MAPE*} = \frac{\sum_{i=1}^{12} |F_i - S_i|}{\sum_{i=1}^{12} S_i} \text{ ; S: Sales, F: Forecast.} \qquad (1)$$

This modification of MAPE has been used earlier e.g. by Zotteri et al. (2005).

The performance of the forecasts created by the sales people is compared with forecasts that are created with a simple time series technique, moving average. Moving average (MA) was selected for this comparison, because it is one of the simplest time series techniques. For forecasting intermittent demand, Croston's method (C) is considered to be a "standard" forecasting method (e.g. Syntetos & Boylan, 2005), so it was selected for comparison. Croston's method is described in the Appendix.

To use these forecasting techniques, parameters needed to be selected; time period for the moving average and the smoothing constant α for the Croston's method. The parameters were selected so that the parameters that would have given minimum errors on a 12-month time period were named as optimal parameters. Parameters that would have given maximum errors on a 12-month time period were named as unoptimal parameters. These parameters were used for producing the forecasts for the next 12 months. The unoptimal parameters were used only to give reference values, to demonstrate what is the impact of the parameters to the forecast accuracy in this case. The values in table 1 are averages weighted with the sales volume the same way as described in formula (1).

Table 1: Forecast errors in detailed forecasts and the AD-approach

Prod. group	MAPE* in detailed forecasts made by salespeople	MAPE* in detailed forecasts made with MA, optimal time period	MAPE* in detailed forecasts made with MA, unoptimal time period	MAPE* in detailed forecasts made with C, optimal α	MAPE* in detailed forecasts made with C, unoptimal α
A	65%	87%	65%	100%	97%
B	44%	55%	61%	59%	95%
C	59%	87%	93%	87%	111%
D	43%	63%	71%	62%	95%
E	39%	59%	55%	61%	89%

T-tests show on a 0.05 significance level that the forecasts created by the salespeople are more accurate than the forecasts made with time series techniques. This indicates that salespeople have some contextual information that is valuable in forecasting. In this case, Croston's method did not provide more accurate forecasts than moving averages. This is because in the data set, the actual demand rarely followed repeated patterns. T-tests show that on a 0.05 significance level it cannot be assumed that optimizing the forecasting parameters improves forecast accuracy in this case.

It is a known fact that when forecasts are aggregated, they are more accurate than detailed forecasts. An important question is whether AD provides better accuracy than AF, when forecast errors are viewed on the aggregate level. In table 2, the performance of some simple time series techniques are compared to the AD approach. The parameters for the techniques have been chosen the same way as for table 1.

Table 2: Errors in aggregate demand forecasts – comparison of different methods

Product group	MAPE* in the AD	MAPE* in AF: MA with optimal time period	MAPE* in AF: MA with unoptimal time period	MAPE* in AF: exponential smoothing with optimal α	MAPE* in AF: exponential smoothing with unoptimal α
A	56 %	26%	30%	26%	62%
B	19 %	21%	31%	24%	35%
C	24 %	31%	43%	31%	51%
D	22 %	20%	28%	20%	21%
E	15 %	24%	48%	22%	28%

When producing forecasts for individual customers, the salespeople provide more accurate forecasts than simple time series methods, but when the forecasts are viewed on the aggregate level, the performance of the time series methods comes close to the performance of the salespeople's forecasts. For some product groups, A and D, the time series methods provided even better accuracy than the AD approach. A t-test shows that on a 0.05 significance level there is no difference between the forecast accuracy provided by the AD approach and the statistical methods with optimized parameters.

In the case of Moving Average, t-test points this out that with 0.05 significance level it can be assumed that "optimal" forecasting parameters provided better accuracy than the "unoptimal" parameters. In the case of exponential smoothing, this cannot be assumed, but with a 0.1 significance level yes. However, the main point of this paper is not optimizing the forecasting parameters, but rather to identify to which extent judgmental/statistical forecasting should be applied. Optimizing the forecasting parameters can be more relevant in the later phases of the development work. Therefore, parameter selection is not discussed further in this paper.

Next, forecast accuracy in SAF is analysed. There is no data available that would tell how well salespeople can forecast the demand of each customer category, but it can be estimated by looking at the detailed forecasts that are aggregated by the customer category. Table 3 shows the forecast accuracy in each customer category and product group. The forecast accuracy has been calculated both by the 6-month moving average and by aggregating detailed forecasts by customer category. 6-month time period was selected for this example since it provided on aggregate level closely the same forecast accuracy as "optimized" time period, and it was simple to use same parameter for all the product groups and customer categories. It can be seen in table 3 that in most cases, aggregating detailed forecasts provides better forecast accuracy, but within customer category 1, the 6-month moving average provides more accurate forecasts in 3 cases of 4.

Table3: MAPE in different customer categories / product groups*

	Customer category 1	Customer category 2	Customer category 3	Customer category 4
Procuct group A				
6-month moving average	32 %	39%	86%	78 %
Detailed forecasts aggregated	26 %	19%	5%	89 %
Sales volume	1178	595	1600	5327
Number of customers	2	1	1	4
Product group B				
6-month moving average	71%	92 %	61%	31 %
Detailed forecasts aggregated	101%	51 %	64%	19 %
Sales volume	660	1132	824	7832
Number of customers	1	2	1	6
Product group C				
6-month moving average	93%	39 %	50 %	51 %
Detailed forecasts aggregated	360%	28 %	27 %	32 %
Sales volume	181	1349	859	6941
Number of customers	4	8	2	8
Product group D				
6-month moving average	85 %	29 %	58 %	25 %
Detailed forecasts aggregated	125 %	24 %	7%	33 %
Sales volume	367	3089	595	3313
Number of customers	2	8	2	6
Product group E				
6-month moving average		21 %	711%	50 %
Detailed forecasts aggregated		16 %	4%	41 %
Sales volume		13570	45	7211
Number of customers	0	9	1	9

The problem with selecting forecasting methods for customer categories is that the nature of the customers' demand may change over time, and therefore a choice made in the past may not be optimal in the future. Thus it is relevant to check the performance of alternative methods in more than one period of time. Therefore, the performance of the 6-month moving average and aggregated detailed forecasts have been compared in two 6 month test periods. The results can be seen in table 4.

In customer category 1, the orders are typically relatively small and the lead time from the company to the customer is short. In this category, the moving average provides better accuracy almost perpetually. In customer categories 2 and 3 the orders are larger, the end demand is more continuous, and the delivery times to the customers are longer than in category 1. In categories 2 and 3, the salespeople's forecasts perform slightly better than the averages. In customer category 4, neither one of the forecasting approaches can be recommended over the other. In customer category 4, the end demand is partly continuous, partly discrete. It can be seen in table 4 that data analysis supports the assumption that the suitability of forecasting approaches depends on the customer's business, and that using different methods in different customer categories is justified.

Table 4: Winner methods in different product groups / customer categories: two test periods

	Customer category 1	Customer category 2	Customer category 3	Customer category 4
Procuct group A				
Test period 1	X	Detailed	Detailed	Detailed
Test period 2	Detailed	X	Detailed	Average
Product group B				
Test period 1		Detailed	Average	Detailed
Test period 2	Average	Detailed	detailed	Detailed
Product group C				
Test period 1	Average	Detailed	Detailed	Average
Test period 2	Average	X	Detailed	Detailed
Product group D				
Test period 1	Average	Detailed	Detailed	Average
Test period 2	Average	X	Detailed	Detailed
Product group E				
Test period 1		X	Detailed	Average
Test period 2		Detailed	Detailed	Detailed

Detailed: AD provide better forecast accuracy.
Average: 6-month moving average as the forecast provides better accuracy.
X: Both methods provide equal accuracy (the difference between absolute forecast errors provided by different methods is less than 5 %).

4.3 Effort needed in creating a forecast

In the sample data set, the total number of customers per product group is about 15. If the total number of product groups is 20 in each sales unit, it makes 300 forecasts per sales unit. If the sales person uses 5 minutes per month for updating each forecast, it takes 25 hours each month to update the forecasts. This is a hypothetical calculation. In practice the effort will be focused on the tasks that are considered most essential from the point of view of the salespeople.

If there are on average 20 product groups per sales unit, and if updating one forecast takes 5 minutes, the aggregated approach takes one hour and 40 minutes per month. It is realistic to expect that salespeople in each sales unit can spend this much time for forecasting each month. In SAF, the number of forecasts in this example is 80, so updating the forecasts takes almost seven hours.

3.4 Using forecasts in capacity planning

Forecasts are made in order to allocate production capacity in production units and between production units. To achieve economical lot sizes, orders from a two-month period are reviewed when the final schedules are made. Still, if the timing of the demand errs only with 1 month, this shows as a forecast error in the present measurement system. This problem has been more closely discussed e.g. by Kerkkänen & Huiskonen 2007, where a smoothing algorithm is suggested for smoothing out minor timing errors when measuring forecast error. However, in this paper a more simple smoothing procedure is used, since the aim is only to compare methods on a general level, rather than to suggest a detailed approach for error measurement.

To analyse the forecast accuracy from the point of view of capacity planning, the time scales have been aggregated from 1 month into 2 months. So, the forecast errors have been calculated by comparing 2-month sales with 2-month forecasts. The results can be seen in table 5. The forecast error in the aggregated forecasting approach has been calculated with the 6-month moving average as the forecast. When the time scales are aggregated like this, the forecast errors in all the product groups decrease. However, the amount of decrease varies between product groups.

*Table 5: MAPE * provided by different approaches when the time scale is aggregated from 1 month to 2 months*

Product group	Forecast error: AF -approach	Forecast error: AD
A	43 %	54 %
B	21 %	11 %
C	31 %	21 %
D	11 %	16 %
E	19 %	9 %

When weighted with the sales volume, the average forecast error in aggregated forecasting is 24%, and in the AD 19%. AD performs best for product group E. In product group E, customer category 2 represents the majority of the demand, but the customer categories do not fully explain why AD performs the best for some product groups and aggregated forecasting for some others.

3. 5 Challenges in managing the approach

The major problem in AD is that it is difficult to control the input of the system, as it is scattered into many sales units. There is a lot of variation in the forecasting accuracy levels across the sales units, and it is difficult to separate irreducible forecast error from forecast error that is a result of less than perfect forecasting.

The downside of AF is that information about individual customers is lost. This can be harmful if the demand changes of individual customers have a dramatic effect on the aggregate demand. Therefore, even if forecasts are made on the aggregate level, linking essential customer information, e.g. the number of contracts with customers, into the forecast is justified. From the organizational point of view, implementing the aggregated approach is complicated because it is believed that better forecast accuracy can be achieved with the AD approach, as the salespeople have the “best knowledge” about customers. Forecasting is confused with planning, so that if there is lack of capacity, the forecasts are trimmed to meet the capacity by searching for flexibility throughout the customer base. In the AF approach this practice can no longer be used.

One problem with the semi-aggregate approach is that in some sales units there are only one or two customers per customer category, so in these cases SAF comes close to AD. Actually, this approach differs clearly from AD only if the customers are aggregated across sales units. Another problem is that the categories that are defined on the basis of sales-related factors are not necessarily the best for forecasting purposes. Even though customer categories 1, 2 and 3 seem to be quite homogeneous from the forecasting point of view, in customer category 4 the customer base is heterogeneous. Re-categorization of customers would call for extra effort.

4. 6 Summary of the comparisons

A summary of the case results is presented in table 6. The preliminary results received from the sample data set give a reason to expect that moving towards a more aggregated approach is an option to be considered seriously in the case company, and the company has already moved towards a more aggregated approach in one customer category. To make more general conclusions for the case company, a larger analysis of data is needed. In addition to that, the performance of AF will improve if demand is aggregated across sales units, and possibly improve if forecasts produced with AF are judgmentally adjusted. These are potential areas for further analysis.

AD has an undisputable strength that aggregate approach lacks, linking information about individual customers to the forecast, but the true value of this strength remains fuzzy. In the AD, the forecast accuracy improves if the input from customers improves, e.g. customers provide accurate forecasts or if such policies as vendor-managed inventory is implemented with the customer. So it should be analyzed if such development trends are realistic, and if the improvement of forecast accuracy is truly valuable.

Table 6: Summary of case results

	AD	AF	SAF
Information base for creating the forecasts	Unconfirmed orders Contracts Demand history Judgement	Demand history (Contracts)	Defined by customer category
MAPE* in the data sample	24 %	28-29%	24-29%
Effort needed in creating the forecast	Number of forecasts per sales unit: 300	Number of forecasts per sales unit: 20	Number of forecasts per sales unit: 80
Forecast accuracy when time scale is changed from 1 to 2 months	19 %	24 %	19-24%
Challenges in managing the approach	Controlling the input in the forecasting process	Lack of confidence in the forecast	Forming homogeneous customer categories

5. Conclusions and further research

Major part of forecasting literature is focused forecasting methods, but less attention has been paid on the implementation of methodologies in real contexts. From a managerial point of view it is relevant to study what kind of problems there are in applying forecasting methods, and how improving forecasting practices can be supported. In this paper, a situation is described, in which forecasting approach is to be updated in a case company. The aim is to use forecasting resources efficiently, so both forecast accuracy and forecasting efforts are considered. In this case, selecting the forecasting aggregation level is interlinked with method selection, though in former literature these two decisions are typically discussed separately. In this paper, three forecasting approached were compared against each other. The comparison works as a part of improvement process. When it is distinguished where the forecasts made by salespeople are more accurate than statistical forecasts, it is easier to focus the forecasting efforts of the salespeople as well as other improvement efforts.

In this paper, an illustrative example of the comparison with a limited data set was provided. The example points out a couple of issues. Firstly, forecast accuracy is not a sufficient criterion for selecting between different forecasting approaches. The results of the data sample show that the forecast accuracy in different forecasting approaches is nearly the same. In this type of situation the ease of use emphasizes in method selection. Secondly, though it is a known fact that forecast accuracy improves when forecasts are aggregated, the amount of accuracy improvement is different in different customer categories. This is important to notice, since it implies that different forecasting approaches can be suggested for different customer categories. The examples point out that even though on a detailed level the forecasts made by salespeople are more accurate than statistical forecasts, in most cases the difference disappears when forecast accuracy is measured on the same level as the forecasts are used.

In the industrial context, the choice of the proper forecasting process is a complex multi-criteria decision that calls for systematic review and illustration, so that the decision can be properly managed. In an environment that is similar to the case company, this type of analysis may help to identify objects of development in the forecasting process. In addition, it can be used to illustrate how improvement in individual customers' demand predictions affects the accuracy of the aggregate forecast. This analysis will serve as a useful basis for discussion, when the forecasting approach is selected or changed. The data set used in this paper is very limited, but even with this limited data it is possible to gain understanding about the nature of the method selection situation, and to draw tentative conclusions on where to focus the salespeople's forecasting efforts. This kind of comparison is relevant especially in industrial context, where it is common to apply salesforce forecasting, but there is also demand history available.

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Appendix

Croston's method forecasts separately the time between consecutive transactions p_t and the magnitude of the individual transactions z_t. At the review period *t*, if no demand occurs in a review period, the estimates of the demand size and inter-arrival time at the end of time *t*, $\hat{z}_t$ and $\hat{p}_t$ respectively, remain unchanged. If the demand occurs so that $z_t > 0$, the estimates are updated by

$$\hat{z}_t = \alpha z_t + (1-\alpha)\hat{z}_{t-1},$$
$$\hat{p}_t = \alpha p_t + (1-\alpha)\hat{p}_{t-1},$$

where α is a smoothing constant between zero and one. Hence, the forecast of demand per period at given time t is given as

$$C_t = \frac{\hat{z}_t}{\hat{p}_t}.$$

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THE ROLE OF CONTEXTUAL INFORMATION IN DEMAND FORECASTING

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ABSTRACT
The paper deals with clarifying the role of contextual information in demand forecasting. It is often noted that combining judgmental forecasting methods with statistical methods is needed to provide accurate forecasts. However, in practice it is often difficult to tell when judgmental intervention is needed and when it is not. This paper presents a case example about the difficulty of defining the use of contextual information in forecasting. The paper provides some guidelines on how to evaluate the value of contextual information with probability calculations. The calculations show that in some situations, it is impossible to improve forecast accuracy, even though the contextual information is seemingly valuable. With probability calculations, it is possible to give more objective and specific rules on when contextual information is useful in forecasting and when it is not.

