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Improving demand forecasting with the sales funnel and leading indicators

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Abstract

In turbulent markets, demand forecasting is becoming increasingly difficult. Traditional quantitative models fail to anticipate market fluctuation, whereas managers' judgmental estimates tend to overshoot. Forecasting methods should be responsive to market developments to support proactive business planning. This thesis explores the potential of leading indicators and sales funnel in demand forecasting as a source of real-time market intelligence. Forecasting has been recognized as a key activity of customer relationship management (CRM), but little research has been done on how to actually use CRM systems for this purpose. The sales funnel is a valuable source of real-time market intelligence and prospective demand. Assuming the sales funnel of a firm follows the market conditions of the industry, forecasting visibility can be enhanced by using macroeconomic leading indicators of the sales funnel. How to embed such a forecasting model to the extant forecasting process in the firm is important.

Literature from the fields of forecasting management, CRM and process improvement is used to build a framework for a case study. The case company is a manufacturer of lifting equipment operating in 48 countries, whose current forecasting accuracy is not optimal and is subject to judgmental bias from individual forecasters. A quantitative forecasting technique that incorporates the aforementioned sources of market intelligence is developed to improve its forecasting. The DMAIC model, famous from Six Sigma, is used to formulate a roadmap for improving the forecasting process on the whole. Unstructured interviews were conducted with the key forecasting stakeholders to observe current forecasting processes and accuracy, as well as the impact of potential forecast improvement on their operations.

The sales funnel of the firm was analyzed against leading indicators in 14 countries or regions. If an indicator correlated strongly with the sales funnel of some country after synchronization, it was used for forecasting the funnel's values in-sample. The sales funnel, in turn, was converted to an order-level forecast with a simple optimization model. For most of the countries analyzed, a leading indicator was identified and applied successfully to forecasting the historical funnel base, at an average accuracy of 87%. Forecasting short-term demand from the sales funnel was 17 percentage points more accurate than any previous methods the case company used. The sales funnel was also used as a reality-check for further forecasts to identify major discrepancies, resulting in an improvement of 21 percentage points in historical accuracy. Experts at the case company estimate such an improvement to save at least 10MEUR in costs annually, primarily in capacity planning and procurement.

The sales funnel-based forecasting model is more market-responsive and brings strategic value to the CRM system of the company. Applying the adapted DMAIC model to investigate the forecasting process at the case company revealed further strategic areas of improvement, giving the firm an action plan to improve its forecasting on the whole, taking a major step toward more proactive planning.

Keywords Leading indicators, demand forecasting, market intelligence, sales funnel

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Tiivistelmä

Epävakaat markkinaolosuhteet tekevät kysynnän ennustamisesta vaikeaa. Perinteiset kvantitatiiviset ennustamismallit eivät kykene ennakoimaan markkinaolosuhteiden muutoksia, kun taas johtajien intuitio antaa yleensä ylioptimistisia ennusteita. Ennustamismallien tulisi pystyä reagoimaan markkinoiden tilanteeseen tukeakseen proaktiivista liiketoiminnan suunnittelua. Tämä tutkielma pyrkii vastaamaan tähän tarpeeseen selvittämällä ennakoivien markkinaindikaattorien ja yrityksen myyntifunnelin potentiaalin kysynnän ennustamisessa. Ennustaminen on nimetty yhdeksi asiakkuudenhallinnan (CRM) strategisista tarkoituksista, mutta aiempi tutkimus tällä alalla on vähäistä eikä käytännön malleja ole tarjolla, vaikka myyntifunneli on hyödyllinen kysynnän ja markkinainformaation lähde. Olettaen, että myyntifunneli seuraa markkinatilannetta, voidaan sitä ennustaa alakohtaisilla ennakoivilla indikaattoreilla ja näin laajentaa ennustehorisonttia ajallisesti. Oleellista on myös selvittää, kuinka tällainen ennustamismalli sopii ennustamisprosessiin.

Viitekehys tutkimukselle saadaan hyödyntämällä aiempaa tutkimusta ennustamisen, CRM:n ja liiketoiminnan prosessien parantamisen aloilta sekä case-tutkimuksen avulla. Case-yritys on globaali nostolaitteiden valmistaja, jonka nykyinen ennustamistarkkuus ei ole tyydyttävällä tasolla. Käyttäen yrityksen myyntifunnelidataa ja ennakoivia indikaattoreita markkinainformaationa kehitetään responsiivisempi, kvantitatiivinen ennustamismalli. Ohessa sovelletaan Six Sigman aihepiiristä tuttua DMAIC-mallia yrityksen ennustamisprosessin arvioimiseen ja parantamiseen kokonaisuutena. Analyysin tukena käydään ennusteiden keskeisimmät sidosryhmät läpi avoimilla haastatteluilla, jotta ennustamisprosessi ja sidosryhmien käsitykset sen suorituskyvystä saadaan kartoitettua. Samalla voidaan arvioida, miten parannus ennustamisprosessissa näkyisi yrityksen kannattavuudessa.

Ennakoivat indikaattorit ja myyntifunneli synkronoitiin keskenään ja mitattiin niiden välinen korrelaatio 14 maan tai regioonan otoksessa. Mikäli riippuvuus oli vahva, voitiin indikaattorin avulla rakentaa regressiomalli myyntifunnelin ennustamiseksi. Myyntifunneli taas voitiin kääntää tilausennusteeksi yksinkertaisella optimointimallilla. Suurimmassa osassa tapauksista ennakoiva indikaattori löydettiin ja sen avulla voitiin ennustaa myyntifunnelin arvoja 87% tarkkuudella otoksen sisällä. Myyntifunnelin antama seuraavan kvartaalin tilausennuste oli keskimäärin 17 prosenttiyksikköä tarkempi kuin case-yrityksen oma ennuste. Ennustemallia käytettiin myös tunnistamaan ylioptimistisia ennusteita pidemmälle aikavälille, parantaen ennusteita keskimäärin 21 prosenttiyksikköä. Yrityksessä arvioidaan, että vastaava parannus ennustetarkkuudessa toisi maailmanlaajuisesti yli 10MEUR kustannussäästöt hankintatoimesta ja tuotannonsuunnittelusta.

Myyntifunnelia käyttävä malli on herkempi markkinamuutoksille ja luo strategista lisäarvoa yrityksen CRM-järjestelmälle. DMAIC-malli toi esiin case-yrityksen ennustamisprosessin keskeiset organisatoriset ongelmakohdat ja auttaa yritystä tekemään toimintasuunnitelman niiden parantamiseksi. Yrityksellä on nyt tehokkaampi ennustamistekniikka ja strateginen suunnitelma ennustamisprosessin kehittämiseksi huipputasolle.

Avainsanat Ennakoivat indikaattorit, kysynnän ennustaminen, markkinainformaatio, myyntifunneli

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1. Introduction

Two major trends that motivate companies to improve their demand forecasting are increasing volatility of demand and pressure to cost efficiency. When demand is volatile, traditional forecasting models that rely on historical data will fail to anticipate change which can be costly. This emphasizes the need for *responsive forecasting techniques* that can account for such market dynamics. With the abundance of both internal and external data available to companies, it is becoming increasingly difficult for companies to identify relevant information (Sagar, 2010) for demand forecasting, let alone construct such advanced forecasting models.

The business impacts of forecasting have long been understood. Mentzer and Cox (1984) identified production planning, budgeting decisions, strategic planning and sales analysis as the key uses of forecasts. Forecasts need to be communicated along the supply network and to the shareholders as well (Mentzer, 1999). Demand forecasting has a direct impact on the profitability of the firm. With such a substantial impact on business, there is motivation to explore the possibilities of more market-responsive forecasting techniques.

In a discussion with a long-time forecasting expert in a respected Finnish manufacturing company, the topic of responsive forecasting was brought up. The analyst fully agreed with the fact that it is imperative to use forecasting for more proactive business planning. He even stated that it is a known fact in the company that markets lead their demand very clearly. When asked about how the company utilizes this information in their forecasting process, the analyst replied: "*We would like to, but we don't know how! Our sales funnel is connected to the economic situation, but this information is not leveraged.*". Moreover, he stated that benchmark forecasting models of other firms are not very market-responsive either, and that market information is currently used at the company on a speculative basis.

In the context of a manufacturing firm's demand forecast, one can identify two trends in the common methods used. The first is forecasting with quantitative models reliant on historical data. These models have been popular since the 1970's and received supporting evidence of good performance from (Dalrymple, 1975) and (Mentzer & Cox, 1984). Quantitative models are still widely used in firms regardless of the industry or company size and tend to outperform more subjective methods (Sanders & Manrodt, 2003). Another popular method is judgmental forecasting, relying solely on the practitioner's expertise and estimation. Human judgment has been used in forecasting for a long time and is still used in nearly all companies in some form.

The trouble is, these methods may fail to anticipate the change in demand that market data clearly indicates. Traditional quantitative methods react to changes retrospectively, when the firm has already incurred the costs from inaccurate forecasting. Judgmental estimates, on the other hand, can introduce optimistic bias (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009) into the estimates that will systematically mislead the company. What is needed is a practical method to quantify market intelligence, to develop the responsiveness of forecasting techniques.