Keywords: demand forecasting, contextual information, forecast accuracy

INTRODUCTION
Demand forecasting is one of the fundamental managerial tasks, and there is a vast amount of literature about the issue. Yet, the environment where demand forecasting is applied has changed since the early days of forecasting literature. One of the trends is the increased volatility of demand patterns (Bartezagghi et al. 1999, Miragliotta & Staudacher 2004, Kalchschmidt et al. 2006). Other trend is the increased use of information technology, and the enhanced ability to share information between trading partners (Forslund & Jonsson, 2007).

Forecasting literature has responded to these changes. Some authors suggest information sharing between trading partners as a remedy for the whole supply chain management (Chen 1998, Lin et al. 2002). On the other hand, the role of human judgment has started to gain academic acceptance sine the 1980s (Lawrence et al. 2006, Webby & O'Connor 1996). Even though information sharing and judgemental forecasting are somewhat separate areas in literature, from a managerial point of view they link to same managerial problem; that is matching supply with demand.

It is common for industrial companies to rely on judgmental forecasting methods (Mentzer & Moon, 2005), and the main advantage of these methods is that they provide an opportunity to link the forecaster's domain knowledge and contextual information into the forecasts (Lawrence et al. 2006, Webby & O'Connor 1996). "Contextual information" or "contextual knowledge" is a concept that is mentioned by many authors, e.g. Sanders & Ritzman 1995, Lim & O'Connor 1996, Armstrong 2001, Lawrence et al. 2006, though its contents are not

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strictly defined. It can mean any information about the demand that is received about the customer's demand, excluding actual orders.

However, judgmental forecasting or information sharing do not offer instant remedies in matching together supply and demand. It has been show that information sharing suffers from quality problems (Forslund & Jonsson, 2007), and the experiences about the ability of contextual information in improving forecasts are mixed (Edmundson 1989, Sanders & Ritzman 1995, Lawrence et al. 2000).

Former literature points out that companies are often overconfident about judgmental forecasting (Arkes, 2001), which implies that that the value of contextual information may be overestimated. The content of contextual information that is actually successfully used in forecasting has remained somewhat fuzzy in the literature. There is a need for clear rules when contextual information should be noticed in forecasting and when not.

There are a few reasons why the value of contextual information in forecasting should be understood well. First, when selecting between judgmental and quantitative forecasting methods, it should be evaluated whether there are sufficient prerequisites for the use of judgmental methods. Secondly, to be able to set a realistic target for forecasting accuracy, the theoretical predictability of demand should be known. Traditionally, the predictability of demand has been evaluated by measuring the forecast error. However, this measure reveals only the performance of the present forecasting system, but does not show the accuracy that could be achieved if the forecasting process was managed more efficiently. In many real-life situations the customer base is heterogeneous, and individuals in the organization develop their own views on the predictability of demand on the basis of their experiences with certain customers and from their own viewpoint. The views tend to be diverse, due to the differences in job descriptions and different types & depths of contacts with customers. Therefore, there is a need for an approach that can create a more objective picture about the predictability of demand in the company as a whole.

In the following section, we review the literature that deals with contextual information in forecasting. After that, we present an approach for identifying when the forecast accuracy can be improved with contextual information and when not, and how to tell the most important cues that a judgmental forecaster should follow. Finally, we consider the managerial implications and make some concluding remarks.

BACKGROUND

Several surveys show that judgmental forecasting methods are popular in business contexts (e.g. Klassen and Flores 2001, McCatrhy et al. 2006, Moon & Mentzer 2005). According to Lawrence (2006), in the 1980's the attitudes in academic literature were negative against judgmental forecasting methods, but now its role has been accepted.

One of the reasons why judgmental methods gain more interest is that several authors have found that in many industrial contexts, companies are encountering increasingly uncertain and irregular demand (Bartezagghi et al. 1999, Miragliotta & Staudacher 2004, Kalchschmidt et al. 2006). Several approaches have been suggested for forecasting irregular/lumpy demand. One approach is to apply the traditional forecasting techniques based on the analysis of past demand information, but these techniques are prone to large forecast errors, since lumpiness breaks the series. Another option is to model the demand creation process, focusing on forecasting not only order sizes but also order intervals (Syntetos & Boylan 2001).

When the demand is irregular and statistical methods provide unreliable forecasts, one option is to extend the information base of forecasting by looking directly at future requirements. In the method called early sales method (Bartezzaghi, 1999), the main idea is that the estimation of unknown future demand is based on the actual orders that have already been received for future delivery. One approach to anticipate future requirements is to exploit the early information that a customer generates during his purchasing process before he places his actual order. This kind of approach has been described, e.g. by Bartezzaghi (1995), who has named the approach order overplanning. In the approaches that use direct customer information, the forecaster needs to judge the reliability of the information, and therefore these approaches can be called judgmental methods. The advantage of judgmental forecasting is the possibility to combine contextual information and domain knowledge into the forecasts.

Definition of contextual information

Many authors use the concept of "contextual knowledge" or "contextual information", but the definition of it is not very precise. According to Sanders & Ritzman (2004) "*Contextual knowledge is information gained through experience on the job with the specific time series and products being forecasted.*" According to Webby and O'Connor (1996), contextual information is: "*information, other than the time series and general experience, which helps the explanation, interpretation and anticipation of time series behavior* "

Several terms are used in the literature that are similar to "contextual information", e.g. "causal knowledge", which pertains to an understanding of the cause-effect relationships involved (Webby & O'Connor, 1996), product knowledge (Edmundson et al., 1988) and extra-model knowledge (Pankratz, 1989). According to Mintzberg (1975), much of the information processed by managers is of an informal, verbal, qualitative or "soft" in nature. Experience of similar forecasting cases can be also seen as contextual information. Using such information, that is, analogies, in forecasting has been studies e.g. by, Hoch and Schkade (1996), Green& Armstrong (2007) and Lee et al. (2007).

Fildes and Goodwin (2007) mention information about "special events, such as new sales-promotion campaigns, international conflicts or strikes" as examples about contextual information. Sanders and Ritzman (2004) mention" rumors of competitor launching a promotion, a planned consolidation between competitors, or a sudden shift in consumer preferences due to changes in technology" and "causal information, such as relationship between snow shovels and snow fall, or temperature and ice cream sales." Lawrence (2000) has mentioned "new marketing initiatives, promotion plans, actions of competitors, industry developments" as examples of contextual information that is actually discussed in forecasting meetings of manufacturing companies. In addition to these pieces of information, customers own forecasts can be considered as contextual information. According to a survey reported by Forslund & Jonsson (2007), 87% of suppliers received forecast information from their customers. However, customer forecasts suffer from quality problems.

Methods for using contextual information in forecasting

There are some basic approaches for using contextual information in forecasting. One approach is using purely judgmental forecasting methods, such as direct use of managers expectations, and surveys on forecasting practice typically show substantial use of this approach (McCarthy et al., 2006). Other option is to integrate statistical forecasts with judgmental forecasts. Goodwin (2000) has named two different integration methods as *combining and correcting.* Combining means that the forecast is obtained by calculating a simple or weighted average of independent judgmental and statistical forecasts. Correcting methods involve the use of regression to forecast errors in judgmental forecasts. Each judgmental forecast is then corrected by removing its expected error (Goodwin, 2000). There is also one common method, called *judgmental adjustment* (Sanders & Ritzman, 2001), which means that statistical forecast is adjusted according to contextual information. In addition, the last method is *Judgment as input to model building*, which means that judgment is used to select variables, specifying model structure, and set parameters (Sanders & Ritzman, 2004).

Former studies about the contribution of contextual information in forecasting

The impact of judgment on demand forecasting has been studied both with laboratory research (e.g. Wright & Goodwin, 1998, p. 91-113) and some field studies. In this section, studies that deal with the performance of judgmental forecasts versus statistical forecasts are reviewed.

Edmudson et al. (1988) tested the value of contextual knowledge in a business setting. Judgmental forecasts were generated and tested based on three knowledge levels of knowledge. The first level were students with considerable technical knowledge, but no contextual knowledge. The second level were practitioners with moderate amount of contextual knowledge, having forecasting experience in the industry. The third level were practitioners with considerable contextual knowledge, including industry forecast experience and specific product familiarity. Of the knowledge levels tested, specific product familiarity was the factor found most significant in improving forecast accuracy.

In a case study by Sanders and Ritzman (1995), real business data was collected from a national public warehouse. Planners created forecasts based on contextual information. To be compared with, also a group of students made judgmental forecasts. Contextual information that warehouse planners possess was described in the following way: "The planners know that some of their customers show seasonal patterns of activity, such as spring time sales of lawn-care equipment. Also, they are aware of the recent overall customer activity levels. They know what shipment has been brought in the day or week before and how much was demanded last year at this time." In this study the main finding was found that combining statistically derived forecasts with those of experienced practitioners improved forecast accuracy (over other combinations), especially when demand patterns were volatile.

Lawrence et al. (2000) studied the accuracy, bias and efficiency of judgmental forecasts in thirteen large Australian manufacturing organizations. The study showed that company forecasts were not uniformly more accurate than simple, un-seasonally adjusted, naïve forecast. Most of the source of error was due to both inefficiency (a serial correlation in the errors) and bias in the forecasts. These two factors seemed to mask any contribution of contextual information to accuracy.

Syntetos et al. (2008) evaluated the performance on judgmental adjustments in intermittent demand forecasts. Finding was that negative adjustments were more effective than positive adjustments and large adjustments lead to forecasts that are particularly accurate. These findings are in similar with e.g. Diamantopoulos (1989) who noticed that larger adjustments were more effective in improving accuracy.

Despite the studies, there are no clear rules on when the environment is such that there are sufficient prerequisites for creating judgmental forecasts, and when contextual information is useful in forecasting. In general, it is said judges will outperform models when they have contextual information to help them comprehend discontinuities in the series. Human judgment is most effective if "broken leg cues" are available (Webby & O'Connor, 1996). A broken-leg cue refers to an unusual and important piece of information whose presence would dramatically alter the judgment compared to a model of that judgment (Kleinmuntz, 1990). According to Sanders & Ritzman (1996) contextual knowledge that helps practitioners deal with time series which have a significant amount of explainable variation. Lim and O'Connor (1996) found out in their study that adjustment of forecasts using causal information improved forecast accuracy when causal information was highly reliable. To summarize, contextual information in forecasting is most beneficial if it is highly reliable information about dramatic demand changes, but it is not defined how reliable is highly reliable and how big is dramatic.

Managerial problems relating to judgmental forecasting

One problem is implementing forecasting approaches that uses contextual information. Several studies have found inefficiency in the judgmental forecasting process. Judgmental forecasters carry out voluntary integration of statistical methods and judgmental forecasts inefficiently (Goodwin, 2000). The forecasters tend to ignore cues, especially if there are several available, and people tend to be irrational when it comes to dealing with probabilities (Wright & Goodwin, 1998). Lim and O'Connor (1996) found out in their laboratory study that people often selected less reliable information when there were many types of information available to a forecaster. Salespeople are closest to the customer, so they are assumed to have the best access to contextual information. However, judgmental forecasts, especially when produced by salespeople, are known to be prone to bias and inefficiency (Mentzer & Moon, 2005).

Other managerial problem is how to set accuracy targets for judgmental or judgmentally adjusted forecasts. In real life forecasting is often mixed with planning, and so in practice high accuracy is not the target after all (Lawrence et al., 2000). In some cases, sales are manipulated to meet the target that was set (Lawrence et al., 2006). Bunn and Taylor (2001) state that cross-company comparisons have not generally been relevant or feasible in the area of setting the goals of forecasting quality.

Using qualitative methods in the forecasting process is more time-consuming, and the accuracy achieved usually weaker than with statistical methods (Menzer & Moon, 2005). Therefore, one problem is keeping the forecasting approach cost-effective. In practice this means that most of the forecasting effort should be focused on the most important customers/products, because the time used for forecasting is taken from other activities that the salespeople are responsible for (Mentzer & Moon, 2005). Some authors (Caniato et al. 2005, Thomassey et al. 2005) suggest that proper categorization of customers is a good way to focus forecasting efforts.

Research question of this study

Lawrence et al. (2006), after reviewing 200 studies about judgmental forecasting, state that much remains to be researched to develop improved methods for supporting judgmental forecasters, particularly in identifying when judgmental intervention is needed and when it is not needed. As it was noted earlier, only some very general rules are available on when contextual information is useful.

Some authors see that practical experience allows the forecasters to make rational decisions on when contextual information is useful. Experience-based ability to evaluate the importance of contextual information is called “Domain knowledge” (e.g. Webby et al., 2001)

However, Syntetos et al. (2009) found out in their study that neither statistical forecasts nor judgmentally adjusted forecasts improved over time. This implies that domain knowledge does not develop automatic.

The research question of this paper is: How can the development of domain knowledge be supported?

DESCRIPTION OF A CASE COMPANY

A case company provided a motivation for this study. In this section, it is described how forecasting is performed in the case company, and what kind of managerial problems occur.

The case company is a large international process industry company that has several sales units and several production units. The forecasts are produced individually by salespeople in separate sales units, and collected together to be used in allocating production capacity in production units and between production units.

Contextual information in the case company

The customer base is heterogeneous, and the customers operate in distinct businesses: contractual markets and spot markets. On the latter markets, each order is competed for, so the predictability is considerably lower than in the contractual markets. From different customers, different pieces of information about demand are available in advance. In contractual markets, contracts are made for four months or twelve months ahead. In practice, these contracts define only the maximum volume the customer may receive during the given time period. In addition to this, some customers place preliminary orders before they place their actual order. In the spot markets, customers make inquiries, that indicate customers buying intentions, but inquiries are not as reliable indicators as contracts. Customers are not the end users of the products, so their demand depends on their own customers. Salespeople are usually aware in what kind of end-products the material ends up. However, the demand profiles of the end products vary, some end-products having regular demand and some having irregular demand. In the case company, managers were able to explain major discontinuities in demand patterns beforehand, when they were shown exceptional demand profiles. Reasons for discontinuities were for example that customer substituted the product with cheaper product, or sales were allocated into other sales unit.

In a survey, six managers of the case company were asked how they see the importance of preliminary orders, contracts, customers’ predictions about their future demand and demand history as information sources in forecasting. The managers are responsible for leading the work of forecasters, but they do not personally produce forecasts. The results showed that managers saw customer’s predictions about future demand as important as demand history. Also contracts and preliminary orders were seen important by some managers, thus some disagreed. In this case company, contextual information obviously exists, but it is not clear what is its’ role in forecasting.

Accuracy measurement in the case company

The sales people produce sales forecasts for each customer on a monthly basis, as it is considered natural to produce forecasts on the same level as the everyday communication happens. However, typical order frequency of a single customer is one order per month or less. As a result, the forecasts are often made at a higher frequency than the orders arrive. Orders do not always fall to same moths as the forecasted amounts, so therefore forecast accuracy for individual customers is typically low.

The forecast accuracy is measured on monthly level. The forecast accuracy is calculated by comparing actual sales with forecasts. However, the sales do not represent actual demand, since sales are sometimes manipulated after the forecasts are made. In the case company, their own actions that manipulate the demand include pricing changes, delaying or advancing sales, and re-allocating production from one unit into another. Sales are often manipulated after the forecasts are made. Therefore, measured forecast accuracy may give a misleading view of the predictability of demand. Still, the value of contextual information can be evaluated with comparing judgmental or judgmentally adjusted forecasts by forecasts made on the basis of demand history. Comparisons show that the accuracy of judgmental forecasts is not uniformly better than the accuracy of statistical forecasts. When forecasting the demand of individual customers, judgmental forecasts in some cases are more accurate than statistical forecasts, but when forecasts are aggregated from different customers, statistical forecasts provide closely same accuracy as judgmental forecasts.

Development actions in the case company

It is reasonable to focus the salespeople's efforts on tasks that have the most value in forecasting with adequate rules and tools. Therefore it is justified to categorize customers or products. When forecasts are made separately for product/customer categories that have different predictability of demand, it is easier to get a general view about the reliability of forecasts. However, before categorization, it should be clear when contextual information is of value in demand forecasting and when it is not. This knowledge is called domain knowledge in former literature. In the following section, we show some examples on how to use probability calculus in supporting the development of domain knowledge.

PROBABILITY CALCULATIONS TO EVALUATE THE RELEVANCE OF CONTEXTUAL INFORMATION

In practice, information about the customer's forthcoming orders may include contracts, unconfirmed orders, and/or information about the customer's future plans. These pieces of information differ from each other by their reliability and exactness. If the timing and magnitude of a change in demand is known accurately beforehand, this information can be treated in the same way as a confirmed order. It can be said that contextual information is demand information that is inexact about the timing, magnitude or probability of an arriving order.

The main point in analyzing contextual information is to find out if such contextual information exists that is truly valuable in forecasting and available only for the salespeople. The value of contextual information is easy to overestimate intuitively, but in many cases it can to some extent be concluded with probability calculations. Contextual information is of value in forecasting only if the expected value of a forecast error decreases with using it. This can be illustrated with some examples.

In the following probability calculations, forecast error is measured as absolute values. Some traditional error measures, such as MAPE (Mean Absolute Percentage Error) use absolute values in calculating the error. It has to be noted that using other error measures, such as MSE (Mean Squared Error) would give different results. So, how contextual information impacts the forecast accuracy, depends also on the error measure used. In the case company, the error measurement bases on measuring absolute errors. Therefore, that measure is used in the paper.

Example 1: A sporadic event with uncertain timing

A salesperson produces monthly forecasts for a single customer. The salesperson receives information that in the future there will be a demand peak, and the magnitude of this peak is known accurately. However, the timing of this demand peak is not known exactly. It is assumed that excluding this demand peak, the demand is smooth. It is assumed that the probability of the demand peak is the same each month.

n: number of months in the period when the demand peak is possible
x: magnitude of the demand peak
X: forecast error

If the forecaster does not react to this contextual information, the cumulative expected value of the forecast error from the sum of months is x, (on a single period of time: x/n), since probability that the demand peak occurs in a specific month is 1/n.

If the forecaster adjusts the forecast according to this information, he/she can adjust the forecast with an adjustment parameter a (0 < a < x), so the expected value of the forecast error in one period is:

$$E(X) = \frac{1}{n}(x-a) + \frac{n-1}{n}a = \frac{x+na-2a}{n} \tag{1}$$

The adjustment succeeds in decreasing the expected value of forecast error if $na - 2a < 0$, which is true when n<2, which means that the timing of the demand peak should be known accurately before information about it is of value in the forecasting. This is an example of a situation where seemingly correct contextual information is unable to improve forecast accuracy.

Example 2: More than one sporadic event with uncertain timing: aggregate forecasting

This example is similar to the previous example, but now there is more than one customer that will have a demand peak with uncertain timing, and the forecaster produces an aggregate forecast for the customers.

c: number of customers
n: number of months of the period when demand peaks are possible
x: magnitude of one demand peak

If the forecaster does not react to this contextual information, the cumulated expected value of the forecast errors is xc, on one period of time xc/n.

If the forecaster does adjust the forecast with adjustment parameter a, (cx > a > 0), the expected value of the forecast error on one period will be:

$$E(X) = \sum_{i=0}^{c} |a - ix| \binom{c}{i} \left(1 - \frac{1}{n}\right)^{c-i} \left(\frac{1}{n}\right)^{i} \tag{2}$$

so the adjustment is of value when

$$\sum_{i=0}^{c} |a - ix| \binom{c}{i} \left(1 - \frac{1}{n}\right)^{c-i} \left(\frac{1}{n}\right)^{i} < \frac{cx}{n} \tag{3}$$

For example, if c is 2 and n is 3, the expected value of forecast error can be decreased with adjusting the forecast. The greater the number of customers with similar demand peaks on a certain time period, the more likely it is that adjusting the forecast improves the forecast accuracy. Similarly, the longer the time period where the demand peaks may occur, the less likely it is that adjusting the forecast will improve accuracy. With formula (3) it can be calculated whether the adjustment is of value in a specific situation where n, c, and x are known.

A practical example about a sporadic event with unclear timing is a special event, for example sports event, that affects the end demand, but the actual timing when it impacts the customer's orders is not known because of the customer's unknown production timetables, unknown ordering timetables and inventory policies.

Example 3: A demand level change with uncertain timing
A salesperson produces monthly forecasts for a single customer. The salesperson receives information that in the future there will be a rise in demand level, and the magnitude of this change is known accurately. However, the timing is not known exactly. It is assumed that excluding this change, demand is smooth. It is assumed that the probability of the rise in level is the same in each month, and it is too late for the forecaster to react to the change when it has already occurred.

n: number of months of the time period when the change is possible
x: magnitude of the change

If the forecaster does not react to the contextual information, the cumulative expected value of forecast error on n months is

$$E(X) = x\sum_{i=1}^{n} \tfrac{i}{n} \tag{4}$$

If the forecaster reacts to the contextual information, it is possible to adjust the forecast in each month with an adjustment parameter a_i. If the change is anticipated like this, the cumulative expected value of the forecast error is

$$x\sum_{i=1}^{n} \tfrac{i}{n} - \sum_{i=1}^{n} \frac{a_i i}{n} + \sum_{i=1}^{n} a_i \tfrac{n-i}{n} \tag{5}$$

The adjustment is of value if :

$$x\sum_{i=1}^{n} \tfrac{i}{n} - \sum_{i=1}^{n} \frac{a_i i}{n} + \sum_{i=1}^{n} a_i \tfrac{n-i}{n} < x\sum_{i=1}^{n} \tfrac{i}{n} \quad \rightarrow \tag{6}$$

$$\sum_{i=1}^{n} a_i (n - 2i) < 0 \tag{7}$$

This shows that adjustment can always be of value, not depending on n. The decrease in the expected value of the forecast error depends on adjustment parameter a_i. When i > n/2, it is best to adjust the forecast with parameter a=x. When i < n/2, it is best not to adjust the forecast, so a=0. This shows that, where is a permanent demand level change with uncertain timing, the forecast should always be adjusted, and it should be assumed that the level change happens at the middle of the time period when the change is possible.

A practical example of this type of demand change is a situation where a customer increases its buying volume because of entering new markets, but it is not known exactly when.

Example 4: A demand level change with uncertain probability: aggregate forecasting
A salesperson produces forecasts for single customers. The salesperson receives information that the level of demand will rise in the future. However, this change is not certain. The probability of the change should be over 50% for this contextual information to be of value in forecasting. But if there is more than one customer that may have a similar change, then even the cases where the probability of a level change is less than 50%, contextual information can improve the forecast accuracy.

c: number of customers
p: probability of demand level rise
x: magnitude of demand level rise

In a certain time period, the expected value of forecast error without adjustment is

$$E(X) = \sum_{i=1}^{c} p_i x_i \tag{8}$$

The forecast can be adjusted with adjustment parameter a. The expected value of the forecast error with adjustment

$$E(X) = \sum_{i=1}^{c} p_i x_i - a + a\sum_{i=1}^{c}(1 - p_i)\,, \tag{9}$$

so the adjustment is of value when

$$\sum_{i=1}^{c}(1 - p_i) < 1 \tag{10}$$

A practical example of an uncertain level-change is a situation where customers are selecting a supplier, but it is not certain whether the company will win the competition.

MANAGERIAL IMPLICATIONS
The availability of relevant contextual information can be estimated by looking back at the demand history and analysing the contextual information that has been available. By comparing the amount of relevant contextual information and the demand volume it is related to with the total demand volume, it is in principle possible to calculate a numeric value for the availability of relevant contextual information.

Figure 1 illustrates different categories for predictability. The objects to be categorized can be customers, products or product families, depending on the forecasting task. The idea in forming these categories is to focus the forecasting resources and facilitate the choice of the forecasting method and practices. Measuring forecast accuracy in these categories gives a better picture about the predictability of demand as a whole. If the demand patterns are highly irregular, and relevant contextual information is not available, the prerequisites for forecasting are low, regardless of the method used. In other cases, the choice of the forecasting method is made on the basis of the regularity of demand history and the availability of relevant contextual information.

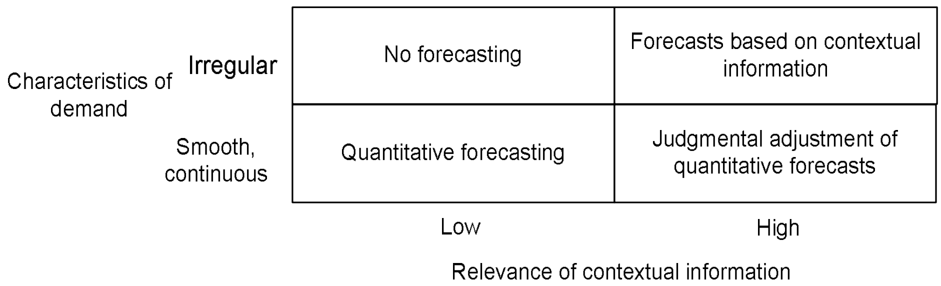

Figure 1: Predictability of demand and its implications for forecasting

CONCLUSIONS

Former research about forecasting practice shows that so-called contextual information plays a crucial role in demand forecasting. Judgmental forecasting is commonly applied in industrial companies, and the performance of judgmental forecasts depends on the contextual information used. However, it is also noted that there are problems with managing judgmental forecasting approaches, and judgmental methods do not always provide more accurate forecasts than statistical methods. The definition of contextual information is not very precise, and there are no clear rules on when contextual information is useful in forecasting and when it is not.

As the case company's example shows, the heterogeneity of the customer base brings extra challenge in managing demand forecasting. The type of contextual information that is available varies by customer and by product, and therefore it is difficult to get a general view about the predictability of demand. Therefore, it would be reasonable to classify customers and products on the basis of available contextual information. However, there are no ready-made criteria with which the customers or products could be categorized. Former studies show that people tend to be irrational when dealing with probabilities; so that that implies that an objective measurement tool for the value of contextual information could be useful.

In this paper, a probability-based approach for evaluating the value of contextual information was presented. With the approach, it is possible to demonstrate when incomplete demand information is useful in forecasting and when it is not. With the approach, it is possible to gain more objective suggestions about when a cue should be followed and when advance demand information is too imprecise to be used in forecasting. The approach may be most useful in a situation, where there is uncertainty on many levels; uncertainty about the probability of demand change, uncertainty about the magnitude of a change and uncertainty about the timing of the change. In addition, approach can be used in modeling situations where expected demand change involves many customers. The results of probability calculations show that contextual information that is unable to improve forecast accuracy on a detailed level, can be useful when making forecasts on the aggregate level. This suggests that it is justified to aggregate the demand of customers in forecasting, even if there is detailed information available about individual customers' demand.

The approach is not limited to the case company, but the case company only served as a motivation for this approach. The case example shows that there is a need to evaluate the value of contextual information in a more systematic way. However, the approach presented is only a tool in evaluating the value of contextual information, and its potential managerial contribution depends on how and when it is applied. This study differs from former studies dealing with contextual information. In former literature, the performance of judgmental forecasts has been compared with statistical forecasts, but in this paper the approach is more theoretical. The aim was to evaluate the value of contextual information regardless of the forecasting approach that is actually applied.

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Demand forecasting errors in industrial context: Measurement and impacts

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A B S T R A C T

It is important to know the impacts that sales forecast errors have on the supply chain. Knowing the role of forecasting and the impacts of forecast errors creates a basis for defining a realistic target for forecast accuracy, identifying the most important customers and/or products to be forecasted, and finding a suitable way to measure forecasting performance.

This paper provides a case study about assessing the impacts of sales forecast errors. The analysis steps include defining the planning flow and the role of sales forecasts in production planning and inventory management and analyzing the characteristics of sales forecasting errors of a company. The case company is a large process industry company that seeks out to improve the accuracy of their sales forecasts and to improve control over the inventory policy decisions of different sales divisions.

This case study points out some managerial problems that companies run into when demand forecasting is applied in an industrial context. One of the problems is the insufficiency of traditional error measures. The problem is analyzed and an alternative measurement practice is presented.

1. Introduction

Demand forecasting is commonly applied in companies that operate in consumer markets. When demand patterns are relatively smooth and continuous, demand forecasts based on historical demand are usually quite accurate. Success stories about demand forecasting typically report lower inventory levels and improved customer service. After the success of forecasting in consumer markets, there has been growing interest in applying demand forecasting in companies operating in industrial markets to apply demand forecasting, despite the fact that environment is different. In industrial markets, the importance of single customers is greater, so demand patterns are more volatile. In this environment, the historical demand does not always predict the future demand sufficiently, so human judgment plays a more important role in the forecasting process.

When the demand forecasting system is implemented in a company, there is a tendency that concepts, targets and principles are imitated from other companies to speed up the implementation. Since most of the forecasting approaches have been developed for consumer products, there is a risk that unrealistic accuracy targets and deceptive error measures are adopted, if the environment is different. Companies operating in industrial markets have special characteristics that should be addressed and understood before any techniques or approaches are applied.

Forecasting should not be considered as an individual function, but as an important part of supply-chain management. However, most research emhasizes producing the forecasts, not their usage in decision making or their impacts in the whole supply chain. Also earlier empirical research points out that in practical work, producing the forecasts is more consciously managed

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than evaluating its impacts in the supply-chain management (Mentzer and Moon, 2005). For example, in many companies forecast accuracy is measured, but assessing the impacts of forecast errors on supply-chain management is not managed equally well.

Many forecasting studies start from the premise that the use of forecasts and the required forecast accuracy is defined before the approach for producing the forecasts is chosen, see e.g. Heizer (2001). This does not always happen in practice, however, as the nature of sales forecasting management is more iterative. That is why it is important to get a general view about the whole forecasting process in a company, illustrate it, and communicate about it in the organization.

The emphasis of this paper is on the usage of forecasts and on the impacts of forecast errors. Through an explorative case study, we illustrate that forecasting systems in companies are not always rational with respect to the real impacts of forecast errors. The impacts of forecast errors are analyzed in order to find a target, focus, and suitable performance measurement for forecasting that fit the characteristics and needs of the case company.

In the next two sections, the literature on forecast error measurement and setting the targets for forecast accuracy is reviewed. After that, the case company's planning and forecasting operations are analyzed. At the end of the paper, managerial impacts of the analysis are reviewed and the last section provides some concluding remarks.

2. Measuring forecast errors

Forecasts are used for many purposes: marketing, sales, finance/accounting, production/purchasing, and logistics. In this paper, the focus is on forecasting from the perspective of production planning and inventory control.

An abundance of forecasting techniques exists and is available to the sales forecasting manager. In fact, it often seems that too many techniques are available, so that the choice decision can border on information overload. There are over 70 different time series techniques alone (Mentzer and Moon, 2005). In this paper the focus is on the forecasts that are produced by salespeople and then combined into a consensus forecast. This method, which is popular within industrial companies, is usually called the salesforce composite method (Mentzer and Moon, 2005).

There are different causes for forecast errors, and they may coexist. When salespeople produce forecasts, there are three main hazards, summarized by Kerkkänen et al. (2006): (1) game playing, which means that salesperson uses forecasting to serve his own purposes, (2) low motivation, which means that the salesperson does not see any point in forecasting, as he does not benefit from forecasting accurately, and (3) lack of ability, which means that the salesperson lacks tools and/or abilities to produce reliable forecasts. For these reasons and because of the special characteristics of each company, individual types of error take place in different companies. E.g. game playing may cause a systematic bias towards positive or negative direction. Demand variability varies between companies, as well as the magnitude of errors.