Forecasting methods in general have reveled in the academic limelight for long, but the more advanced the method, the more difficult it is to sell. Integrating external market intelligence and internal ERP-data need not make the forecasting model insurmountably complex to work. Not only are the companies that incorporate quantitative market data into forecasting scarce, but the research on the topic is virtually non-extant. There seems to be a research gap for simple, practical yet responsive forecasting methods. Exploring the possibilities in this field would give valuable insight to firms aspiring towards more responsive forecasting.

So what is a company to do? It has access to substantial amounts of external market intelligence, internal ERP-data and human knowledge. Any judgmental forecasts are not likely to do well if they are not based on solid facts and traditional quantitative models will not be responsive. The sales funnel of the firm containing prospective demand is a good place to start. Best practices of customer relationship management (CRM) strategy dictate that CRM systems such as the sales funnel should be used for forecasting to provide cross-functional support to the organization (Cooper & Budd, 2007; Dong, 2010; Harris, 2003; Söhnchen & Albers, 2010). This is a market-responsive tool for short-term demand forecasts. What is more interesting is that the sales funnel is often impacted by the economic situation. Finding a way to quantify this relationship and applying it to forecasting is worth exploring.

One way to do this is to examine the applicability and potential of macroeconomic leading indicators in a firm's demand forecasting model. When an indicator *leads* another, the latter mimics the former after a given period of time (called lag). Hence the name *leading indicator*. (Leading Indicator Definition Investopedia, 2003). By creating a forecasting model that uses external market intelligence (leading indicators) and the firm's internal sales funnel, we expect to both improve the accuracy of traditional forecasts as well as extend the forecasting horizon based on real-time data.

In this study, the potential of leading indicators and the sales funnel is examined through a real business case. It is particularly interesting to use actual data because this permits us to assess the performance of the model in tangible terms. Furthermore, the results of a real business case can motivate further research in this field.

1.1 Research question and objectives

The aim is to formulate a quantitative forecasting model by using publicly available leading indicators and the sales funnel of a firm. The idea is to create a practical model that is readily constructible from resources most firms have access to. To apply this theory to a real business context, a case study will be included.

Essentially, the principal aim of this paper is to develop a market-responsive forecasting model that will improve the forecasting process at the case company. The benefits of this goal setting are twofold. First, the case study will provide the necessary data to test the feasibility of a quantitative forecasting model that uses leading indicators and the sales funnel. Secondly, the model can be tested to improve the problematic forecasting performance at the case company. By charting the current forecasting process and identifying its pitfalls, an action plan can be formulated for the case company, thus providing valuable information on how other firms might improve their forecasting performance as well.

Following this, the research question is:

"Can we construct a feasible demand forecasting model using leading indicators and the sales funnel?"

Determining whether the forecasting model can be constructed is case-specific, but firms operating in the same industry that have similar tools and forecasting needs can adopt the idea and test it in their own context. Feasibility is herein defined as the capacity to produce useable forecasts that are more accurate than current methods at a reasonable cost/effort. The research question coexists with a wider set of objectives this study aims to accomplish. These objectives can be classified into generic and case-specific:

1. *Describe the most important considerations in the development of the forecasting model (generic)*
2. *Describe the applicability of the model in the business context (generic)*
3. *Develop an implementation plan of the forecasting model for the case company to improve the forecasting process on the whole (case-specific)*

Objectives one and two are concentrated on building the generic forecasting model that uses the sales funnel and leading indicators, as well as understanding how it should be used. These findings are transferrable to other research settings and are more generic by nature. Objective three integrates the new forecasting model into a more comprehensive problem: how to implement the model to improve the generic forecasting process at the case company. These findings reflect the perspective of the case company and are not fully generalizable as such, but certain learnings will be provided for the reader that can apply in other companies as well.

1.2 Methodology

This thesis can be characterized as empirical exploratory research that combines theory-building and action research components to solve a real problem in a single case company. Eisenhardt (1989) notes that quantitative and qualitative data can be combined in a case study. In this thesis, both quantitative and qualitative data will be collected from the case company in the forms of sales funnel, order level data and open-ended interviews. It should be noted that the approach of this thesis is not purely either theory-building or action research. It is a hybrid of the two, since:

- The context of the case study is to solve a real practical forecasting problem and build applicable theory from the findings.
- Although a prerequisite of theory-building research is not to have initial presumptions (Eisenhardt, 1989), this thesis proposes that a generic forecasting model can be built. The aim is to find out how.

Action research aims to solve a practical problem in a real context while building theory from the findings (Davison, Martinsons, & Kock, 2004). Such is the setting of this study as well: a real business case is solved while theory is produced in the process. Moreover, the *cyclical process model* (CPM) as described by Davison et al. (2004) is closely related to the problem-solving approach introduced later in the literature review. The process consists of the phases of diagnosis, action planning, taking action and learning.

As a distinction, *Canonical action research* (CAR) emphasizes iteration of activities in the problem-setting, continuous problem diagnosis and mutually beneficial teamwork between the researcher and the client (Davison et al., 2004). From the perspective of this thesis, these CAR components will be relevant. First, the forecasting problem will be solved by iterating through key stakeholders and finding the best possible method using the data available. Secondly, stakeholders of the problem will be continuously consulted when solving the problem.

In addition to the case study, a literature review will be included. Due to the lack of direct research on the topic of sales funnel and leading indicator integration, the literature review will serve to introduce the key concepts in this study and to build a theoretical framework. This way we can create a link between previous research and the findings of this study. This is important for the generalizability of the results (Eisenhardt, 1989). Fortunately, there exists good research on the topics of forecasting management and implementation to support the formulation of a forecasting process improvement plan.

The case study will consist of quantitative analysis for the construction of a forecasting model and qualitative interviews to gain an understanding of the dynamics behind the currently problematic situation at the case company, observing the current forecasting process in its actual setting (Lee, 1989). The interviews will be unstructured, meaning that they do not adhere to any predetermined structure or format, but are rather uncoordinated and relaxed meetings with relevant parties where key topics are discussed. The interviews serve to examine current perceptions of the forecasting process and build a picture of the relationships of the stakeholders in the forecasting process. They will complement the quantitative research by providing a more profound understanding of the problem setting (Silverman, 2013). Moreover, they will give the forecasting stakeholders a chance to express their honest opinion without the constraints of a formal meeting environment (Gill, Stewart, Treasure, & Chadwick, 2008) and add practical business value to this study.

The sales funnel data will be cross-analyzed with the publicly available composite leading indicators chosen for this study. The aim is to discover whether these indicators correlate strongly enough with a given lag so that they can be used for forecasting the sales funnel. The data will be used to first estimate historical forecast accuracy and then formulate a method of using the sales funnel and leading indicators in forecasting. To summarize, building the forecasting model will require all three sources of data: macroeconomic leading indicators, historical sales funnel data and historical order levels. Thereafter, the qualitative insight from interviews and learnings from literature will be combined to develop an implementation plan for the new model.

The nature of the research question in this thesis, along with the coeval problem-setting at the case company justifies the use of the case study as a research method (Yin, 2013). Answering the research question requires access to actual sales funnel data and a real forecasting environment, available only through a case study. Meeting the objectives requires reviewing relevant literature and conducting the interviews on top of the analysis. Thus both the quantitative and the qualitative components of the case study will be used to build theory and formulate the final, big picture of improving forecasting performance with the model developed in this study.

1.3 Structure

The structure of this study is as follows. Unorthodoxly, section two will comprise both the literature review and the assembly of the theoretical framework used for this research. This is done to provide the reader with the knowledge required for the case study in a single section, rather than two disparate sections. Moreover, the nature of this research topic allows for such an approach, since the contents of the literature review pertain so strongly to the theoretical framework.

Section three is the case study reported in its entirety, along with the limitations that come with its findings. The case study is divided into smaller components that follow the structure of the theoretical framework. Section four will discuss the case study from the viewpoint of the research objectives and summarize the research.

Finally, section five reports the key findings of this study along with select managerial implications and recommendations for areas of future research.

1.4 Terminology

Below is a list of key terminology consistently used in this paper.

Baseline forecast	A system-produced forecast that is adjusted with experts' opinions
Business Confidence Index (BCI)	An index measuring the sentiment of managers, published by the OECD
Composite Leading Indicator (CLI)	An aggregate indicator published by the OEDC for many countries
Consensus forecast	A general concurrence or agreement of forecasting board, where individual estimates are compiled into one final forecast

Conversion rate	A proportion of offers or hot offers that are realized into orders
Customer Relationship Management (CRM)	Systems and culture for the strategic management of the relationship of a company and its customers
Cycle time	Process throughput time for a sales case from the sales funnel to orders
DMAIC	Popular process improvement method comprising the phases Define, Measure, Analyze, Improve and Control
Hot offer	An offer that will likely be won, definition varies firm to firm
Judgmental forecasting	Human estimates or adjustments to forecasts
Key Performance Indicator (KPI)	Metrics of company performance that are critical for success (Parmenter, 2010)
Leading indicators	Indicators that precede another variable in behavior
Manufacturing Purchasing Managers' Index (MPMI)	An index measuring market sentiment in the manufacturing industry, published by Markit Economics
Mean Average Percentage Error (MAPE)	Metric of forecasting accuracy, calculated by taking the average of absolute percentage errors of forecast and actual value
Sales funnel	Pipeline of a firm's prospective sales cases in various stages before becoming an order or sale
Synchronization	Applying lag to an indicator until it coincides with variable, lining up peaks and troughs (Berk & Bikker, 1995)
Volatility	Variation in a variable, e.g. the indicators or the sales funnel volumes

2. Theoretical framework

The purpose of this section is to introduce the key concepts and theory used in this thesis in more detail. The forecasting model proposed in this study has no direct counterpart from previous literature, but a link to extant literature can be established by reviewing the main concepts used in its formulation and explaining the roles they have in the new model. A generic model with descriptions to its limitations and applicability promote the generalizability of the findings of this thesis for other research contexts (Eisenhardt, 1989). On the other hand, the organizational factors of forecasting management are more widely researched topics and relevant literature is available for consultation with regards to the objectives of this thesis. The key learnings of previous research enable us to identify certain best practices and pitfalls in managing forecasting processes.

This section will be structured in the following way. First, the research gap for a simple, yet responsive forecasting model will be explored in more detail to justify the need for this study and explain the logic behind using the selected sources of information and data. Bearing in mind that managers and decision makers everywhere will use their personal judgment in forecasting to some extent, it is pertinent to address the benefits and perils of judgmental forecasting. Next the actual components of the generic forecasting model will be introduced. The function of leading indicators will be briefly explained along with a few words on their performance and applicability. Similarly, the role of the sales funnel in a firm will be discussed to show the logic behind using it in forecasting.

An approach for assessing and improving the forecasting process on the whole is developed using the DMAIC problem-solving method known from Six Sigma. This approach constitutes the backbone of the case study as well.

2.1 Toward responsive forecasting

Back in the 60s, Winters (1960) recognized the growing need for responsive demand forecasting models and described an exponentially weighted moving average model. Variants of this model are still widely used across industries today. In general, quantitative forecasting methods have been observed to outperform qualitative methods provided that they have the right amount of the right data (Armstrong, 2001). Quantitative methods that rely on historical data may work well for some companies, but if the demand fluctuation is relatively synchronized with the market's cycles, these methods fail to respond rapidly. Under such volatility, firms using historical data often build up costly buffer inventory (Helms, Ettkin, & Chapman, 2000).

Firms are faced with a few options in their forecasting approach. They may resort to historical data and develop a quantitative model. The primary source of data for this would be the firm's own historical demand patterns. On the other hand, they may do what most companies do to at least some extent: rely on the managers' expertise in forecasting. Doing what's popular in the industry seems to be an easy choice in demand forecasting (Armstrong, 2001). Those firms who truly strive for responsiveness under uncertain demand should look for relevant market intelligence (Fildes & Hastings, 1994). Leveraging market information has been shown to correlate positively with forecasting performance in a study of 343 manufacturing companies from 6 countries (Danese & Kalchschmidt, 2011). However, market intelligence should have a quantifiable effect on the variable to be forecasted, as human interpretation of market intelligence is often inaccurate (Fildes et al., 2009).

Fildes and Hastings (1994) studied the organizational dynamics of market forecasting. They note that the forecast practitioners in their study expressed the lack of relevant market information to use in forecasting as problematic, and that providing this kind of data would have a positive impact on forecasting performance. In a study of 50 American companies, over half of which are industrial manufacturers, 67% reported that demand forecasting is the principal benefit of market intelligence collected by the firm (Lackman, Saban, & Lanasa, 2000). These studies were conducted more than 15 years ago, and we have come a long way in terms of both easily accessible internal and external information that could be used in forecasting. Computer processing capabilities, the amount of internet data and more advanced ERP-systems give firms access to sources of data that were never available to the pioneers of demand forecasting. On the other hand, it highlights the importance of focusing on the right sources of information (Helms et al., 2000).

In a longitudinal study of 20 years of forecasting practices and performance, it was found that the overall satisfaction and familiarity with both quantitative and qualitative forecasting methods is decreasing (McCarthy, Davis, Golicic, & Mentzer, 2006). Furthermore, the overall forecast accuracy was found to be substantially lower despite an increase on the understanding of forecast business impact. These alarming trends may be related to the growing volatility of the market environment firms operate in and emphasize the importance of research in the field of responsive forecasting methods.

In the optimal scenario, a firm would use the best sources of internal data, combined with key external intelligence and the expert judgment of humans with valuable insight of the product to construct a responsive forecasting model. Before venturing deeper into how one such model could be constructed, it is prudent to discuss judgmental forecasting, as it is present in nearly all firms.

2.2 Judgmental forecasting

Judgmental forecasting refers to the use of human judgment in producing or adjusting a forecast. Back in the day, Dalrymple (1987) studied American companies and found that judgmental forecasting was the single most used forecasting method in the sample. This is still the case today, as most companies make judgmental adjustments to any baseline forecasts (Fildes et al., 2009). One argument for using qualitative forecasting techniques such as judgmental forecasting is the fact that they are simple (Luxhøj, Riis, & Stensballe, 1996).

Judgmental forecasting has been widely studied from a number of perspectives ranging from social psychology to operations management. Especially the performance of judgmental forecasting techniques compared to quantitative methods has received a lot of attention. The findings, however, seem to contradict each other. Many studies, e.g. (Edmundson, Lawrence, & O'Connor, 1988) and (Fildes et al., 2009) have reported judgmental forecasting to underperform very simple quantitative models due to *bias*. Bias could be explained as a tendency to systematically overestimate or underestimate the forecasted variable. These are called optimistic and pessimistic bias, respectively.

Contradicting the previous findings, judgmental forecasting has been shown to improve forecasting performance as well. In a study of by Mathews and Diamantopoulos (1986), it was found that the managers' judgmental adjustments improved forecasting performance. They recognize the possibility that these adjustments may still introduce bias into the forecasts. In a case study of a U.K. health care company, Mathews and Diamantopoulos (1990) discovered that managers adjusted those forecasts whose general performance was the poorest. These forecasts were usually too low in their opinion. Through an improvement in forecast accuracy, the authors concluded that the managers seemed to be able to identify the right forecasts to adjust.

When there is bias in a judgmental forecast, it is generally optimistic (Stewart & Lusk, 1994). This holds true to smaller, routine adjustments of baseline forecasts, but often the bigger the adjustment, the better the performance of the forecast (Fildes et al., 2009). This highlights the critical benefit of human judgment in forecasts: contextual knowledge. Humans know things the computer does not and can anticipate change. It is of paramount importance to incorporate this knowledge to any system-produced forecasts, but it needs to be based on factual intelligence as opposed to a mere gut feeling (Armstrong, 2001; Fildes et al., 2009; Moon, Mentzer, Smith, & Garver, 1998).

What should a company then do to ensure it gets the most out of judgmental forecasting while minimizing the bias? First of all, in the event that managers adjust a system forecast, it is imperative that the system forecast is performing well on its own and that the managers understand how the baseline forecast is produced (Stewart & Lusk, 1994). A crucial success factor of judgmental forecasting is using the consensus approach. In a study of 20 companies that were leaders in market share or other financial metrics, cross-functional collaboration was identified as a key element of forecasting management (Mentzer, Bienstock, & Kahn, 1999). This means that all the necessary functions of the firm are represented in the production of demand forecasts. This way relevant intelligence from within the company can be shared and factored into one single consensus forecast.

Graefe and Armstrong (2011) studied the differences in forecasting performance of groups versus individual forecasts. They assessed a couple of group estimation methods, but found none of them significantly more accurate than each other. However, all of the structured group estimates were more accurate than an individual forecast. Similar results were achieved at the clothing manufacturer Sport Obermeyer, were consensus forecasting was implemented and forecasting performance was substantially enhanced (Fisher, Hammond, Obermeyer, & Raman, 1994). It is evident that consensus forecasts can remedy individual bias. Graefe and Armstrong (2011) theorize that whenever contextual, product-specific knowledge is present, sharing it will substantially improve forecast performance. They also promote the importance of using an appropriately structured group method, as groupthink and peer pressure can deteriorate the performance of these forecasts. This was observed by Mentzer et al. (1999) as well, who note that in early stages of sales forecasting management coordinated meetings can be dominated by one or two functions of the firm. Graefe and Armstrong (2011) note that retaining anonymity in giving or adjusting the individual estimates mitigates the risk of groupthink. These findings can be used to improve judgmental forecasting process in any firm. To summarize:

- Make sure managers are adjusting the right forecasts
- Make sure the baseline forecast is good
- Whenever applicable, implement a structured consensus approach to judgmental forecasting

Improving the baseline forecast is the central topic of this thesis. In the next subsections, the components used to construct our actual forecasting model will be introduced and explained in more detail.

2.3 Leading indicators as a source of market intelligence

After acknowledging the relationship between external market intelligence and the responsiveness of the forecasting model, it is necessary for a company to identify what market information to use and how to use it. One solution to the problem is using leading indicators in demand forecasting.