Literature provides several different measures for forecast error. Some of the most popular ones are mean absolute deviation, mean absolute percentage error (MAPE), mean squared error, cumulative error, and average error or bias (Russell, 2000; Chopra and Meindl, 2001; Mentzer and Moon, 2005). Some authors suggest that forecast bias is significantly more detrimental to organizational cost than forecast standard deviation in the warehouse environment, at high levels of bias (Sanders and Ritzman, 2004).

According to Chopra and Meindl (2001), measuring forecast accuracy serves two main purposes: (1) managers can use error analysis to determine whether the current forecasting method predicts the systematic component of demand accurately. For example, if a forecasting method consistently results in a positive error, the manager can assume that the forecasting method is overpredicting the systematic component and take appropriate corrective action. (2) Managers estimate forecast error because any contingency plan must account for such an error.

According to some authors, measuring forecast errors improves forecast accuracy (Wacker and Sprague, 1995; Mentzer and Moon, 2005), but simply measuring forecast errors on a general level does not provide enough information for setting targets for forecast accuracy and finding development areas in demand management. Different types of forecast errors cause different kinds of impacts in production planning and inventory management. For example, if the forecasts are obviously systematically wrong, it is more likely that they can be judgmentally adjusted.

In principle, when choosing forecasting procedures, we are concerned with keeping the expected total relevant costs as low as possible up to some future decision horizon. The costs should include both the cost of obtaining a forecast and the cost resulting from forecasting errors. In practice, the application of this apparently simple expected total cost criterion is limited because it is difficult to measure the relative cost of the resulting forecast errors (Silver, 1998). However, assessing the impacts even roughly may help in focusing the forecasting effort on the most important product and/or customers.

3. Assessing the impacts of forecast errors

Potential impacts of forecast errors have been reviewed in earlier literature by e.g. Kahn (2003), and many studies have dealt with assessing the impacts of forecast errors on some specific part of supply-chain management, e.g. MRP nervousness (Ho and Ireland, 1998), MRP system inventory costs and shortages (Lee and Adam, 1986), and schedule instability and system service level (Xie et al., 2004). Possible impacts of forecast errors can be summarized into three main categories (Table 1): (1) planning impacts, (2) capacity impacts, and (3) inventory impacts. *Planning impacts* include excess planning work and related costs, *capacity impacts* include the loss of capacity and

Table 1
Potential impacts of sales forecast errors

Planning impacts	Capacity impacts	Inventory impacts
• Schedule instability	• Lost capacity • Uneconomical use of capacity	• Excess inventory • Inventory holding cost • Obsolescence • Reduced margin • Lost "sales" cost

related costs, and *inventory impacts* include improper inventory levels and related costs.

The basic literature of operations management or supply-chain management does not usually provide approaches for assessing the impacts of forecast errors (Heizer, 2001; Russell, 2000; Silver, 1998; Stadtler and Kilger, 2002; Chopra and Meindl, 2001). Still, Mentzer and Moon (2005) stress that companies should assess sales forecasting accuracy in terms of its impact on business performance.

Numerous studies have explored the relationship between forecast errors and organizational performance measures. They demonstrate that the impact of forecast errors is not constant but varies upon organizational characteristics (Sanders and Ritzman, 2004). The difficulty to clarify the relationship between forecast errors and manufacturing performance has been recognized by many authors, see e.g. Ritzman and King (1993). Some manufacturing simulations have been made in order to asses the impact of forecast errors on master production scheduling. On general level, the results are contradictory. Some simulation studies, e.g. Xie et al.(2004) and Zhao and Xie (2002), show that forecasting errors have significant impacts on the total cost, schedule instability, and system service level. Ho and Ireland (1998) have examined the impact of forecasting errors on the scheduling instability in the material requirements planning operating environment. They found that forecasting errors may not cause a higher degree of scheduling instability, and they propose that the selection of an appropriate lot-sizing rule is capable of coping with forecast errors.

A common factor in most earlier studies is that they do not deal with real companies and real data, and therefore organizational issues are not considered. Management decisions, however, cannot be easily modeled, the case study approach is necessary when assessing the real impacts of real forecast errors. In practice, forecast and demand information often enters the planning process in many phases and from various sources. In addition, in real life forecast errors are not necessarily random, but may include systematic characteristics that are specific to each company.

Although it has been reported that measuring the impacts of forecast errors is very difficult, if not impossible, we claim that due to the importance of this task, providing even suggestive results is necessary. We claim that the analysis should start from the organizational point of view: it is important to understand who uses the forecast and demand information and when, for what, and how, and what type of forecast errors exist. In the next section, an analysis about a case is presented, which starts from clarifying the planning flow and the use of forecast and demand data in the planning process.

4. Introduction to the case

The purpose of assessing the impacts of different types of sales forecast errors is to answer the following questions: (1) how to define the target for forecast accuracy, (2) what are the most important products to be forecasted, and (3) what is a suitable way to measure forecasting performance.

Analyzing the impacts of forecast errors requires first defining the planning flow between forecasts and the sales. After that, it must be analyzed what is the role of demand information in the planning process. In addition, it must be understood how the forecasts are produced, what are the most substantial sources of errors and how these sources can be affected.

The case company is a large international process industry company that has several sales units and several production units. Production is mainly to order, but capacity is allocated to forecast and this is the main use of the forecasts. The sales force produces the forecasts. Forecasts are made for each month and for each customer separately. Forecast errors are calculated as a distinction between actual sales and forecast sales 2 months before the sales month.

One machine in one of the production units and four largest sales units, representing 2/3 of the sales volume, were chosen to be the source of case data. The data were analyzed from a 9-month analysis period. The product is a bulk product, but finished to customers' orders. The business is considered to be continuous; 19% of the customers place an order every month and 39% place an order every second month or more often.

The company has set a target that forecast errors should be halved, but there is no clear picture as to how this would affect production planning and inventory management.

5. The role of forecasting in planning

The planning flow of the company was analyzed on the basis of written reports and interviews. The planning flow of the company is described in Fig. 1.

The forecasts are produced at the sales units, and every month a consensus team of the headquarters produces a consensus forecast for the production units. The main point of making the consensus forecast is to match the accepted orders, commitments, and forecasts with the capacity. If the accepted orders, commitments, and forecasts per planned month exceed the capacity, the situation is called shortfall and the forecasts are adjusted. Capacity allocations mean that the consensus forecast is freezed for 1 month. All in all, the forecasts are not adjusted if there is no shortage of capacity.

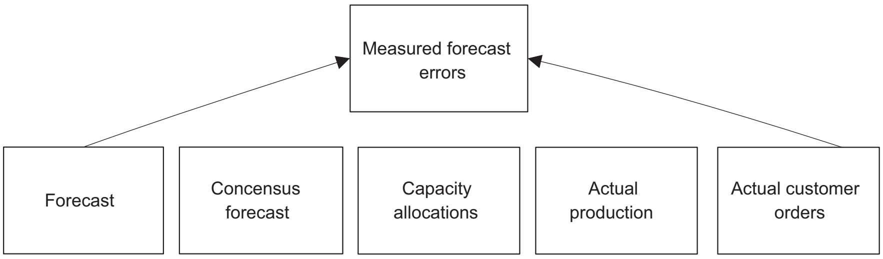

Fig. 1. Measured forecast accuracy and the planning flow in the case company.

Actual production is made to order only, but before scheduling it must be decided which ones of the actual orders are accepted for production. So that is why forecasts are necessary for capacity planning. If it seems that there is a lack of capacity, some of the orders may be delayed, but this is always discussed with the customers. It is also possible to redirect some of the orders to another production unit. If it seems that there is excess capacity, the actions are contrary to this; production is made beforehand, but only after order confirmations from the customers. Also the sales efforts may be increased. A continuous positive bias of the demand forecasts has been noticed at the production unit, and if the shortfall shows about 10% lack of capacity, no action is seen necessary.

In the planning flow of the case company, the forecasts do not serve as a direct input in any decisions concerning production. Hence impacts of forecast errors cannot be quantitatively measured, since forecast errors do not directly cause capacity losses or and production is made to order only. In this case, forecast errors cause difficulties to decide what kind of action is needed for smoothing the capacity, as well as extra work due to checking the customer-specific sales and forecast information. Being so, the numerical analysis focuses on analyzing the deviations in the forecast and production data.

To know the role of demand information in the production planning, it was analyzed how well the timing of production actually follows the timing of demand. The length of the production cycle is about 2 weeks. On average, products were produced 3 weeks before they were supposed to exit the production unit, but the timing varied, with a range of several weeks. Mismatches between production timing and actual customer demand timing exist, because production planning seeks to reach acceptable production runs (lot sizes). There are sufficient margins in the timing of production planning, but especially in the case of low-volume customers the production timing is not dictated by the timing of actual sales, and therefore it is not critical to forecast exactly on a monthly level. Since the capacity planning is made on so rough a level, the main objective being the maximum use of capacity, from the point of view of production planning it is not critical to know the exact month when the actual order arrives. Still, if the timing of the demand errs only with 1 month, this shows as a forecast error in the present measurement system.

6. Characteristics of the forecast errors in the case company

There are a few things that are characteristic to the forecast errors of the case company. First of all, forecasts are positively biased. Secondly, there are irregularities in demand patterns that are due to company's own actions such as redirecting orders between sales units or substituting a product with a similar product. Third, there are minor errors in timing, since typical order frequency is close to the length of the forecasting period. Because of these three factors, it is difficult to observe the true uncertainty of demand with traditional error measures.

The forecast error is defined as the absolute difference between the forecast and actual sales. Forecasts larger/smaller than the actual sales are referred to as over/under-forecasts. This definition is preferred to the traditional measures because of the separate indications for over- and under-forecasting, which is important as these two error types have different (cost) consequences as discussed before.

Calculated from the whole data set, the average monthly forecasts are biased, over-forecasts being about 50% and under-forecasts being 20% compared with the sales, so the net error is 30% over-forecasts.

In the case example, 20% of the products represent 86% of the total sales volume. In this group, the errors were slightly lower than in the total data set: over-forecasts 43%, under-forecasts 17%, and the net error being 26% over-forecasts. The rest 80% of products (that represent 14% of the total sales) resulted as follows: over-forecasts 101%, under-forecasts 51%, net error being 50% over-forecasts.

It is important to identify the main sources of forecast errors so that development can be focused. Management of bias and focusing measurement on true demand instead of actual sales is undoubtedly important, but solving these problems requires very company-specific managerial means. Hence, in this paper we focus on another interesting issue, the problem of timing errors, which is more general in nature.

The salespeople estimate the demand of each customer on a monthly level. To analyze the value of their efforts we calculated a reference value for forecast errors. The reference value was calculated using the average value of the monthly forecasts instead of a real forecast. The average value of monthly forecasts was named "average

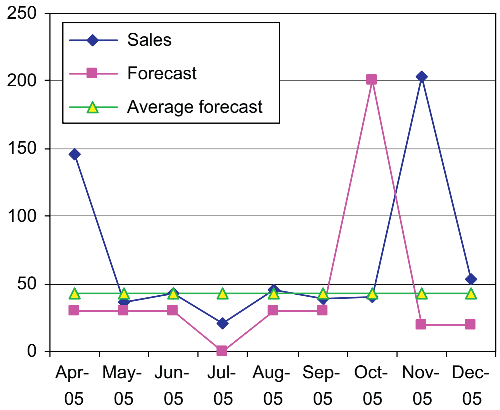

Fig. 2. Timing error in December–November.

forecast". A real example is illustrated in Fig. 2. As it can be seen in Fig. 2, using the "average forecast" instead of forecast results in smaller forecast errors almost every month during this analysis period. In the example illustrated in Fig. 2 the sum of absolute forecast errors during the analysis period is 557 units, whereas the reference value calculated with "average forecast" results 247 units less: 310 units. Performing the same comparison within the whole data set, the surprising result was that replacing all the forecasts with corresponding average values would have decreased the total over-forecast errors with 7% and total under-forecast errors with 3%. The mean absolute error decreased with 3.3%. This indicates that the attempt to time the demand forecasts on a monthly level has failed. Despite the fact that the total demand was forecasted relatively well in the case in Fig. 2, the monthly level forecast accuracy looks bad: the 9-month MAPE is 93% and the mean absolute error 61.9 units.

Failing the timing causes managerial problems. Since exact timing of demand is not critical for planning, and attempts to get the timing right continuously fail, it undermines the salespeople's motivation to forecast. Salespeople are unwilling to accept feedback, since the measurement of forecasting performance is seen irrelevant. In the next section it is demonstrated how timing errors can be screened out from other errors so that it is possible to focus on forecast errors that are seen relevant.

7. Separating timing errors from the other forecast errors

This type of errors, which are considered harmless, but disturb the planners' work and hinder the picture of "real" accuracy, should be screened out from other errors when measuring forecast accuracy. As simple it might sound, methods for that task do not exist. For example, using moving averages does not really help in smoothing such timing errors. In theory, forecasters could be asked to define the exactness of their timing evaluations, but increasing the responsibility of the salespeople cannot be justified in this connection.

Table 2
A smoothing algorithm

Month	S	F	E_A	E_B	E_C	Smoothed forecast error
September	39	30	–	–	−9	–
October	40	200	−151	−23	160	−13
November	203	20	−23	−216	−183	−36
December	53	20	–	–	−33	–

It was tested if 1-month timing errors could be screened out with a special "smoothing algorithm". The example is described below.

F_n is the forecast for month n; S_n the sales for month n; E the forecast error for month n; SE the smoothed forecast error for month n

$$E_A = (F_{n-1} + F_n) - (S_n + S_{n+1})$$

$$E_B = (F_n + F_{n+1}) - (S_{n-1} + S_n)$$

$$E_C = F_n - S_n$$

$$|SE| = \min\{|E_A|, |E_B|, |E_C|\}$$

E_A shows small values if the sales lag behind the forecasts with 1 month, and E_B shows small values if the forecasts lag behind the sales with 1 month.

Using this smoothing algorithm in the case of Fig. 2, the MAPE results in 33% and the mean absolute error is 13.7 units, which represent other than timing errors in forecasting, and should be used in assessing the forecasting performance. Applying the smoothing algorithm in the whole data set, using the smoothing algorithm, the total mean errors decrease by 10–20% (Table 2).

8. Managerial implications

A short description about the actions that resulted from doing this analysis in the case company will point out the managerial implications.

8.1. Target for forecast accuracy

Since forecasts are used for capacity planning only, it is difficult to rationalize forecasting accuracy targets. During this study, capacity utilization rate was so low that it did not justify reaching for better forecast accuracy. However, capacity utilization rate is occasionally higher, so the importance of forecasting emphasizes at intervals.

8.2. Priorization of forecasts

If the purpose of forecasts is to aid the capacity planning, and the production is still made to order, it must be known how well the production timing follows the demand timing. It was noticed that for low-volume customers the relevant lot size dominates the accurate timing, and hence the monthly level forecast accuracy is not all that important. It can be concluded that not too much effort should be put on the forecast accuracy of low-volume customers. In addition, if the total absolute errors were halved in the group of 20% best selling products, the total forecast errors would decrease by 35% on a factory level, so it would be advisable to focus the forecasting efforts on these products.

Also, it could be useful to categorize the customers according to the predictability of the business. That way it can be seen, which part of the demand forecast is very likely to come true and which part of the demand forecast is less likely to come true.

8.3. A way to screen out minor timing errors from other forecast errors

Monthly timing of the demand in this environment is not critical, but the planning processes require using monthly periods, the measures for forecast errors should fit these characteristics of the company. Therefore, along with the present systems, the forecast accuracy should be measured in a way in which the 1-month timing errors are sorted out. An example of such an algorithm was developed in the previous section. The approach was found useful in the case company and it was decided to implement a pilot version.