A leading indicator is a measurable time-series that changes before the economy or some other reference index starts to behave similarly. The purpose of a leading indicator is to predict the reference index (adapted from (Leading Indicator Definition Investopedia, 2003)). The term *leading* refers to how far in advance the indicator behaves like the reference index. *Coincident* indicators change at the same time as the reference index, and *lagging* indicators follow the reference index. A *composite leading indicator* (CLI) is a weighted aggregate of individual variables into one, in order to reflect the desired reference index more accurately (Berk & Bikker, 1995).

Leading indicators have been primarily used for predicting economic fluctuations on a macroeconomic scale or predicting the price developments of financial securities. The forecasting performance of composite leading indicators (CLIs) has been studied in several different contexts for long time horizons. Diebold and Rudebusch (1989) analyzed the short-term forecasting performance of CLIs and found them to predict fluctuations quite well. In a separate study, ex-post analysis showed that CLIs predicted industrial production admirably in-sample, but performed poorly when approaching real-time forecasts (Diebold & Rudebusch, 1991). These findings are supported by Auerbach (1982) and Koch & Rasche (1988).

A *confidence index* is an indexed weighted measure of market sentiment that is used to predict business cycles. The most prominent are perhaps the Business Confidence Index (BCI) and the Purchasing Manager's Index (PMI). They are formulated based on comprehensive survey answers to measure changes in firms' new orders, purchases, employment, inventories and other variables. A positive or negative change in these variables constitutes an increase or drop in the index.

The true forecasting capacity of these indicators should be measured out of sample. Marcellino (2006) notes that composite leading indicators failed to accurately predict the last two U.S. recessions, and that it is hard to select the indicators for the composite index as the weights may change over time. Essentially, CLIs should be transparent, coherent and comprehensible (Munda & Nardo, 2009).

This thesis will concentrate on three quantifiable sources of external market intelligence: OECD's *Composite Leading Indicator* (CLI) and *Business Confidence Index* (BCI), as well as Markit Economics' *Manufacturing Purchasing Managers' Index* (MPMI). Although these are undoubtedly used for forecasting in some companies, research on a practical model for business purposes is non-extant. The logic for selecting these particular indicators is the following. The CLI is the least sensitive of the indicators and aims to represent economic cycles, whereas the BCI and MPMI are more sensitive indicators that contain business sentiment of managers. Additionally, the MPMI is focused on solely manufacturing companies. Essentially, having these three indicators brings us diversification in terms of industry and sensitivity.

OECD's composite leading indicator's forecasting performance was found to be at par with a simple autoregressive model in predicting economic fluctuation in a study of France, Germany, Italy and the U.K. (Camba-Mendez, KapetanioS, Weale, & Smith, 1999). Another study by Dreger and Schumacher (2005) found that the CLI was able to predict fluctuations in the German economy well, but could not outperform the autoregressive model in out of sample tests. These findings imply that leading indicators should be used carefully when integrating them into a forecasting model. Confidence indices have been observed to correlate significantly with economic cycles in the U.K., France, Italy and Netherlands over the time period 1983-1998 (Taylor & McNabb, 2007). Despite these encouraging findings, using this kind of external market intelligence in a quantitative forecast model behooves the practitioner to understand the limitations and risks in forecasting performance. That is, their performance and applicability to forecasting should be monitored continuously.

The selection of the CLI, BCI and MPMI for this study is not based on any pre-existing theory. The argumentation behind these indicators is that the CLI is less sensitive, but reflects quite accurately economic fluctuations at least in Europe. The BCI is included because it portrays the general sentiment and expectations of the immediate future in enterprises (OECD, 2015). The MPMI is perhaps the most sensitive of these indicators, but it is assumed to reflect the purchasing sentiment of manufacturing firms in particular, in accordance with the case company of this thesis. Thus we have diversification in terms of sensitivity and industry focus. Each of these indicators is updated monthly (or quarterly for a few exceptions) for each country and published on the website of the respective organization.

As mentioned earlier, leading indicators have mostly been applied to macroeconomic or financial contexts. However, they have been successfully applied to e.g. forecasting demand levels in the tourism industry (Song & Li, 2008) and for the prediction of construction contract price levels (Akintoye, Bowen, & Hardcastle, 1998). Cho (2001) explored the power of using economic leading indicators in forecasting tourist demand levels by first measuring the correlations between the indicators and the demand. The leading indicators were *lagged* as many periods as the correlation would improve. Then incorporating this information into an autoregressive model, the forecasting performance was enhanced in several countries. Akintoye et al. (1998) used a similar approach to successfully identify leading indicators of construction contract prices.

In this study, the approach will be relatively similar. We will investigate the correlations of our select leading indicators and the sales funnel by finding the optimal lag, i.e. how many periods in advance does the indicator lead the variable. This process is called *synchronization* (Berk & Bikker, 1995) and will be repeated for several countries or regions in the case company to identify the leading indicator for each one.

Having introduced the leading indicators and their function, it is time to move on to the sales funnel or pipeline. The next section will briefly cover the concept, structure and purpose of the sales funnel and why it might have a beneficial role in forecasting demand.

2.4 Sales funnel

The sales funnel, or pipeline, is a tool used as part of a wider area of business: customer relationship management (CRM). CRM systems are used to facilitate and automate the company-customer relationships to the highest degree (Rigby & Ledingham, 2004). Firms have started investing heavily into these systems for competitive advantage, although many firms state they have not been able to leveraged the CRM systems sufficiently for a sufficient return on investment (Dong, 2010; Rigby & Ledingham, 2004). This is a pity, as the sales funnel contains valuable information that could be used in decision making (Harris, 2003).

The sales funnel is a pipeline through which sales prospects travel to become orders. The funnel consists of several stages and the structure varies firm to firm. The logic is the same though: the probability of closing the sale increases as you travel further down the funnel (Heiman, Sanchez, & Tuleja, 1998). Figure 2-1 below is an illustration of the sales funnel.

Figure 2-1: Sales funnel

As we can see, a prospective sales case would theoretically enter the funnel as a lead. From there it would advance through the funnel into an opportunity and an offer, and finally be closed into an order. In reality, however, sales cases may enter the funnel at various phases. For example, a sales case might enter the funnel directly as an offer. Sales cases may also leave the funnel if the lead is not pursued or an offer is lost. This is why firms aspiring to forecast from the sales funnel should focus on the end of the funnel. At the case company this would mean offers and hot offers. Hot offers are offers with high probability of success. The logic behind this is twofold:

1. The probability of a sales case converting to an order is higher at the end of the funnel and hence it is easier to forecast orders from these phases of the funnel
2. A sales case might enter the funnel only at the end, so using earlier phases might neglect some demand. Similarly, a sales case can leave the funnel before becoming an offer.

Kotler et al. (2006) argue that the sales funnel being a key tool of sales management, it should be used for forecasting. This is supported by (Söhnchen & Albers, 2010; Storbacka, Polsa, & Sääksjärvi, 2011). Dong (2010) and Cooper & Budd (2007) state that sales funnel-based forecasts may enhance short-term forecasting accuracy. Why is this? Rigby and Ledingham (2004) hit the nail on the head: the CRM sales funnel gives you real-time market data of your sales prospects. This data is not based on any historical estimates, but is rather a dynamic reservoir of sales intelligence that the firm should certainly incorporate into forecasting their short-term order levels. Furthermore, companies that feel they create subpar value from their CRM systems should focus on producing meaningful information from their CRM systems and integrating it cross-functionally to support decision making processes (Kotler et al., 2006). Demand forecasting is one valuable, cross-functional use of the CRM system.

Despite the wide implementation of CRM systems, using the sales funnel for order level forecasts is perhaps the biggest research gap in this study. How should the data in the sales funnel be used to produce an order level forecast? Naturally, the structure of the funnel and the nature of the business will determine the specific method and applicability of sales funnel-based forecasts. However, the basic logic behind such models is based on the assumption that a transaction probability or conversion rate of sales cases to actual orders can be estimated (Söhnchen & Albers, 2010). In fact, this boils down to a simple optimization problem provided that the sales funnel's cycle time is not too fast. In industrial manufacturing of durable technology, especially for larger products with longer lead times, the lag between the sales funnel and a realized order is sufficient for this type of model. Essentially, once the firm has an estimate of the conversion rate, they may produce a short-term forecasting model using the sales funnel. Such an attempt will be made in the case study section of this thesis, using real sales funnel data from the case company.

Firms aspiring towards sales funnel-based forecasts must monitor and maintain the CRM systems' data quality because it impacts the performance of any forecasting model using the sales funnel (Storbacka et al., 2011). They should also establish a supportive role for CRM in the company culture and target those functions who could benefit the most from CRM intelligence; such as those responsible for demand or sales forecasting (Kotler et al., 2006; Rigby & Ledingham, 2004). This is in line with the findings of Moon et al. (1998) who note that the forecasting process needs to be cross-functional in order to make use of intelligence from various functions of the firm.

2.5. Building the conceptual forecast model

The previous subsections introduced in more detail leading indicators and the sales funnel proposed to be used in our forecasting model. This subsection is dedicated to explaining how they actually work together and form a quantitative forecasting model that firms might use. This model will then be tested in the case study section using actual indicator and sales funnel data.

The logic behind using leading indicators and the sales funnel is the following. Theoretically, the sales funnel will reflect the economic conditions more accurately than the order levels. The order levels may not necessarily reflect market developments so well, since salesforce win rates of offers from the sales funnel play a significant role in order levels. The sales funnel will always contain the mass of prospective sales cases initiated to the best efforts of the sales force. When the economy fluctuates, the sales funnel volumes are assumed to follow after a given lag. If the sales funnel is led by some indicator, we may project the funnel's volume n periods into the future, given a lag n, with a linear regression model. This will extend the forecasting horizon of the model.

As established earlier, the sales funnel provides real-time market information of the firm's prospective sales cases. Thus it is theorized to be superior in responsiveness compared to any quantitative models relying on historical demand data as well as superior in accuracy compared to purely judgmental forecasts. The sales funnel volumes will be assumed to convert to orders with a fixed rate. This is an unrealistic assumption, as offer win rates may change over time, but necessary for the formulation of the forecasting model. Companies should re-evaluate the conversion rates on a regular basis to maintain the performance of the model. To find the conversion rate, we formulate the following optimization problem:

- Determine appropriate forecasting horizon for sales funnel-based estimates
- Find the optimal parameter that converts current sales funnel volumes into future orders, while minimizing the desired forecasting error metric

This problem will be examined in more detail and solved in the case study section. The conversion rates will be individually solved for each country or region, since the sales funnel will translate to orders differently in each case, i.e. the regional win rates vary.

Essentially, the goal is to construct a quantitative forecasting model that incorporates leading indicators and the sales funnel, to enhance the accuracy and responsiveness to market conditions. The technical formulation, analysis of performance and applicability will be accomplished by applying the conceptual model to actual case company data. Figure 2-2 below illustrates the relationships of the individual components used in the model, assuming that leading indicators do not correlate directly with order intake. The methods for quantifying the relationships are indicated inside the arrows connecting the components.

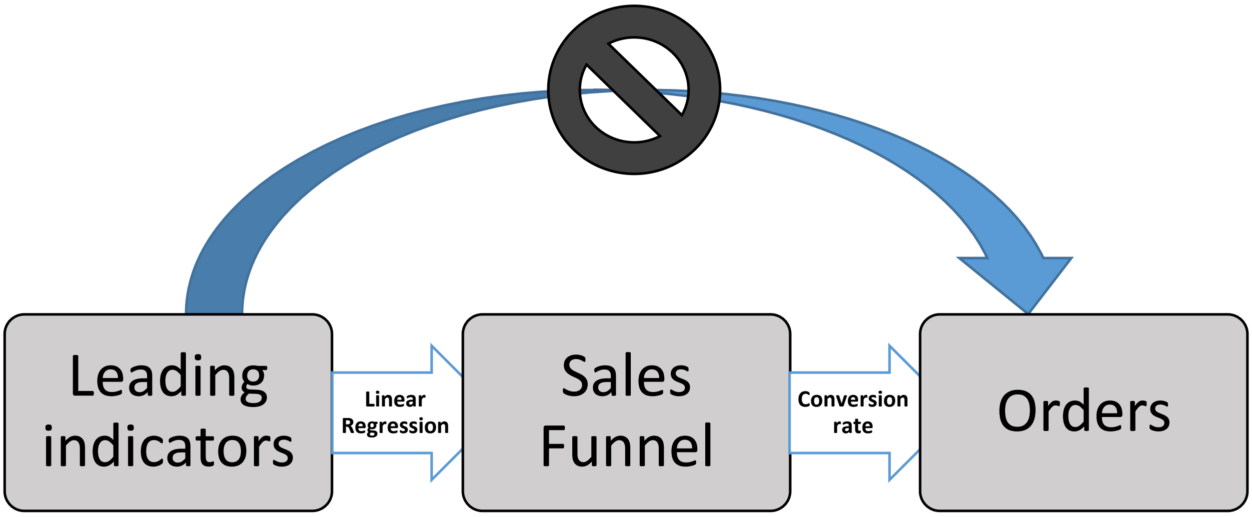


Figure 2-2. The use of leading indicators through the sales funnel

What is the role of judgmental forecasting in this model then? As mentioned earlier, judgmental forecasting is a very popular forecasting method across industries (Dalrymple, 1975; Fildes et al., 2009). In most companies, managers will adjust the baseline forecasts produced by the system. Human intelligence should not be left out of the equation, as managers can provide valuable contextual knowledge to the forecasting process (Edmundson et al., 1988; Fildes et al., 2009). Stewart and Lusk (1994) note that identifying external indicators of demand and enhancing the capability of the system's baseline forecast has a positive impact on forecasting performance. Thus it is important that the system forecast is as good as possible. As explained earlier, the sales funnel-based forecasting model aims to achieve two characteristics that are key to a good baseline forecast:

1. Use leading indicators (external intelligence) to extend the forecast horizon of the model with a linear regression model
2. Use the sales funnel for real-time market information of the firm's prospective sales cases (more accurate estimate of short-term demand) estimating the conversion rate to orders

Aside from improving the quantitative system forecast, the firm would do well to ascertain that its judgmental forecast adjustments are based on solid facts. The following points from the section on judgmental forecasting are important:

- Make sure managers are adjusting the right forecasts

- Make sure the baseline forecast is good
- Whenever applicable, implement a structured consensus approach to judgmental forecasting

The first and the last points are vitally important to understand. First, managers should not tamper with forecasts that are performing well on their own *unless* they have fact-based, contextual and better information to justify their adjustment. Otherwise routine adjustments “out of habit” will subject the forecasting performance to systematic bias in the long run (Fildes et al., 2009). Second, the judgmental forecast estimate or adjustments to baseline forecasts should be based on a consensus. The consensus forecasting board must have a comprehensive representation of all necessary functions that can contribute to forecasting. This was earlier referred to as functional integration (Mentzer et al., 1999) and will be revisited later. When forming a group for consensus forecasting, it must be ensured that no single group has dominance over the rest of the team, as this will lead to bias due to negligence of relevant information (Graefe & Armstrong, 2011). If the baseline forecast given to the forecasting group is market-responsive, the forecasting performance can be assumed to increase (Armstrong, 2001; Danese & Kalchschmidt, 2011; Moon et al., 1998). Figure 2-3 visualizes this causality in the context of our model.

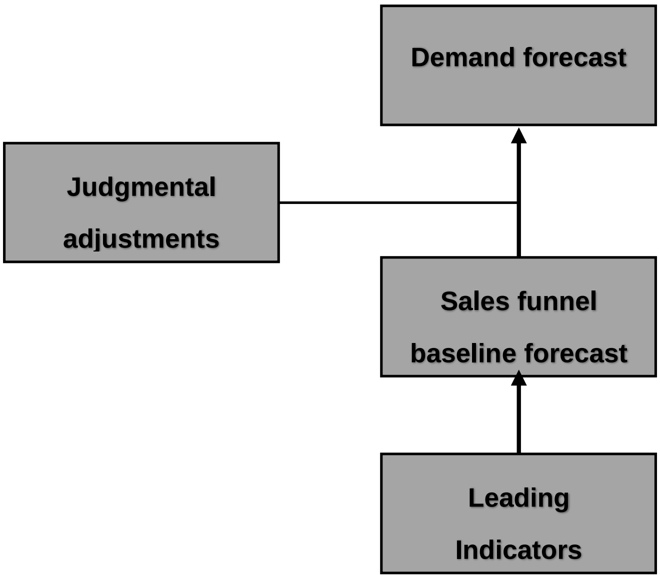


Figure 2-3. Components of the forecasting model

As can be observed from the figure, the sales funnel-based model is proposed to serve as the quantitative baseline forecast that is then complemented by qualitative intelligence and adjusted accordingly. The final end-product is thus a forecast that leverages both quantitative and qualitative data. The forecast performance should benefit from the responsive nature of its key components, namely leading indicators, the sales funnel and human intelligence. These components reflect changes in demand based on current observations, as opposed to reliance on purely historical data.

How should this model be implemented into the forecasting process of a firm? The next subsection assembles certain organizational best practices from the field of forecasting management and behavioral science to build an understanding of what needs to be done for the model to be successfully adopted in the firm.

2.6. Adopting the model into the forecasting process

Presenting the management with a new forecasting model is getting only half way there. On the flipside, the improved forecasting model needs to be implemented in a way that it will actually create value. How a forecasting model like the one proposed in this thesis should be implemented depends greatly on the current state of the forecasting process at the company. This entails understanding who is responsible for the forecast, what data is being used, how the forecasts perform and what the scope or purpose of the forecast actually is.

Menzter et al. (1999) introduced a rubric of forecasting management that charts four levels of proficiency across four dimensions of key forecasting success factors. The framework was assembled based on the best practices of 20 companies with excellent market or financial performance. This rubric is useful for gauging the current state of the firm's forecasting capacity onto a predetermined evaluation template. After managers have evaluated their position on the rubric, they may estimate what the potentially improved forecasting technique would necessitate in terms of these dimensions. Table 2-1 below illustrates an adapted version of the rubric tailored to the context of this thesis.