9. Conclusions

Forecasting is an attractive area for a technique application, which may direct the whole forecasting function in a company. Too often the real needs of forecasting in the form of impacts of errors get forgotten. Assessing the impacts of forecast errors is important but challenging. Complexity and interrelations in the planning processes make it difficult to separate the impacts of forecast errors from other planning. Therefore, analyzing a whole planning flow is needed to create a general view about the whole forecasting process, including the interrelations with production planning and inventory management.

The case example shows that forecast accuracy targets are not always justified, and therefore it is important to get a general view of the whole forecasting chain in the company and to be able to communicate and illustrate it in the company. The presented analysis of the whole planning flow can be used for analyzing the forecasting system performance, critical assessment of its objectives, and to support decision making when targets are set for forecasting. The presented approach could be applied in similar industrial contexts.

Forecasting is a cross-functional process, and therefore managing it demands same kind of tools as managing other cross-functional processes. The forecasting process involves personnel from many functions, and not everybody is aware of the forecasting process as a whole. Production planning, inventory management, and forecasting should be understood as a whole, before it is possible to set justified targets for an individual part of it.

It would be interesting to extend the research to include more cases to clarify, whether companies' forecasting systems are in line with the real impacts of forecast errors. Another area for further research could also be to answer the question of how to define formally what the right accuracy target is when various impacts have been considered.

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Analysing inaccurate judgemental sales forecasts

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Abstract: This paper deals with categorising errors that exist in qualitative sales forecasts, so that it can be defined what kind of development is needed to improve forecast accuracy. A framework for pointing out different types of sales forecast errors is presented. The framework includes analysing demand profiles of customers and the continuity of under-/over-forecast errors. The error types are named as random error, positive bidirectional error, negative bidirectional error, systematic under/over estimation error and unforecasted sales. The differences between the approaches for reducing each type of error are explained. The use of the framework is illustrated with sales and forecast data of a large process industry company. The analysis steps are illustrated and actions for reducing different types of sales forecast errors are suggested.
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1 Introduction

Forecasting means estimating a future event or condition which is outside an organisation's control and that which provides a basis for managerial planning. Forecasting techniques range from simple to complex, and include the use of executive judgement, surveys, time-series analysis, correlation methods and market tests. Many companies do not know their future demands and have to rely on demand forecasts to make production planning decisions.

There is evidence that in the industrial markets, companies rely commonly on judgemental demand forecasting (Mentzer and Moon, 2005). The contribution of human judgement in forecasting has also started to gain wider academic acceptance since the 1980s (Lawrence et al., 2006; Webby and O'Connor, 1996). Despite the great efforts that have been put on forecasting research, many companies still face a situation where forecasts do not meet the targets that have been set.

In industrial markets, demand patterns are often such that it is difficult to forecast demand based only on history and applying technical methods to data. A larger part of demand errors are due to judgemental part of forecasting and therefore due to behavioural elements of forecasting.

In former literature, the importance of information flow has been emphasised as a remedy for the whole supply chain management (Chen, 1998; Lin et al., 2002). The lack of information technology is nowadays hardly the reason for poor forecasting performance. In particular, new information technology has made real-time, online communications among parties within the supply chain possible (Hanfield and Nicholas, 1999). However, sharing information more efficiently does not guarantee efficiency in the supply chain management if the information that is shared is not valid. When the forecasts are produced by sales people, which is common in the industrial markets, it is difficult to control the quality of the data that enters the forecasting system. The weakness of the forecasting process is then rather managerial than technical or mathematical in nature. Managing such a complex, cross-functional process as demand forecasting requires tools for illustrating and communicating the problems of sales forecasting in the organisation.

It is important to identify that there are different motives behind forecasting in the organisation that cause errors in the forecasts. If the behavioural elements are substantial in forecasting, it is reasonable to focus development into managerial, not only technical aspects of forecasting process. It is impossible to detect the deepest underlying causes to forecast errors from data, but it is possible to identify regularities to which development acts can be directed to. This paper presents a framework for analysing sales and forecast data produced by the sales people. The idea is to categorise forecast errors so that it is possible to point out distinct policies for reducing forecast errors in separate categories. The approach presented in this paper is only a first, but still a very important step in order to find a way into better sales forecasting management.

In Section 1, we consider the literature on judgemental forecasting and explanations and remedies for poor forecasting performance. In Section 2, we explain the use of the suggested research method. Section 3 presents the framework for categorising forecast errors. In Section 4, we illustrate the use of the framework in the case company. Section 5 discusses the managerial implications in the case company and Section 6 offers some concluding comments.

2 Literature review

In former literature, there are two main approaches to forecasting; quantitative techniques meaning that forecasts are produced based on historical data only, and qualitative techniques meaning that forecasts aim at anticipating future demand. In this paper, the focus is on the latter approach, and to be more specific, on forecasts that are the responsibility of sales people. This, forecasting method is usually called 'salesforce composite method' or 'salesforce forecasting'.

Salesforce forecasting is seen as a possibility to estimate future demand, as estimating intermittent/lumpy demand based on historical data has been noticed to be difficult. Anyhow, it has been known for long that the forecasts that are on the responsibility of sales force tend to bias (Lines, 1996; Moon and Mentzer, 1999). In this section, theories for the poor forecasting accuracy are presented and the suggested approaches for overcoming the weaknesses are reviewed.

2.1 Causes and approaches for overcoming poor forecasting performance

The poor performance of the forecasts produced by sales force is usually explained by the conflicts between the roles of forecaster and a salesman. The reasons for poor forecasting performance can be divided into three categories:

1 game playing

2 low motivation

3 lack of ability.

Game playing means that the salesman uses forecasting to serve his own purposes. The forecasts reflect the salesman's optimism about the future sales, as he seeks to guarantee the availability of the products to the customers. *Low motivation* means that the salesman does not see any point in forecasting, as he does not benefit from forecasting accurately. *Lack of ability* means that the salesman lacks tools and/or abilities to produce reliable forecasts. This includes also lack of information from the customers.

Lines (1996) emphasises the game playing reason:

> "Because a saleman's *raison d'être* is to improve the level of sales over what has been seen in the past, however, if entrusted with forecasting he may be tempted to alter the value of any forecast produced by extrapolation techniques to reflect his optimism."

Lines stresses that proper control is needed in order to reduce the forecast error, though he admits that it is still difficult to get the timing right although the general message might be correct.

Moon and Mentzer (1999) emphasise the lack of motivation most. In an in-depth study of the sales-forecasting management practices of 33 companies, they found some resistance from the salespeople concerning their forecasting responsibilities in almost all the studied companies. Many salespersons felt that it was not their job to forecast and the time spent on forecasting was time taken away from their real job of managing customer relationships and selling products and services.

The suggestions for overcoming the problem by Mentzer and Moon (1999) aim at facilitation of forecasting. They suggest the following:

1 make forecasting part of the sales people's job by including forecasting as a part of their job descriptions, by creating incentives for high performance in forecasting, and by providing feedback and training

2 minimise game playing by making forecasting accuracy an important outcome for the sales people and by clearly separating sales quotas from forecasts

3 keep it simple by asking the sales people only to adjust statistically generated forecasts rather than produce forecasts from scratch and by providing them with adequate tools that enable them to complete their forecasting work as efficiently as possible

4 keep it focused by having the sales people deal only with the products and customers that are truly important and where their input can significantly affect the company's supply chain.

Some approaches that remind the suggestions of Mentzer and Moon have been developed. For example, Holmström (1998) has presented an approach called 'assortment forecasting'. The approach focuses on reducing the time spent on forecasting by working with an entire assortment at a time instead of producing a forecast for each product individually. The approach has been tested by Småros and Hellström (2004) with a case company that provides supermarkets, video rentals and the like with pick-and-mix sweets.

Mentzer and Kahn (1997) describe a problem they call 'islands of analysis', which is a consequence of game playing:

> "Islands of analysis are systems phenomena where one individual or group develops a sales forecast based upon their own information and needs, and does not share that information of forecast with others in the company. The resultant sales forecasts may be significantly different than forecasts developed elsewhere in the company (other islands) and these differences lead to conflicting plans."

Helms et al. (2000) emphasise the poor management of forecasting. They claim that forecasting is often the most maligned department in any company. They claim that the 'islands of analysis' problem could be tackled with better management of forecasting. The approach they suggest is titled as Collaborative forecasting, and it emphasises the cooperation between sales units and production units, and creating a consensus forecast. According to Helms et al. the process should include analysis of the actual sales versus the forecast and the creation of a baseline forecast based on historical information.

Some approaches even expand the collaboration across trading partners. Since the mid-1990s, academics have emphasised the importance of creating a seamless supply chain, using concepts like Vendor Managed Inventory (VMI), Collaborative forecasting and Replenishment (CPFR) and Continuous Replenishment (CR). Yet, mainstream implementation of these concepts has been less prominent as expected, despite the benefits that have been claimed (Holweg et al., 2005).

As a contrast to Collaborative forecasting, there is an anecdote reported in the study of Helms et al. (2000): "In the past, marketing folks would put together a forecast, but production personnel would put together what they considered to be a more accurate forecast". The abovementioned anecdote calls to mind another approach for improving forecast accuracy, splitting the forecasting responsibility between sales units and production unit. This approach has been presented by Zotteri and Verganti (2001).

Zotteri and Verganti see the exaggerated sales forecasts provided by sales force as an approach to manage demand uncertainty, and call this approach 'order overplanning'. This method was originally introduced in the study of Bartezzaghi and Verganti (1995). This is just another example of game playing.

In their study, Zotteri and Verganti (2001) examine whether the manufacturing or the sales units should manage demand uncertainty. The first option is a decentralised approach, where slack is incorporated into the overstated forecasts provided by the sales units. The second option is a centralised approach, where slack is set by the manufacturing unit on the basis of information gathered by the sales units. In the centralised approach, each sales unit must specify not only the production level they believe to be optimal, but also the probability associated with each single potential customer order. In this approach, the management of demand uncertainty is split between the manufacturing (where the slack is defined) and sales (where the forecasts are made).

Even though many authors emphasise organisational issues (game playing and low motivation) when it comes to salesforce forecasting, it must be kept in mind that forecasts produced by sales force may error from same reasons as the forecasts in general; internal factors like unsuitable time horizon and external factors like lumpiness of the demand affect the forecasting accuracy.

It is very likely that different causes for forecast errors coexist, and therefore it is important to analyse how the errors mainly build up, before implementing a solution to reduce forecast errors. In the next section, an approach is presented, which helps pointing out the magnitude of different types of forecast errors so that the suitability of different kinds of corrective actions can be estimated.

3 Methodological viewpoints

Especially in the case of qualitative forecasting, managing the forecasting process is a complex issue, including for example target setting, forming basic assumptions about the nature of the demand and leading the practical work of the forecasters. The practical problem the case company is facing is how to operate in a situation where qualitative forecasts do not meet the targets that have been set. At the same time as forecast errors are examined, also the targets must be kept under critical assessment; are they relevant and realistic? Therefore, improving the performance of the forecasting process is a multidimensional managerial problem, and solving it requires broader methodological view than attempting to create a generic solution algorithm.

In these kind of situations, another type of approach is often suggested, in which the decision-maker is offered supporting tools to recognise the type of the problem and some potentially effective actions (e.g. heuristic rules). The decision-maker is left with the task of integrating the context-dependent information and also all the intuitive (tacit) knowledge which he may possess and find relevant in the situation. This kind of approach belongs to the paradigm of design sciences (e.g. Van Aken, 2004), of which purpose is to provide knowledge to support the design of interventions that managers need to do in various decision-making situations. It is based on the claim that in complex situations only the design knowledge (on the potential types of actions) can be general (i.e. valid for classes of cases), but the problem of the manager is always unique and specific (Van Aken, 2004).

4 A framework for analysing demand forecasts

The framework presented in this paper is designed for a situation where forecasts are developed for each customer separately, but aggregated from several sales units into a higher level, for example, product family level. This is a common situation in the industrial markets. Though in the industrial markets, the number of customers is lower than in the consumer markets, it is still time consuming to go through the buying behaviour of each single customer, and in that way, trying to find out the deepest causes of forecast inaccuracy, and finding out possible remedies for them. Therefore, a framework is needed that points out where the greatest improvement potential lies, so that development actions can be rationally focused. Demand and forecast data is easily available, so it is economical to begin the development work by analysing that data and thereby identifying and evaluating the further steps of development work. This kind of analysis tool is not meant for regular use, but rather to be performed once a year to illustrate the performance of the forecasting process.

The idea of the analysis framework is to sort out different types of forecast errors, because different types of errors call for different approaches to improve the forecast accuracy. The categorisation of errors that we suggest is presented in Table 1. Firstly, under-forecasts (demand exceeds the forecast) and over-forecasts (forecast exceeds the demand) must be separated from each other. Examining under-forecasts and over-forecasts separately enables deeper analysis of forecast bias. For example, then it is possible to detect, how bias (negative or positive) relates to individual forecasters.

Table 1 Definitions of the error types

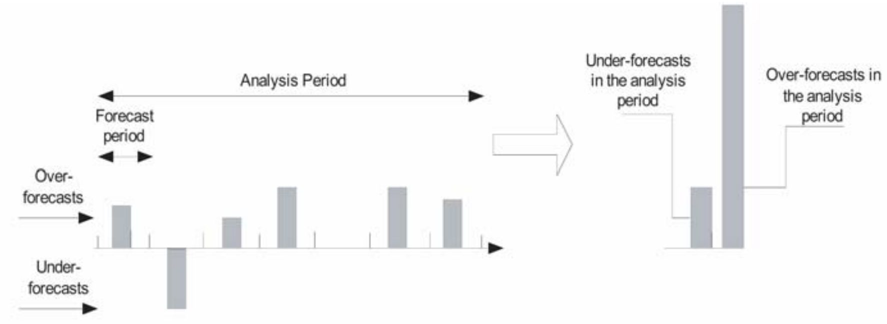
Error type	*Definition*
Unforecasted sales	The sales of the customer are not forecasted in the analysis period
Systematic over-estimation	The sales of the customer are always over-forecasted in the analysis period
Systematic under-estimation	The sales of the customer are always under-forecasted in the analysis period
Positive bidirectional error	The sales of the customer are both under-forecasted and over-forecasted, but the net error in the analysis period is over-forecasting
Negative bidirectional error	The sales of the customer are both under-forecasted and over-forecasted, but the net error in the analysis period is under-forecasting
Random error	The sales of the customer are both under-forecasted and over-forecasted, but the under- and over forecast errors cancel each other in the analysis period

Secondly, the regularity of over/under-forecasting must be analysed. Systematic over-forecasting errors are assumed to be easier to reduce than the irregular errors, because forecasts could be trimmed down/up to some extent without increasing forecast errors on any period. If bias is not systematic, it indicates that there is an exceptional period in demand, for example, the so-called demand pike. In these cases, reducing the forecast errors requires finding out the reason for unpredicted exception in the demand, in addition with the reduction of bias.

In addition, it is distinguished which part of the under-forecasting errors occur because the forecasts are not made, and which part of the forecast errors can be considered random.

Figure 1 clarifies the way the forecast errors in one customer's demand during analysis period are summed. For example, if forecasts are produced on a monthly basis, the 'forecasting period' is one month. The forecast errors are counted up from a chosen analysis period that is a multiple of the forecasting period (seven months in the example). Counting up the negative and positive errors separately gives a picture if the forecast has been biased in the long run.

Figure 1 Forecast errors on the forecast horizon and in the analysis period (example of a positive bidirectional error)



It is presumable that if the demand is continuous, there are better premises to forecast more accurately than if the demand is intermittent. Also, the effectiveness of the actions aiming at improving the forecast accuracy depends on the continuity of demand. If the forecast period is extended, for example from one month to two months, the forecast accuracy improves in all demand categories, but in the category of intermittent demand, there is relatively more potential to accuracy improvement. That is why forecast errors should be examined separately in different demand profile categories. Hence, demand profiles are categorised roughly into 0-demand (no demand), intermittent demand and continuous demand.