Table 2-1: Forecasting management rubric (adapted from Mentzer et al. (1999b))

Stage	**Functional Integration**	**Forecasting Approach**	**Systems**	**Performance Measurement**
1	• Disconnection between areas and lack of accountability	• Naïve forecasts • No real understanding of market environment in forecasting context	• Systems not linked electronically, manual transfer of data • No performance metrics in reports	• Accuracy not measured • Forecast performance not tied to any measure

2	• Coordinated meetings, but dominated by few areas	• Recognition of forecasts' business impact • Intuitive understanding of market environment	• Cross-functional links between systems • Performance measures available	• Accuracy measured • Performance measured based on accuracy
3	• Real consensus between functions • Rewards for accuracy	• Cross-functional forecast input • Strong management support • Advanced forecasting methods that incorporate market intelligence	• System allows for subjective input • Ad-hoc reports available • Systems are developed and respond to evolving needs	• Holistic understanding of the impact of forecast performance
4	• Forecasting is separate functional area • Cross-collaboration • Feedback loops	• Forecast and business plan are developed hand in hand • Top management committed to continuous improvement in forecasting • Continuous training in new methods	• Systems are open, so all internal stakeholders can provide input	• Multidimensional metrics of forecast performance • Forecast error triggers problem-solving process

To assess the forecasting capacity of the company, the state in the dimensions of functional integration, forecasting approach, systems and performance measurement must be evaluated. This is best achieved by comprehensive interviews with key forecasting stakeholders in the firm. In the course of this study, the interviews will also reveal what stage of proficiency the firm needs to be in these dimensions in order for the newly proposed forecasting model to be successfully implemented.

More detailed discussion of the dimensions is in order. *Functional integration* can be understood as the degree of collaboration between different functions in the firm, the highest stage representing seamless consensus-based forecasting (Mentzer et al., 1999). This means that those functions of the firm that can contribute to the forecasting process are consulted to produce a single, consensus demand forecast. This has been recognized as a key success factor in forecasting by Danese & Kalchschmidt (2011) and Moon et al. (1998) as well. It seems that information is often compiled from various sources, but assembled separately by forecast practitioners (McCarthy et al., 2006). It is sensible to include those who possess such information in the forecasting process from the start, as this ensures buy-in for the forecast right from the beginning (Davis & Mentzer, 2007). Furthermore, consensus forecasting alleviates bias (Graefe & Armstrong, 2011).

Cross-functional collaboration will not only facilitate forecasting processes, but it is also one of the key principles of successful sales and operations planning (S&OP), emphasizing the positive impact of collaborative culture and shared managerial responsibility (Hoover Jr, Eloranta, Holmström, & Huttunen, 2002). Different functions can contribute to the forecasting process in *consensus planning* by bringing contextual knowledge to the table, although incentivizing the consensus board is vital to mitigate the risks of bias (Cecere, 2013). By implementing a similar approach as Sport Obermeyer (Fisher et al., 1994), the average of the individual functions' point estimates can form the consensus forecast and theoretically improve forecasting performance.

Forecasting approach is herein interpreted as the concrete process of producing the forecast, ranging from what data and methods are used to how often a forecast is produced, who is involved and what the forecast is used for. As mentioned earlier, forecasting techniques fall into quantitative and qualitative categories, or hybrids of the two. Qualitative forecasts have been theorized to be subject to bias and misinterpretation (Fildes et al., 2009), whereas quantitative models relying solely on historical data may fail to anticipate change due to negligence of market events (Fildes & Hastings, 1994; Helms et al., 2000). According to Mentzer et al. (1999), becoming more proficient in the dimension of forecasting approach necessitates incorporating market intelligence into the forecasting model, with a management committed to continuous improvement and development in the forecasting process. This is in line with the findings of Helms et al. (2000) and Davis & Mentzer (2007).

Mentzer et al. (1999) recognize *systems* as one of the key dimensions of forecasting management. Systems can be interpreted to refer to the software, tools or databases used for producing the forecast. This is supported by the findings of the comprehensive study by Davis and Mentzer (2007) who note from surveying 516 forecasting practitioners that IT is a vital component of forecasting. This notion seems rather obvious today, but the central point is that systems play a critical role in forecasting. They also note that the more manual input there is in the process, the more room there is for error. Data collection and manual work were also found to be key weaknesses in forecasting by Fildes and Hastings (1994), and that the systems should be developed so as to minimize the two. Developing the systems to allow for input of market intelligence is another direction of improvement particularly interesting from the perspective of this thesis. Mentzer et al. (1999) describe that in the highest level of systems proficiency the systems would be open to cross-functional input, constantly developed and automated to the highest degree.

Performance measurement is the final key dimension of forecasting management (Mentzer et al., 1999). In advanced performance measurement, accuracy is not the only metric of forecasting performance. Furthermore, the cross-organizational impact of forecasting performance must be understood. Performance measurement and accountability were also identified to be of utmost importance in improving forecasting by Fildes and Hastings (1994). In a 20-year longitudinal study of forecasting practices, McCarthy et al. (2006) found that the amount of overall forecasting performance measurement and the understanding of its impact was increasing, but the average forecasting accuracy was decreasing. Fildes et al. (2009) argue that forecast practitioners may generally be unfamiliar error measurement practices. Though a valid point, it is often more likely that the problem exists in the culture of the firm. In other words, there is often no incentive to maintain good forecasting performance, nor is there accountability for forecasting error – as proposed by Davis and Mentzer (2007).

To expand the rubric proposed by Mentzer et al. (1999), the state of the **corporate culture** in terms of forecasting processes should be considered. Corporate culture, especially in larger organizations, plays a substantial role in forecasting performance. The impact of organizational culture on forecasting competence has been recognized by Davis and Mentzer (2007). It is necessary to consider the cultural implications of forecasting process improvement in organizations, if permanent change is pursued.

Some key learnings regarding organizational culture can be borrowed from lean management. Mi dahlgaard-Park, Dahlgaard and Mi Dahlgaard-Park (2006) state that implementing lean management requires the right company culture. They further argue that quality must be both a core value and a core competence in the firm. These attributes must be considered on the individual, team and organizational levels (Mi Dahlgaard-Park et al., 2006). Riis and Neergaard (1995) note that organizational learning occurs on the individual and collective level, implying that change should be instilled to individuals as well as the entire organization. This logic can be extended to forecasting performance as well. Not only do the forecasting practitioners need to adopt forecasting performance as a core value and competence, but the stakeholder business areas must demand quality in forecasting performance. It is vital to understand that forecast practitioners are not the only ones who must strive for good forecasting performance, but it must be emphasized by management as well.

An important success factor in this is motivation. Motivation can be classified as intrinsic, where a person does something because she enjoys it, or *extrinsic*, where she receives some tangible form of benefit for doing it (Ryan & Deci, 2000). If the forecast practitioners can benefit from a distinct outcome of good forecasting performance, they would be motivated to maintain the performance or even improve it. One extrinsic motivator that could work in forecasting is *incentivization*. That is, the forecasters are rewarded tangibly for good performance. Cox (1989) notes that the salespeople responsible for the initial frontline forecasts should be provided with an incentive system to motivate excellent performance. However, Mentzer and Davis (2007) argue that giving the sales force incentives for forecasting performance distorts the true performance and makes them inclined to play games with the figures, by e.g. saving up quotas for the next period. Cox's (1989) idea targets the initial unadjusted forecasts, but incentivizing a functionally integrated consensus forecast could work just as well, while mitigating the risk of game playing.

Drawing from this rubric of forecasting management by Mentzer et al. (1999), the first step towards implementing an improved forecasting method is to position the current practices of the firm onto the rubric. This should be done by interviewing key forecasting stakeholders from pertinent functions to assess where the company is currently situated on the framework in each dimension. Another useful concept was introduced by Moon, Mentzer and Smith (2003): *the three phases of forecasting*. These phases represent a path of improvement for the focal company:

1. The "As-is phase"
2. The "As-should-be" phase
3. The "Way forward"

It is proposed here that the three phase model by Moon et al. (2003) be used in concert with the forecasting management rubric by Mentzer et al. (1999). The first phase is essentially what was proposed above, i.e. mapping out the current forecasting process and its performance. In this thesis, the *as-is* phase will constitute positioning the firm onto the rubric by Mentzer et al. (1999). The second or the *as-should-be* phase will probably be interpreted subjectively in each firm, but it should essentially reflect how the forecasting process *needs* to perform. In the context of this thesis, the second phase will represent the requirements of our new forecasting model in terms of the forecasting management rubric's stages of proficiency. The final phase, i.e. the *way forward*, refers simply to the dimensions that need to be developed, or essentially, what needs to be done in each dimension to get to *as-should-be* from *as-is*.

To summarize, the forecasting management rubric and the three phases are helpful tools for planning the implementation of a new forecasting method. They will be revisited in the case study section of this thesis, once the new model has been built and tested against historical forecasting performance. First, the key stakeholders will be interviewed to position the case company onto the rubric in terms of proficiency in each dimension. Then, after formulating the new model and provided it is superior to current practices at the case company, its requirements in the same dimensions will be assessed. This information will then be used to produce a rudimentary plan for what needs to be done in order to successfully implement the new model.

The next subsection will introduce an approach for gauging the entire forecasting process. Developing a new forecasting technique is unfortunately not always enough to solve problems in forecasting performance, since the problem can reside elsewhere in the company. A tool for assessing the entire process from an improvement perspective is needed.