In summary, we suggest that the categorisation follows the three-step analysis framework described below:

Step 1 Set the parameters that are needed for categorising the forecast errors. These parameters include the length of proper analysis period and the bounds of error categories.

Step 2 Divide forecast errors into over- and under-forecasts and classify the data according to demand profile.

Step 3 Divide forecast errors into error types that were introduced in Table 1.

Full categorisation of forecast errors is presented in Table 2. After categorising forecast errors, possible corrective actions for different error categories can be suggested.

For some error categories, it is relatively easy to define the corrective actions. If there is no existing demand, but forecasts are still continuously produced, it is rational to calculate if the forecast accuracy is better if the forecast was 0, and then guide the forecasters accordingly.

Unforecasted sales are more understandable in the intermittent demand category than in the continuous demand category. If the demand is continuous, but forecasts do not exist, it is likely that forecaster has just forgotten to produce forecasts for that customer. If demand is intermittent, so that in some periods demand does not exist and in some periods it exists, neglecting the forecasting can be rational behaviour from the forecaster. If the forecaster is unsure of the periods when demand will exist, entering guesses to the forecasts easily results in more forecast errors than if making the forecasts is fully neglected. In this kind of situation, the forecaster is still able to make a forecast, but only on a longer forecasting period.

Table 2 Categorisation of forecast errors and actions needed to reduce the forecasts

Unforecasted sales	–	Find out reasons for neglecting forecasting. Consider using longer forecast period	Find out reasons for neglecting forecasting
Systematic over-forecasting	Consider refraining from making forecasts	Trim the forecast down. Consider using longer forecast period	Trim the forecast down
Systematic under-forecasting	–	Trim the forecast up. Consider using longer forecast period	Trim the forecast up
Positive bidirectional errors	–	Find out the reason for the exception in forecast errors	Find out the reason for the exception in forecast errors
Negative bidirectional errors	–		
Random errors	–	No universal rules for reducing errors, longer forecasting periods should be considered	No universal rules for reducing errors
	0-demand	Intermittent demand	Continuous demand

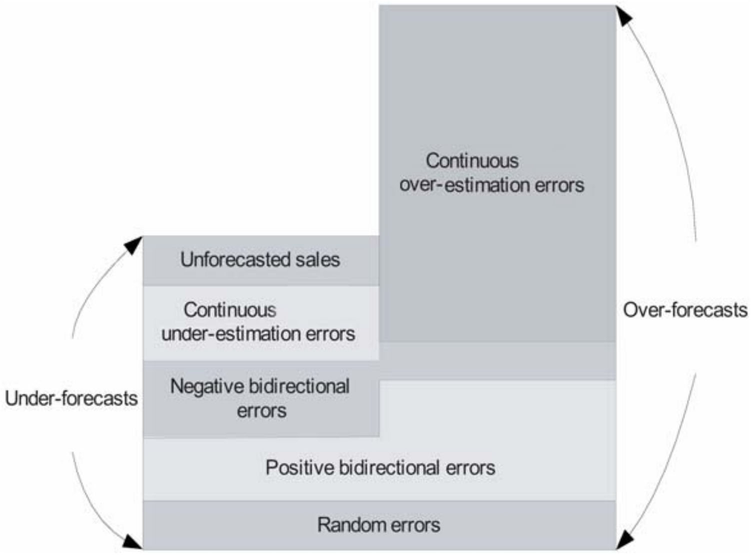
Systematic over-forecasting is typical for the forecasts that are produced by sales force, since sales people seek to minimise the possibility of under-forecasting. In this kind of situation, forecasts can be cut down to some extent without increasing forecast errors on any period. If the demand is intermittent, systematic over-forecasting can be rational behaviour from the forecaster. If the forecaster is unsure of the periods when demand will exist, entering guesses to the forecasts easily results in more forecast errors than if forecasts were evenly divided to each period. In this kind of situation, the forecaster may still be able to make a reasonable forecast, but only on a longer forecasting period.

In the case of bidirectional errors, demand is almost systematically under- or over-forecasted, but there is an exception that turns the situation the other way around for a while. Reducing the forecast errors in this category requires checking if there is an exception in the demand pattern and then finding out the reason for the exception. One possible reason for that kind of exception is a seasonal pattern that is either not recognised or reacted with a delay. If the irregularity can be explained, it is possible to give relevant feedback to the people in question.

Random errors mean that forecast is not positively or negatively biased in the long run. Some random errors will always exist, and there is no universal rule how to reduce it. Still, it is important to tell which part of the forecast errors is 'natural' or 'noise'. Using longer forecasting period will smooth out a part of these errors.

Figure 2 illustrates the different types of errors from which the overall over- and under-forecasting errors (introduced in Figure 1) consist of. This analysis can be performed both on factory level and at sales unit level. Figure 2 illustrates that the net error may be the same, though the weight of separate error categories is different.

Figure 2 Categorisation of different types of forecast errors



5 Application of the framework in the case company

The framework was designed to improve the forecasting process in a large international process industry company that has several sales units and several production units. In the case company, the forecasts are produced by salespeople and then aggregated from several sales units into product family level. The company uses demand forecast for capacity planning. Capacity is allocated to forecast, but the actual production is made to order. It is possible to allocate the production between separate production units. The problem that the inaccurate demand forecasts cause is the inability to see the real capacity situation and to react to it in advance. Because the forecasts are used for capacity planning, it is justified to study absolute forecast errors, because largest absolute errors cause largest absolute problems. Also, in this situation, it is essential to know if the error is negative or positive.

The management of the company also wishes to enhance the control over the inventory policy decisions of the sales units, and this is the other reason why the forecast accuracy is under inspection. It is known that forecasts are in error, on the factory level, the net error compared to sales was 24%, but for single customers, the errors were greater, so the sum of over-forecast errors relative to actual sales was 60% and the sum of under-forecast errors was 36%. There are strong assumptions that forecasting accuracy should be better, but it is not yet identified where exactly the improvement potential lies and how it could be realised. In the beginning, there was an assumption that forecast errors are caused mostly by the sales people who are not active enough to update the demand forecasts.

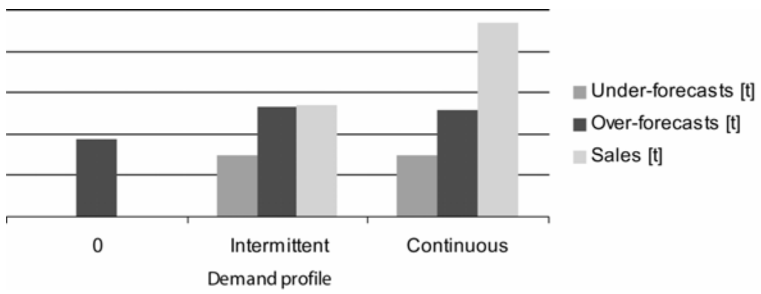
To test the analysis framework, one machine from one of the production units was chosen to be the source of case data. At this machine, the forecast errors were higher than average. The data set included data on monthly level from 33 sales units and over 600 customers. The product is a bulk product, but finished to customer orders. The forecast errors were calculated as a distinction between actual sales and forecast sales two months before the sales month. The data needed for the analysis was available for a seven months' time period, which was considered to be sufficiently long. Table 3 illustrates the data that was needed for the analysis.

Table 3 A piece of input data for the analysis; one product, factory level

Time	*Sales unit*	*Customer*	*Forecast*	*Sales*	*Under-forecast*	*Over-forecast*
200X/April	Sales unit 33	Customer 1	70	70		
200X/April	Sales unit 33	Customer 500	176	110		66
200X/April	Sales unit 33	Customer 13	0	50	50	
200X/May	Sales unit 1	Customer 83	72	48		24
200X/May	Sales unit 1	Customer 7	25	20		5
200X/May	Sales unit 2	Customer 606	44	0		44
200X/May	Sales unit 2	Customer 69	34	0		34

Figure 3 shows the results of categorising the forecast errors by demand profile. The demand profiles where categorised roughly into 3 categories: *0-demand:* No actual orders during the seven-month period (179 customers), *Intermittent demand*: 1–4 ordering months during the seven-month period (355 customers) and *Continuous demand*: 5–7 ordering months during the seven-month period (91 customers). The amount of sales in each demand category is added into Figure 3 in order to illustrate the percentage value of the forecast errors relative to sales.

Figure 3 Results of the analysis step 2: the magnitude of factory level forecast errors and sales by demand profile



It can be seen in Figure 3 that 25% of the over-forecast errors were caused by the 0-demand customers, and from the net error, this is as high as 50%. The results of the analysis strengthened the presumption that those sales units that have no settled, continuously ordering customers, give more inaccurate forecasts than the sales units with continuously ordering customers. Table 4 shows some comparisons between four example sales units. For example, at sales unit S4, even 89% of the over-forecast errors appeared in the 0-demand category, whereas in S2, only 3% appeared in that category. It can be concluded that this is one of the key figures that can be used when choosing different approaches for improving the forecast accuracy in different sales units. For example, the forecasts of S4 would possibly improve from adding a probability factor to the forecasts, whereas in S2, that would probably be just a waste of time. The differences in forecasting performance between the sales units that have similar demand profiles also give basis for benchmarking.

Table 4 Sales and forecast errors in tons categorised by demand profile: comparisons between four sales units

	Sales unit S1	*Sales unit S2*	*Sales unit S3*	*Sales unit S4*
Sales volume				
Total	29,967	18,847	6225	189
Intermittent demand	3900 (13%)	1297 (7%)	298 (5%)	189 (100%)
Continuous demand	26,067 (87%)	17,550 (93%)	5927 (95%)	0 (0%)
Over-forecasts				
Total	16,955	14,562	593	981
Relation to the sales	57%	77%	10%	519%
0-demand	3050 (18%)	384 (3%)	148 (25%)	870 (89%)
Intermittent demand	3628 (21%)	2010 (14%)	77 (13%)	111 (11%)
Continuous demand	10,277 (61%)	12,168 (84%)	368 (62 %)	0 (0%)
Under-forecasts				
Total	12,043	5837	2091	129
Relation to the sales	40%	31%	34%	68%
Intermittent demand	3155 (26%)	662 (11%)	251(12%)	129 (100%)
Continuous demand	8888 (74%)	5175 (87%)	1840 (88%)	0 (0%)

It can be seen in Table 4 that in S1, S2 and S3, most of the absolute forecast errors (as well as sales) appear in the category of continuous demand, so that is why that category is studied further. Figure 4 shows the results of step 3, categorising the continuous demand forecast errors more specifically on factory level. It is easy to separate forecasts that were systematically overestimated or underestimated. Separating the random errors from bidirectional errors is more complicated. In this case, the following simplification was made: When the forecast error in the analysis period was less than ±20%, the errors were categorised as random errors, and when the forecast error in the analysis period was more than ±20%, the errors were categorised as bidirectional errors. Using this parameter is discretionary, however. Table 5 shows comparisons between three sales units, analysing the continuous demand category. The analysis step 3 can also be performed for the intermittent demand category.

Figure 4 Results of the analysis step 3 on factory level, continuous demand

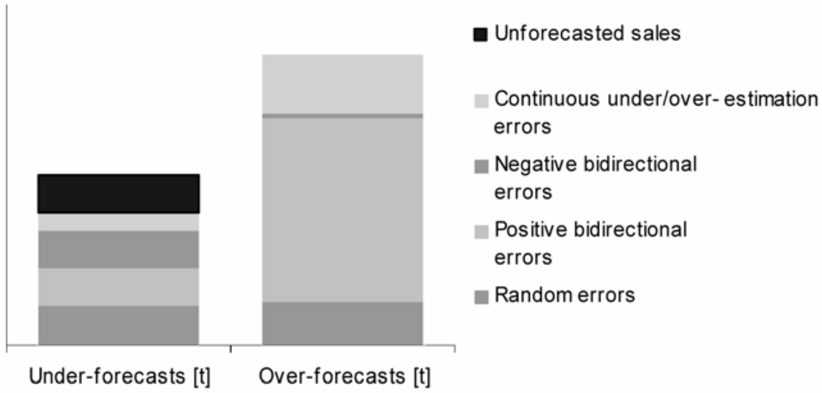


Table 5 Forecast errors of the continuous demand category divided into different types: comparisons between three sales units, S1, S2 and S3

Errors [t]	*S1*		*S2*		*S3*	
	UF	*OF*	*UF*	*OF*	*UF*	*OF*
Total	8888	10,277	5175	12,168	1840	368
R	2671 (30%)	3125 (30%)	1698 (33%)	1735 (14%)	0	0
PBE	1077 (12%)	6353 (62%)	2033 (39%)	7225 (59%)	82 (4%)	368 (100%)
NBE	794(9%)	235 (2%)	1097 (21%)	26 (0%)	0	0
S	0	564 (5%)	0	3182 (26%)	1758 (96%)	
U	4346 (49%)		347 (7%)		0	

Note: UF: Under-forecasts; NBE: Negative bidirectional errors; OF: Over-forecasts; S: Systematic over/under – estimation errors; R: Random errors; U: unforecasted sales; PBE: Positive bidirectional error.

Compared with traditional error measures, this analysis gives more information about the roots of forecast errors. In the sales unit 1, the MAPE was 86%, and in the sales unit 2, the MAPE was as high as 448%. When MAPE gives such high numbers, it is questionable if the error measure is applicable at all, and at least, it is worth studying further what causes these high numbers. Even if the error numbers were lower, MAPE does not tell if the accuracy of aggregate forecast is the result of forecasting accurately for individual customers or a lucky combination of bad forecasts that dampen each other. Therefore, using only MAPE does not provide enough basis for evaluating the potential benefits of corrective actions on forecasting performance. The other common error measures such as MAD or MSE have the same insufficiency.

The results show that there are differences between sales units in how the forecast errors are divided in different types of errors. According to this analysis, some suggestions can be made for the sales units. Sales unit S3 is doing relatively well, but has improvement potential with reducing systematic under-forecasting. Sales unit S1 has many unforecasted sales, so the reason to this should be found out. Sales unit S2 has improvement potential in reducing positive bidirectional errors, which cause 59% of the over-forecast errors in this demand category.

Examining positive bidirectional errors further revealed that usually in these cases, the demand followed a pattern where demand dropped down for a month or two, but then rose higher than average for the next one or two months. Forecast did not notice this pattern or reacted to it with a delay and this lead to bidirectional errors. Reducing bidirectional errors requires examining these demand patterns further. An analysis like this does not reveal the reasons behind these demand patterns, but points out the customers whose demand patterns should be studied further.

The analysis framework provides better understanding on how the forecast errors build up in different sales units, and where the improvement potential lies. Secondly, the differences in the forecasting performance between the sales units may enable benchmarking, which could be performed in different fields of forecasting, like dealing with new customers, communication procedures with the long-term customers, and using historical data as a basis for doing the forecast. However, the analysis results should be used only as a tool to help the managers to find out better where the problem lies in the forecasting.

6 Managerial implications

Since many kinds of development work is carried out in the case company the same time, it is impossible to reliably and quantitatively measure the benefits of this analysis framework. In addition, resulting benefits depend on the implementation of corrective actions which can take time. Still, a short description about the actions that resulted from doing this analysis in the case company will give an idea how the managerial implications were like.

First of all, taking a closer look at the forecasts revealed that the forecast errors cannot be explained by forecasters being lazy, that was the assumption in the beginning. Obviously, forecasters need more specific instructions about how, when and why forecasts should be made. It was noticed that all the forecasters had not been following the instructions that had been given, but entered very unlikely orders to forecasts. From the net errors, 50% was related to this behaviour. Feedback was decided to be given to the salespeople in question.