2.7 DMAIC problem solving approach

The DMAIC approach, short for Define, Measure, Analyze, Improve and Control, was originally designed for reducing variation in the context of quality control and Six Sigma process improvement (Chakravorty, 2009). In the course of time, it has evolved into a generic problem solving method with a wide range of applications (McAdam & Lafferty, 2004). De Mast and Lokkerbol (2012) studied the DMAIC approach from the theoretical perspective of problem solving and assessed its applicability to different kinds of problems. They conclude that the DMAIC approach is best applied to structured or semi-structured problems and that the key benefit of using the DMAIC approach is precisely the structured form it gives the problem solving task. Inversely, the DMAIC approach should not be applied to smaller, unstructured problems (De Mast & Lokkerbol, 2012) that are loosely defined.

Applying the DMAIC approach to forecasting appears to be a novel field of research. This thesis will not analyze the approach critically using further literature, but will simply adopt the DMAIC model to improving forecasting performance at the case company. This is based on the underlying assumption that improving forecasting performance is an extensive problem and that it has a recognizable structure. Whether the DMAIC approach works well or not will be determined in the case study. In practice, this means that the steps included in each phase of the DMAIC model will be based on the author’s subjective perception of how the DMAIC model would best fit the forecasting problem. Table 2-2 below lists each phase of the DMAIC approach with the proposed activities in a forecasting context, respectively.

Table 2-2: The DMAIC approach in forecasting

DMAIC Phase	Activity
Define	• Assess the current forecasting process on the key dimensions of Mentzer et al. (1999b) rubric • Interview the key stakeholders of the forecasting process for their current perceptions
Measure	• Measure the performance of the current forecasting method • Rudimentary quantification of the business impact of forecasting

Analyze	• Construct the new forecasting model by:
	  ○ Cross-analyzing leading indicators, the sales funnel and actual order intake
	  ○ Build improved quantitative model
	  ○ Comparing the new model against historical performance

Improve	• Establish the requirements of the new model in terms of the forecasting management rubric and the "way forward" (Moon et al., 2003) • Determine what needs to be improved
Control	• Communicate the new model to all relevant parties and secure management support • Emphasize importance of performance measurement and accountability in forecasting, push towards core value and competence in organizational culture

The breakdown of the adapted DMAIC approach in Table 2-2 will serve as the checklist for the case study. Such a structure is valuable, as the task of forecasting process improvement indeed seems to an extensive problem. De Mast and Lokkerbol (2012) highlight that the DMAIC framework may not provide a final solution to the problem, but rather that some problems require continuous monitoring and improvement. This is undoubtedly the case in forecasting as well because the forecasting model deemed superior today may not be so a year from now. This is because the dependencies of the firm's order intake, leading indicators and the sales funnel may change over time due to developments in the market share or organizational restructuring.

Before applying the adapted DMAIC approach to the case study, it is vital to understand the importance scoping the problem and communicating the business benefit to stakeholders (Lynch, Bertolino, & Cloutier, 2003). When solving an extensive problem like this, it is crucial to narrow the problem down to solvable sub-components so as to avoid scope creep (Davidson, 2002). In the context of this thesis, the case study will be limited to the aforementioned adapted DMAIC phases, excluding the following:

- Exhaustive estimation of financial impact
- Concrete systems development plans
- A training and incentive plan

The aim of this section was to introduce the key concepts used in the formulation of our new forecasting model. These components were three select macroeconomic indicators and the sales funnel of a company. In addition to these quantitative components, judgmental forecasting practices were briefly discussed as they are likely to impact the end forecasts regardless of the model used. Thereafter, the forecasting management rubric by Mentzer et al. (1999) and the three forecasting phases by Moon et al. (2003) were adapted to the context of this thesis, complemented by a few pointers on the importance of organizational culture in forecasting performance. Finally, the DMAIC approach was introduced and adapted to the needs of this study, so that each phase of the DMAIC approach was allocated a set of activities for improving forecasting performance at the case company.

Now it is time to apply the theoretical framework to be used in a case study. The case study gives us access to real data and gives us a chance to try our hands at building a more responsive and accurate forecasting model for a case company that currently deals with subpar forecasting performance. Moreover, the DMAIC approach will be applied to the entire forecasting process of the case company with hopes of identifying areas of improvement.

3. Case Study

The case study section of this thesis will adhere to the DMAIC structure introduced in the previous section. After a brief introduction to the case company, the current forecasting process at the firm will be defined with the help of open-ended interviews with key forecasting stakeholder functions. The current practices will be mapped onto the forecasting management rubric adapted from research by Mentzer et al. (1999). This will constitute the "Define" phase of the DMAIC approach. In the "Measure" phase, the historical performance of the current method, along with the stakeholders' current perceptions will be reported. Additionally, rudimentary estimates on the business impact of forecasting will be provided to give a ballpark estimate of what an improvement in forecasting performance might mean in cost savings.

In the "Analyze" phase, the cross-analysis of the sales funnel against the leading indicators and historical order levels will be reported. Based on the findings from this analysis, a conceptual and intuitive quantitative model will be formulated and tested against the performance of the case company's current method. The results will be reported in the same section.

In the final phases of the DMAIC approach, i.e. "Improve" and "Control", we draw information from the interviews and previous research and devise an implementation plan for the new model to improve the forecasting process as a whole. It is important to find a way for the new model to coexist with current processes to ensure that it will secure a supportive role in decision making, as opposed to a direct challenge to extant practices.

Finally, the limitations and applicability of the case study findings will be discussed to highlight what should be learned and when our forecasting model can be used.

3.1 The case company and data

The case company is a global manufacturer of lifting equipment and solutions and a provider of services for lifting equipment and machine tools, operating in 48 countries.

The focus of this thesis will be on product line X. These products vary in size and price, but they are physical heavy-lifting equipment that can be classified and delivered as individual products. This is a distinction from product line Y which are larger, long scope implementations of lifting solutions, e.g. harbors. The nature of X product demand is more appropriate for this thesis, as the unit demand volumes of these products is higher, and individual larger orders do not distort order level data as much as in Y products. This is vital to the predictability of both the sales funnel and the order levels. X products are relatively slow-moving, so the sales funnel is assumed to convert to orders at a rate that can support the forecasting horizons of the case company.

The CRM system at the firm is new and sales funnel data is available from a 16 months' period of time. This means there are 16 month-to-month observations to be analyzed against leading indicators for each country or region.. This thesis will focus on 10 countries and four regions with the highest historical order volumes to keep the amount data at a palatable level. A region is simply an aggregate of countries that represents some geographical business area. Accordingly, improved forecasting performance in this sample has the biggest potential financial impact. The countries and regions are listed below. Due to confidentiality, three of the regions are not named, but they roughly represent the Asia, Afica and North & South America.

- USA, Germany, Canada, UK, Australia, China, France, Austria, Sweden, India
- Europe and Regions 2-4

In short, this study will focus on producing improved financial country-level or regional order level forecasts using the respective sales funnel data and leading indicators.

To gauge and identify areas of improvement in the entire forecasting process, unstructured interviews with the key stakeholders of the forecasts are conducted. The stakeholders are represented by a top-level executive from each function, to ensure they partake in strategic decision making and see the big picture. The interview questions will pertain to the same topics for each function, i.e. to establish their role and use for forecasts, as well as to gauge their current perceptions of the case company's forecasting performance. By refraining from too much structure in the interviews, it is more likely to get the stakeholders to express their honest opinions and biggest concerns regarding the forecasting process. The forecasting stakeholders are introduced in the next subsection.

3.2 Define: current forecasting processes

Currently, the frontline order forecasts at the case company are produced individually in each country. These country-level forecasts are then aggregated into regional forecasts. The forecasts are done on a rolling quarterly basis for the following time horizons:

- 3m (next quarter, Q)
- 6m (two quarters away, Q+1)

- 9m (three quarters away, Q+2)
- 12m (four quarters away, Q+3)

The forecasting horizon is illustrated in Figure 3-1. below.

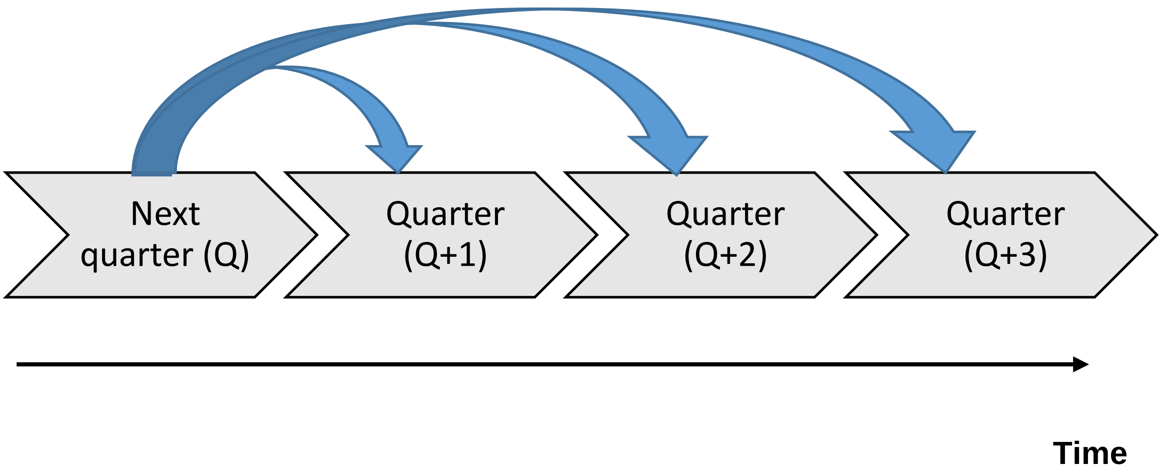


Figure 3-1: Forecasting horizon at the case company

In addition to these rolling quarterly forecasts, an annual forecast is produced for the next year each December. The order level forecasts are often done by a single expert representing his respective country, who may or may not consult other functions in the process, and then communicated to different functions of the organization. The firm already has the methods to translate orders into sales forecasts quite reliably, so forecasting demand essentially refers to forecasting order intake.