When assessing forecast accuracy, it turned out that the exact timing of demand was not critical for the capacity planning. So one month inaccuracy in timing was meaningless. Still, the one month forecasting period was maintained, but a new way to measure the forecast error was developed. The measure screens out the errors, where timing errs only with one month.

One development action that is under construction is making forecasts separately for the businesses that operate on stable markets and for the businesses that operate on volatile markets. Therefore, the predictability of demand in different customer groups is under evaluation to set realistic targets for forecast accuracy in different customer groups.

In the beginning, all the forecasts were the responsibility of sales people. One area of further research is finding out which customer groups or product groups should be taken out from the sales people's responsibility. This will be accomplished by evaluating, when the salespeople have true access to such demand information that enables better forecasting than mathematical models.

7 Conclusions

Forecasts that are produced by sales people are in jeopardy to err for different reasons. Practice shows that managing judgemental sales forecasting can turn out so challenging that traditional error measures are not sufficient in controlling the forecasting process. Because of the heterogeneity of customer base and heterogeneity of people who are producing the forecasts, it is difficult to generate a general view about what are the most substantive weaknesses of the forecasting process. Therefore, a proper analysis framework is needed. Analysing historical demand and forecasting data is an economical way to begin the development work, because such data is easily available.

The analysis framework presented in this paper enables categorising forecast errors into different types, and thereby helps to point out proper approaches for reducing the sales forecast errors. The results of the case company show that performing this kind of analysis is of use before a specific forecasting technique or incentive system is implemented.

The possible benefits of this kind of analysis are the following:

1 enhancing the understanding and challenging the assumptions about the achievable forecasting performance

2 enabling internal benchmarking in making the forecasts for different market areas and customer groups

3 finding out the most significant sources or forecast errors, and in this way, focusing the development resources

4 clarifying the feedback given to the forecasters about their forecasting performance.

It must be kept in mind that the approach presented here is only one step towards better forecasting performance. The benefit of this kind of analysis is that it is quick and easy to repeat, but it has its restrictions. Considerable amount of demand information is in qualitative form, and therefore it impossible to finally solve all the problems of forecasting with categorising quantitative information. Anyhow, the descriptive statistics that result can be used as an objective basis for forming hypotheses about the reasons of errors for a qualitative study, for example interview study.

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Assessing Demand Forecasting Practices in the B2B Environment

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Abstract
Forecasting techniques have developed in recent years, but there is evidence that forecasting practices in companies have not developed accordingly. In order to study this gap between theory and practice, a model is presented that aims at assessing demand forecasting practices in companies operating in the business to business environment. The model serves as a tool for facilitating the development of forecasting practices.

Keywords: Forecasting practice, forecasting management, supply chain

Introduction
Forecasting future demand is one of the fundamental tasks of management, and it has gained similar interest also in research. Demand forecasting is still a contemporary issue, as during past years the uncertainty of demand environments has grown. At the same time companies are able to gather and handle more forecasting-related data, so practitioners are encountering new challenges in managing the forecasting processes.

In forecasting literature, much of the focus has been on forecast methods, sources of forecast error, and reducing the forecast error. The selection of quantitative and qualitative forecasting techniques has grown. Yet, despite these advances, studies that deal with forecasting practices show that forecasting sophistication, forecasting performance and satisfaction with techniques, systems or management processes have not improved in recent decades. For this reason, it is justified to focus on the managerial side of forecasting, and to develop tools to support managers in developing the forecasting process.

In this paper, a model for assessing demand forecasting practices in the B2B environment is presented. The model focuses on evaluating how structured and justified the current forecasting practices are. One premise is that justified and structured forecasting practices are more efficient that unjustified and unstructured ones. Another premise is that if a company operates in an environment where the customer base is heterogeneous and multiple information sources are available, companies are in jeopardy to end up in unjustified and/or unstructured practices. The aim of the model is both to point out development areas in the forecasting process and to enhance organizational learning.

The structuring of this paper is the following: first, the literature about forecasting practices is reviewed. Based on the literature, the main factors that should be included in a forecasting practice assessment model are defined. On the basis of this framework and empirical data from a case company operating in the B2B environment, an assessment model is presented. Finally, we make some concluding remarks.

Research on forecasting practices

Research has paid major attention to demand forecasting. It has been noted that the main focus of forecasting research has been on the development of forecasting methods (Wacker & Lummus, 2002, Moon et al. 2003), and to be more specific, on statistical methods (Fildes & Goodwin 2007, McCarthy et al. 2006). From a different perspective, the literature has also studied concerned practices.

Many studies on forecasting practices rely on surveys (Cerullo et al. 1975, Dalrympe 1987, Reyna et al. 1991, Sanders 1992, Peterson 1993, Sanders & Mandrot. 1994, Wisner & Stanley1994, Kahn & Mentzer 1995, Mentzer & Kahn 1995, Lam 1996, Mentzer and Kahn 1997, Duran & Flores 1998, Mady 2000, Klassen & Flores 2001, Jain 2003-2006, Lynn et al. 1999, McCarthy et al. 2006, Tokle & Krumwiede 2006, Zotteri & Kalchschmidt 2007) Many of the surveys focus on the methods that are actually used in companies, and the accuracy that is received. These surveys also provide information about how business firms prepare sales forecasts, e.g. who makes the forecasts. McCarty et al. (2006) summarize that surveys on forecasting practices typically show substantial use of purely judgmental approaches to forecasting. According to Davis & Mentzer (2007), surveys on forecasting practices continue to report only marginal gains in sales forecasting performance. However, the reasons behind certain behaviors remain unclear. To gain deeper understanding of the forecasting process and its challenges, it is justified to use also other research methods.

Some authors have followed surveys with case studies (Watson 1996, Hughes 2001). These studies emphasize the role of organizational issues in sales forecasting. Some articles deal with the area of system implementation, and according to Moon et al. (2003) they suggest that forecasting implementation entails more than the application of more accurate forecasting techniques and that effective forecasting management, as with effective systems implementation, may lead to improved operating and business performance.

From a practitioner’s point of view, it is justified to take a normative approach to forecasting research. However, normative studies that take into consideration the whole forecasting process are somewhat rare. Only a few authors have presented frameworks to serve as standards with which forecasting processes can be compared.

In the *Principles of Forecasting*, by Armstrong (2001) 139 “principles of forecasting” are listed. They cover formulating a problem, obtaining information about it, selecting and applying methods, evaluating methods, and using forecasts. Each principle is described along with its purpose, by the conditions under which it is relevant, and the strength and sources of evidence. A checklist is provided in auditing the forecasting process.

Moon et al. (2003) present a four-dimensional framework based partly on former theoretical frameworks and partly on empirical research. They propose that, in order to adequately understand the overall management of the forecasting process in a company, that process must be investigated along the following four dimensions: (1) *Functional* *integration*, concerned with the role of collaboration, communication, and coordination of forecasting management with other business functional areas of marketing, sales, finance, production, and logistics; (2) *Approach*, concerned witch products and services that are forecast, the forecasting techniques used, and the relationship between forecasting and planning; (3) *Systems*, addressing the evaluation and selection of hardware and software combinations to support the sales forecasting function as well as the integration of forecasting systems with other planning and management systems in the organization; and (4) *Performance measurement*, considering the metrics used to measure sales forecasting effectiveness and its impact on business operations. In addition to identifying these four dimensions of forecasting management, Moon & Mentzer (2003) articulate four stages of effectiveness within each dimension. The article provides a description of the characteristics that can be found at each of the four stages of effectiveness within each of the four dimensions.

Fildes and Goodwin (2007) focus on judgmental forecasting, and list eleven principles that show how forecasters should use judgment and assess its effectiveness. These 11 principles have been identified from the *Principles of Forecasting* (Armstrong 2001). Fildes and Goodwin (2007) found out that many companies do not follow the principles.

The strength of these studies is that the analysis is not limited to the forecasting methods, but the whole forecasting process is concerned. However, there is one aspect that has not gained attention by these audit models. Companies use forecasts for different purposes and collect information for the forecasts from different sources, so it is likely that forecasting in general is not of equal importance in all companies. Being so, it may be difficult to provide principles about forecasting that are equally relevant in every environment. From the managerial point of view, it would be easier to apply principles if the principles are limited and priorized to fit the operational environment the managers encounter. Forecasting practices of industrial companies differ from the ones of consumer companies (Kahn & Mentzer 1995), so it is likely that also the problems that managers face and some of the principles they should follow are different in business-to-customers and business-to-business environments. In this paper the aim is, on a theoretical basis, to highlight problems that are potentially emphasize in B2B environments.

Another issue is that authors using audit models have noticed inefficiencies in companies' forecasting processes, but the reasons for these inefficiencies have still remained unexplained. There are a few potential reasons why forecasters do not adopt forecasting techniques and principles suggested in the literature. e.g.: (1) forecasting is not critical to the success of the company, (2) forecasting does not receive enough attention since its benefits are not identified, (3) or the theory of forecasting does not sufficiently cover the problems that forecasters face.

If the reasons for not using relevant practices and principles can be found out, it is easier to point out development areas both in forecasting research and practice. Not only the whole forecasting process, but also the operational environment where it is conducted, need to be analyzed. Some authors have made suggestions about areas for further research in demand forecasting practice. In the following section, a synthesis is made, collecting together issues that can be included in a forecasting assessment model.

Factors to be noticed when assessing forecasting practices

The analysis model is a tool that maps forecasting practices and their development needs in a company. The basic assumption is that forecasting practices in a company should be systematically chosen, and the operational environment, methods, organizational responsibilities and performance metrics should be structured and aligned, and the participants of the forecasting process should be aware of and agree on the forecasting practices. The framework consists of four phases (see figure 1). At each phase, reasons are given why these factors should be assessed, and what kind of problems the managers are likely to face in the B2B environment.

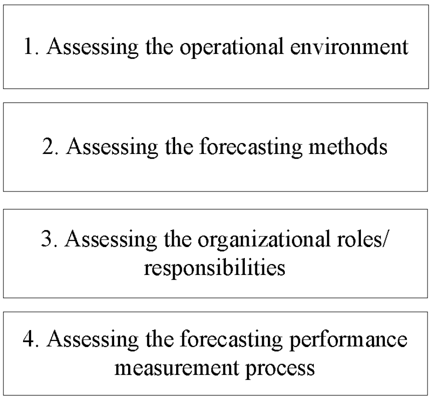

Figure 1: Phases of the forecasting practice assessment model

<u>1. Assessing the operational environment</u>

In an ideal situation, it is clearly defined what are the information sources to be used in forecasting, and what are the decisions to be supported with forecasts and how. If there are different information sources available for customers/products, the customers/products are categorized accordingly.

If the operational environment is not analyzed properly, different members in the organization may have different views about the availability and importance of contextual information, demand history, etc., there are no common practices on how different information sources are used, and therefore valuable information is not necessarily collected efficiently. Insufficient analysis of the operational environment may lead to unjustified selection of forecasting methods, responsibility distribution, or unrealistic accuracy targets. Proper categorization is needed also in focusing forecasting resources. It has been suggested that forecasting should be focused only on the most important customers and products (e.g. by Mentzer & Moon, 2005) and that in a developed forecasting process, customers with VMI (vendor managed inventory) or other solutions ought to be screened out. It is typical that the customer base is heterogeneous, companies may operate in several areas of business, and it is difficult to carry out proper customer categorization in practice.

A typical operating environment that is dealt with in the literature is an environment where the only input in the forecasting process is the demand history, and the forecasts are used in production planning and/or inventory management. However, real life situations do not always fall into this category, but there are more information sources available. Possible information sources are e.g. the demand history, contracts, inquiries, preliminary orders and customers' future plans in various formats. In different business environments, different information sources may be feasible. It is likely that the availability of potential information sources has grown as a result of increasing use of ERP, EDI and related information systems. Some survey results support this, and according to a survey reported by Forslund & Jonsson (2007), 87% of suppliers received forecast information from their customers, and no significant difference was found between MTS (make-to-stock) and MTO (make-to-order) suppliers.

Defining the operational environment includes also defining the use of forecasts. Possible decision areas to be supported with forecasts are for example capacity allocation, purchasing, production planning and inventory management. However, it should be also defined how forecasting is linked to specific decisions. The role of forecasts may be different in separate business areas, so that operations are partly forecast-driven and partly order-driven. Even in the 1980's it was noted that more research is needed on how forecasting should be linked to decision making, but has been noted by Wacker and Lummus (2002) that this issue is inadequately explored and that future forecasting research should focus on broadening the understanding of the role of forecasts in strategic decision making.

There are some research results indicating that more attention should be paid on analyzing the environment in which the forecasting processes are conducted. Otherwise, some findings about companies' behavior will be left unexplained. Such factors as industry type and company size have been linked to some aspects of forecasting practice (e.g. resources available and forecast accuracy), but the data sources utilized have been ignored (Winklhofer et al. 1996). According to some survey results, better performing companies have weaker forecast accuracy than other companies (Zotteri & Kalchschmidt 2007). Explaining this type of findings calls for analyzing the operational environment, that is the information sources and uses of forecast, more deeply.

2. Assessing the forecasting methods

In an ideal situation, the best forecasting methods are selected, meaning that relevant information sources can be exploited in an optimal way, and the methods are simple enough to use. Defining the forecasting methods includes the selection of the methods, and the target of forecasting, which can be different from the forecasting problem.

There is some evidence that the selection of forecasting methods is not always justified. Often the selection of a software package is considered as the main decision (Menzer &

Moon, 2005), or the forecasters rely too heavily on unstructured judgment and insufficiently on statistical methods (Fildes & Goodwin 2007).

One of the problems that companies are likely to face is defining when and how judgmental methods should be used. Many authors suggest that both qualitative and quantitative methods are needed in creating accurate forecasts, and it is important to tell when to use which method (Mentzer & Moon, 2005). However Lawrence et al. (2006), after reviewing 200 studies about judgmental forecasting, suggest that more research is needed in the area of judgmental forecasting, especially in defining when judgmental intervention is needed and when it is not needed. Even though there is not much research evidence about the cognitive processes of judgmental forecasters, there is some evidence that people tend to prefer simpler forecasting methods to complex ones (Sanders & Mandrot 1994), and often ignore cues if there are several available (Wright & Goodwin 1998), or follow less reliable information instead of reliable information (Lim O'Connor, 1996). Problems are likely to occur if there are multiple data sources and no rules on how these information sources should be utilized. So if judgment is used in the forecasting method, instructions on how to make the forecasts need to be sufficiently detailed.

One relevant problem is the selection of the right aggregation level in forecasting. Empirical findings show that the aggregation level of forecasting can be different from the forecasting problem (Zotteri et al. 2005). In such cases the forecast is either disaggregated or aggregated to fit the forecasting problem. However, literature about forecast aggregation is sparse. It has been noted that the forecast should be no more detailed than the resource decision requires (Wacker & Lummus, 2002), or that similar data should be pooled (Armstrong, 2001), and that clustering customers is a good way to focus forecasting efforts (Caniato et al, 2005, Thomassey & Fiordaliso 2006, Fliedner, 1999). On the other hand, some information sources, such as direct information from customers can only be collected on a detailed level. If different information sources are feasible on different aggregation levels, selecting the proper aggregation level may call for comparing different aggregation levels and methods in practice. It is possible that selecting a proper level of aggregation and creating pools for forecasting is a more complex decision that it has been noticed in earlier literature.

The forecasting methods should be structured, if they are quantitative, qualitative, or a combination of these (Armstrong, 2001). According to Yokum & Armstrong (1995), ease of use and simplicity may be as relevant criteria as accuracy. The availability of different information sources increases the number of potential methods and ways to combine methods. Being so, a potential area for research is how to facilitate the selection of forecast methods in such a situation.

3. Assessing organizational roles/responsibilities in the forecasting process

In an ideal situation, the responsibilities in the forecasting process are clear and realistic. The functions involved in the forecasting process are the same that have access to the relevant information sources used or are involved in using the forecasts. Organizational resources are focused and motivational issues are considered.

If there are many potential information sources, and the preparation of the forecast requires combining information from many sources, also the number of alternative ways to distribute responsibility grows. Inherently, organizing such a cross-functional process as forecasting is a complex rather than a simple process. One threat is that organizational responsibilities are not described in sufficient detail, or that some tasks, such as developing the forecasting process are not covered with responsibility.

It is claimed that demand forecasting is the most mal-aligned function in many companies (Helms et al. 2000). Some authors suggest that problem in forecasting nowadays is more of an organizational nature rather than a technical one (Hughes, 2001;), and that organizational structures and their effect on forecasting performance should be studied further (Zotteri & Kalchschmidt 2007). McCarthy et al. (2006) state that sales forecasting performance will not improve until companies pay more attention on organizing the forecasting function.

Salespeople are assumed to have access to the best demand information, since they are closest to the customers. However, it has been found that salespeople have generally low motivation to forecasting, since they do not consider it as their primary task. Therefore, it has been suggested that the workload of the salespeople should be reduced to the most important tasks and their role as forecasters should be supported with incentives and feedback (Mentzer & Moon 2005). According to Fildes and Goodwin (2007), all kinds of judgmental intervention should be limited and justified. There is some evidence that limiting the judgmental intervention in forecasts improves accuracy. Goodwin (1999) found out that asking managers to justify their judgments in writing reduced the number of unnecessary and damaging judgmental adjustments to statistical forecasts from 85 to 35 percent. So, if the responsibility distribution is too loosely defined, it is likely to entail inefficiency.

4. Assessing the performance measurement process

In an ideal situation the performance metrics are relevant and realistic. Although forecasting performance measurement includes also other metrics than forecast accuracy, accuracy measurement is still a part of performance measurement. The aim of forecasting error measurement is twofold. First, it aims at controlling the forecasting process, and secondly it measures the amount of uncertainty the company needs to adapt to.

In all environments, traditional error measures such as MAPE (mean average percentage error) are not applicable, e.g. if the demand is intermittent. If forecast error measurement has two purposes, the forecast error measures should also be divided at least to two components: error that is due to less than perfect forecasting and error that is due to inevitable uncertainty of demand, but in practice it can be difficult to separate these two factors. If accuracy targets are set, they should notice the amount of inevitable uncertainty, but setting accuracy targets can be difficult in practice.

Cross-company comparisons have not generally been relevant or feasible in the area of setting the goals of forecasting quality (Bunn and Taylor, 2001). High forecast accuracy is not necessarily linked to business performance (Zotteri & Kalchschmidt, 2007). In some cases, sales are manipulated to meet the target that was set (Lawrence et al. 2006), so inadequate target setting may be even harmful.

If forecast accuracy is not directly linked to business performance, it is possible that the problem is in error measurement, because traditional error measures do not notice the use of the forecast. Wacker & Lummus (2002) have noted that a potential area for further research is finding out if there are forecast error measures available that relate the accuracy of the forecast with the use of the forecast, and how the forecast accuracy and its related forecast resource decision are evaluated to determine the impact of the forecast error on the effectiveness of the decision. Several authors suggest that companies should use multidimensional performance metrics that include the supply chain costs and customer service. (Armstrong 2001, Moon & Mentzer 2003). In addition to that, the roots of forecast error should be found out to seek corrective actions. It can be assumed that one potential problem area in companies operating in complex environments is how to define company-specific performance metrics that suite the operational environment of the company.

Collecting empirical data

The aim in collecting empirical data for the present study was to assess potential development areas of the forecasting process in a case company, and to test if the development targets mentioned by managers fit the four dimensions listed in figure 1. In addition, the empirical material was used in defining specific questions that can be included in a forecasting practice assessment model.

The case company is a large process industry company. The company has several sales units and production units internationally. The company operates in business to business markets, serving as a materials producer for its customers that operate on different businesses. The company aims at developing its forecasting process so that accurate forecasts are produced with reasonable effort. The main use of the forecasts is in the capacity planning, allocating the capacity in production units and between production units.

It was assumed that the managers are likely to have some variation in their views and suggestions concerning the forecasting process, so that a systematic assessment of the forecasting process could enhance consensus in the organization and thereby facilitate the development of forecasting practices. To assess the consensus about the state of the forecasting management inside the organization, a limited survey was used. Six managers were asked to answer questions with a Likert scale 1-5 (1-I fully disagree, 2-I disagree to some extent, 3 – .. 4 – I agree to some extent, 5 – I fully agree). The questionnaire and its results are included in the appendix.

The results of the survey showed that there are several potential information sources available, but their importance is not agreed upon, especially the role of contracts and preliminary orders is unclear. This indicates that it would be relevant to clarify the roles of each information source in forecasting. In our model this would belong to the phase “defining the operational environment”. There is disagreement also on the target of forecasting (time level, level of detail). In the assessment model these issues would belong to the phase “forecasting approach”. There is also variation in the answers about the suitability of the current responsibility distribution, the acceptability of forecast error and the suitability of the current performance measurement practice. The managers agreed on some issues, such as the importance of forecasting and importance of forecast accuracy. The survey results served as an orientation to a session where the main data was collected.

The main data gathering occasion was carried out in a GDSS (group decision support system) environment. GDSS or Group DSS is an interactive computer-based system that facilitates the solution of semi-structured or unstructured decision problems by several decision makers who work as a group. In a narrow sense, the term GDSS is used to describe a network of computers in a face-to-face environment, such as a conference room, and the software which enables a group to exchange written comments and votes. The purpose of a GDSS is to support a group in cooperating and working together effectively to reach its goals, and to support and develop the group decision making process. GDSS technology supports group decision making by eliminating communication barriers, offering the group different tools and managing the use of time, as well as handling meeting items systematically. The components of a GDSS consist of hardware, software, people and procedures.

The participants of the GDSS session were the process owner of the whole forecasting process and managers responsible for forecasting in their unit, dealing with distinct product categories. Some of the managers were also responsible for the capacity allocation in their unit. All eight participants were managers, so they were not personally responsible for doing the forecasts, but are responsible for controlling the forecasts and providing feedback to the forecasters.

The description of the company’s forecasting process in the company’s own documents was used as a starting point, and the managers were asked to list development areas in each phase of the forecasting process. The managers were advised that the suggestions may concern for example, but not be limited to: the information system, responsibility distribution, rules, or instructions. When the development targets had been listed, they were discussed and the most critical/important development targets were voted for. The steps of the forecasting process are presented in figure 2.

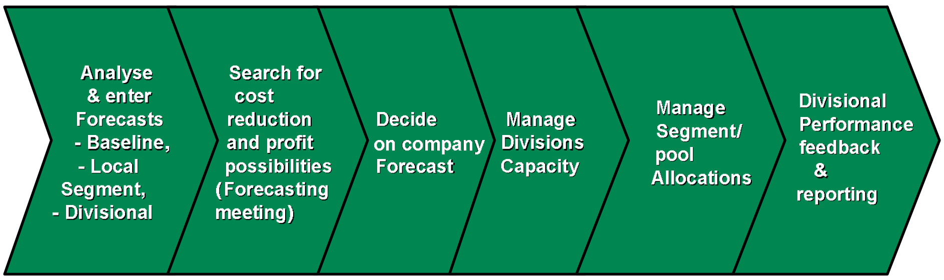

Figure 2: Forecasting process description of the case company

The following findings were made about the nature of the managers' suggestions:

- 28% of the suggestions called for providing instructions/rules
- 25% of the suggestions called for following the existing rules or enhancing the use of existing tools
- 20% of the suggestions dealt with responsibility distribution
- 14% of the suggestions dealt with connecting the forecasting function with other functions (inventory management, capacity management, sales)

The suggestions that gained the most support in voting included increasing the use of pooled forecasts on spot business, and increasing salespeople's commitment to the forecasts. The results showed that problems/development targets were listed in all four areas: operational environment, forecasting methods, organizational responsibilities and performance measurement.

<u>Examples of suggestions/problems concerning defining the operational environment</u>
- "There is no agreed business mix between regular and spot business"
- "No link between price steering and spot forecasting"
- "Taking stocks into account in planning"

<u>Examples of suggestions/problems concerning the forecasting approach</u>
- "Collaborative forecasting is too fragmented or totally lacking process"
- Unclear role of contracts in forecasting
- "Which aggregation level should be forecasted is arguable"

<u>Examples of suggestions/problems concerning with organizational roles / responsibilities</u>
- "Discipline in the forecasting process"
- "Big performance variations across markets"
- "The roles and responsibilities should be clarified"

<u>Examples of suggestions/problems concerning performance measurement</u>
- "Reporting should be based on needs and support the strategy"
- "Clarify a benchmark level in FC accuracy"
- "Feedback does not always go to the right place"
- "Measure what makes sense"

Some of the problems are ones that have been identified as potential areas for further research in earlier studies, for example developing the performance metrics. All the problems cannot be put into the above mentioned four categories. These problems are quite general findings, e.g. "spot business is difficult to forecast" or "forecasts are unrealistic", or notifications about misuse of the forecasting system, e.g. making forecasts beforehand, after knowing the actual demand. These results support the assumption that managers need simple models that aid in making the forecasting practices more structured.

A model for assessing and developing demand forecasting practices

Based on former literature and empirical findings, the following model with specific interview questions was created. The model is supposed to be applied in companies where there are potentially more than one information source to be used in forecasting, and there are some forecast-driven operations. In figure 3 it is described how the forecasting practice assessment model is supposed to be used in improving forecasting process. Conducting the assessment requires for several members of the organization to participate. People from different functions answer the questions. Contradicting answers indicate that there is lack of structures and/or communication. The aim is to develop more justified and structured forecasting practices.

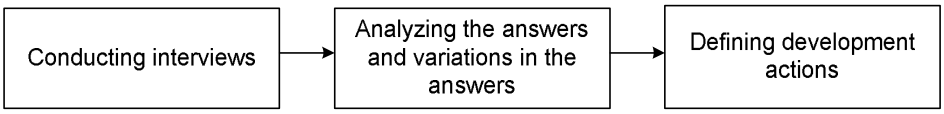

Figure 3: Basic steps of the forecasting development process

Potential development targets can be found in four dimensions, and the development targets in these four dimensions are of different nature. The development targets in the dimension "assessing the operational environment" are likely to call for analyses e.g. in measuring the accuracy of specific information sources or the feasibility of demand history in forecasting. The development targets in the area "assessing forecasting methods" mean making comparisons between different methods or fine-tuning existing methods. The development targets in "organizational responsibilities" mean e.g. clarifying or re-organizing the existing roles, and the development targets in the area of "performance measurement and feedback practices" may include e.g. development of company-specific performance metrics or re-defining accuracy targets.

The questions are supposed to be answered with a 5- point Likert-scale, 1 meaning "the issue is managed very poorly" and 5 meaning "the issue is managed very well".

1 Operational environment

1.1 Categorization of the operational environment

- Are customers/products categorized by available information sources / use of forecasts?
- Is it identified how customer/product groups differ from each other with regard to the predictability of demand?
- How clearly is it stated which ones are the most important customers/products to be forecasted?

1.2 Information sources

- Are the information sources to be used in forecasting clearly stated?
- Are the same information sources used for forecasting in practice?
- Is the availability of information sources adequately assessed?
- Is the reliability of the information sources adequately assessed?

1.3 Target of forecasting

- How well is the time scale needed in forecasting defined?
- How well is the level of detail needed in forecasting defined?
- Is it clearly stated what decisions are affected by the forecasts and how/when ?

2 Forecasting methods

2.1 Fit of methods and forecasting needs

- How well can relevant information sources be utilized within the current forecasting methods?
- Is it clearly defined when forecasts are needed and when not?
- Does the level of detail of the forecasts fit the use of the forecasts?
- Does the infrastructure support the forecasting process sufficiently?

2.2 Justification of methods

- Have the selected forecasting methods been compared with potential alternative methods?
- How well are other criteria than accuracy noticed in selecting forecasting methods?
- Is the aggregation level of the forecasts justified?
- How well are historical demand patterns recorded and analysed?

2.3 Instructions

- How clear are the instructions for creating forecasts in general?
- How clear is the priorization of forecasts?
- How well is it defined when judgmental intervention is needed?
- How well are the forecasters aware of the use of the forecasts?
- How well is the use of different information sources defined?
- How well are the above-mentioned rules followed?

3 Organizational roles

3.1 Clarity of roles

- How well is the access to different information sources guaranteed with organizational responsibilities?
- Are all forecasting tasks sufficiently covered with the responsibilities?
- How well are the above-mentioned rules followed?
- Is it clear who is responsible for which forecast?
- Are alternative ways for responsibility distribution been sufficiently compared?
- Is there sufficient communication between the participants of the forecasting process?

3.2 Responsibilities in practice

- How justified is the forecasting burden in relation with its benefits?
- How well is it defined when judgmental intervention in forecasting is needed and when it is not needed?
- How easy is it to access information sources?

- Is there sufficient training to the forecasting tasks?

4 Performance measurement and feedback practices

4.1 Rationality of metrics
- How well are the accuracy targets defined?
- How realistic are the accuracy targets?
- When defining forecast accuracy targets, is the quality of information sources noticed?
- How well is the forecasting performance measurement linked to the use of the forecasts?

4.2 Using forecast error information
- How well are the main causes behind forecast errors known?
- Is inner benchmarking used in order to enhance learning?
- How well does the feedback hit its target?
- Does the feedback include suggestions for corrective actions?

Discussion

The forecasting practice assessment model presented in this paper is preliminary. The specific interview questions in the model will be developed when the model is used in other companies. As a result, it will provide insight to the relevant problems in today's forecasting management. Empirical observations from the case company indicate that managers face a problem of setting company-specific rules for forecasting tasks. Facilitating the making of the rules is a potential area for further research.

The assessment model presented in this paper is different from former forecasting audit models. First, this assessment model focuses on the B2B environment. Secondly, the assessment model includes analyzing the operational environment, which has been almost ignored in earlier literature. Third, the assessment model does not offer general standards against which the forecasting processes should be compared. Instead, it aims at facilitating the structuring of the practices and creating consensus in the organization. For this assessment model, it is fundamental that interview data is collected from several members in the organization, and the differences in their answers is the main focus of attention. Fourth, the assessment model does not start from the premise that demand forecasting would be of equal importance for any company. It is possible that in some environments, forecasting should not gain as much attention as it does now. Conducting the assessment may improve organizational learning not only about demand forecasting, but also about the tasks that are supposed to be supported with forecasts.

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Table 1: Results of a survey evaluating consensus about the forecasting process

	Average	St.dev.	Max	Min
1. Accurate demand forecasts are indispensable for capacity planning	4.3	0.5	5	4
2. If the market situation is good, the role of demand forecasts is emphasized	4.3	1.2	5	2
3. Demand forecasts help to level the production capacity between production units	4.8	0.4	5	4
4. The main role of demand forecasting is to recognize the ability to supply	3.6	0.9	4	2
5. Forecasts become more reliable if there are more people involved in creating the forecasts	3.3	1.0	4	2
6. The liability distribution of the current forecasting process is suitable	2.3	0.8	4	2
7. Forecasts must be made for each customer separately	2.3	1.4	4	1
8. Monthly level is a suitable time scale for making forecasts	3.5	1.6	5	1
9. Preliminary orders are an important source of information in forecasting	3.5	1.2	5	2
10. Contracts are important information source in forecasting	4.3	1.2	5	2
11. Customers' predictions about their future demand are an important information source in forecasting	4.3	0.5	5	4
12. Demand history is an important information source in demand forecasting	4.3	0.5	5	4
13. There are clear and adequate instructions for creating the forecasts	3.7	1.0	5	2
14. The current forecast accuracy is acceptable	2.2	1.0	4	1
15. Forecast accuracy should be improved	4.7	0.5	5	4
16. The greater the forecast errors are, the more damage they cause to the company	4.3	0.5	5	4
17. The current forecast error measurement practice is working	3.2	1.5	5	2

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