The key stakeholders of the forecasts and their function at the case company is introduced in Table 3-1:

Table 3-1: Forecasting stakeholders and function

Forecast stakeholder	**Uses forecasts for**
Sales	Production of initial frontline forecasts, salesforce allocation
Supply	Procurement of resources to meet demand

Demand & Supply Balancing (DSB)	Translation of monetary order forecasts for production requirements and routing of orders to factories to optimize workloads
Production	Production and delivery of orders
Finance	Financial planning, budgeting and communication to shareholders

The initial frontline demand forecasts are produced by sales in each country, after which they are adjusted by a controlling party and distributed to the rest of the stakeholders. Each function has their own use for forecasts. The company is pursuing a strategic unification in operative planning which means that a single set of forecasts from each country should be communicated to all stakeholders and used consistently. In this sense, the responsibility and independence of country level operations has increased.

Based on unstructured interviews with each stakeholder, it seems that the frontline forecasts received from the countries are not reliable enough to serve as a single guiding forecast for all functions, and that each stakeholder is forced to make their own adjustments to these figures based on their own estimates. This complicates the forecasting process greatly and renders it inefficient, to the point that these forecasts can travel from function to function before being actually reported. This implies that the level of functional integration in this process is not optimal.

Interviewing Sales verified what was assumed to be true by the analysts at the company: market trends are identified, but not incorporated into forecasts by any means. The frontline forecasts were perceived to systematically overestimate demand, but Sales indicated that the problem is mixing up sales targets and sales forecasts. If a frontline sales executive gives their individual forecast, it may be returned by their superior with a side note: "you need to sell more, this is not enough". Such a scenario will systematically overshoot forecasts and result in costly excess capacity. Sales stressed the need to fix this problem. When asked about the historical performance of the order forecasts, Supply and Production immediately responded that there is systematic, optimistic bias in the estimates, and that this compels them to adjust the forecasts to a more realistic level for their operational plans. Finance was dissatisfied with the historical performance, stating that the frontline forecasts are often not based on solid facts, accompanied by Production. This is frustrating for them, as they need to communicate the final forecasts to shareholders and use this information for financial planning.

Every stakeholder expressed their concern with regards to the reliability of the forecasts and emphasized the business impact. Not a single stakeholder was presently fully satisfied with the performance, but DSB indicated that the frontline forecasters are not solely to blame. DSB stated that with the capability of the systems and tools currently in use, the performance of these forecasts is at an acceptable level. Forecasting performance is measured on an ad-hoc basis, but the systems do not currently allow for continuous monitoring. Production and Supply expressed their concern in this and stated that the performance should be continuously evaluated. This indicates that the case company does have an understanding of the impact of forecasting performance, but does not have active processes to maintain it.

Each of the forecast stakeholders had valuable opinions on how to improve the forecasting process as a whole. Every function that was interviewed stated that they need to be more critical in terms of forecasting performance and that feedback should be given back to the frontline forecasters on a regular basis, not only when the forecasting error is substantial. Moreover, the stakeholders expressed a common need for *accountability* in the forecasting process. Sales proposed that a reward system be aligned with forecasting performance. Finance and DSB noted that a consensus between the Sales frontline forecast, Supply and DSB would impact the efficiency and reliability of the current forecasting process positively. Production and Sales were in agreement with this, but noted that the diversity of the organizational culture on a global scale brings issues in the standardization of the consensus approach. DSB also stressed the importance of choosing the right stakeholders for the forecasting board if a consensus approach is to be pursued.

DSB and Finance specifically addressed the need for developing the forecasting systems and their links to operational planning. The case company is currently evaluating their options by meeting with potential suppliers of such systems. DSB stated that the company is moving in the right direction, if the systems used for forecasting can be integrated so as to facilitate both forecasting and the related operational planning activities. Currently, the systems are not integrated together and data is compiled from multiple systems onto numerous spreadsheets.

Based on the interviews, the current state of the case company's forecasting process can be traced onto the key dimensions of the forecasting management rubric by Mentzer et al. (1999). This is presented in Table 3-2.

Table 3-2: Current forecasting proficiency at the case company, Mentzer et al. (1999b)

Stage	**Functional Integration**	**Forecasting Approach**	**Systems**	**Performance Measurement**
1	• Disconnection between areas and lack of accountability	• Naïve forecasts • No real understanding of market environment in forecasting context	• Systems not linked electronically, manual transfer of data • No performance metrics in reports	• Accuracy not measured • Forecast performance not tied to any measure
2	• Coordinated meetings, but dominated by few areas	• Recognition of forecasts' business impact • Intuitive understanding of market environment	• Cross-functional links between systems • Performance measures available	• Accuracy measured • Performance measured based on accuracy
3	• Real consensus between functions • Rewards for accuracy	• Cross-functional forecast input • Strong management support • Advanced forecasting methods that incorporate market intelligence	• System allows for subjective input • Ad-hoc reports available • Systems are developed and respond to evolving needs	• Holistic understanding of the impact of forecast performance
4	• Forecasting is separate functional area • Cross-collaboration • Feedback loops	• Forecast and business plan are developed hand in hand • Top management committed to continuous improvement in forecasting • Continuous training in new methods	• Systems are open, so all internal stakeholders can provide input	• Multidimensional metrics of forecast performance • Forecast error triggers problem-solving process

3.3 Measure: Performance and business impact

With regards to business impact, Supply and Production are the most vital stakeholders of the order forecasts. These functions make capital-intensive decisions in production planning, procurement and resource allocation using the forecasts given to them. So capital intensive, in fact, that they are forced to adjust any estimates they perceive as inaccurate, at the risk of deteriorating the profitability of the entire company. Gauging the quantitative impact of forecasting performance is extremely difficult because forecasting has both a direct and indirect effect on profitability.

When asked to provide rudimentary estimates of how an improvement in forecasting accuracy might impact costs incurred by the case company, the interviewees gave the following answers. The biggest cost savings that improved forecasting performance could bring are in procurement costs and capacity planning. If the forecasts for the next quarter (Q) or the one after that (Q+1) were more reliable, the firm could engage into longer contracts with suppliers and not have to operate on the spot market prices of components or materials. A 1% reduction in procurement costs would result in annual savings of 1MEUR in one factory alone. A further 5MEUR could globally be shaved off by more proactive workforce resourcing, further increased by better allocation of the workforce and reduced need of subcontracted workforce. This was stated to be attainable through a 10% improvement in forecasting accuracy. The true business impact is not quantifiable as the indirect cost savings from operations planning are very difficult to measure. Regardless, even an extremely careful estimate lands the cost savings as over 10MEUR annually according to managers at the case company. On top of these direct savings, facilitated operations planning and an overall more efficient forecasting process will save more costs indirectly, but more importantly, it will save *time*.

Interestingly, when asked about estimates of historical forecasting performance for order levels, the stakeholders could only indicate whether they were satisfied or dissatisfied. This implies that the transparency of the performance is not a satisfactory level, and that performance measurement processes need to be developed. However, every single stakeholder function interviewed expressed their dissatisfaction in the forecasting performance and agreed that something should be done about it. DSB noted that the forecasting performance is not good, but it is acceptable given the tools and systems the practitioners use for producing these estimates. Regardless, DSB agreed fully with a dire need of improvement in the forecasting process.

Analysis of the actual historical order levels vs the forecasted historical order levels revealed that the mean absolute forecasting error (MAPE) of the countries and regions selected for this study averaged at about 40% for the next quarter's (Q) forecasts. Naturally, the further you try to forecast, the more speculative the estimates become. Consequently, the historical forecasting performance for Q+1 is lower, with a MAPE of 51%. Neither of these figures are at a desirable level, justifying the remarks of all the stakeholders. After presenting these MAPE values to the stakeholders, they were surprised to see the severity of the problem. Despite acknowledging the dissatisfactory performance, these figures were worse than they expected. Supply, DSB and Finance expressed particular concern, since they can evaluate the rudimentary impact on profitability better than e.g. Sales. All stakeholders emphasized the need for accountability in the forecasting process, stating that this kind of performance should not be acceptable. Sales put it well: *"If we accept poor forecasting performance, we will get poor forecasting performance."*

After discussing the actual forecasting performance with the stakeholders, they were all very motivated and interested to see whether the sales funnel could be used to improve their forecasts. This will be attempted in the next subsection: the "Analyze" phase of the forecasting DMAIC approach.

3.4 Analyze: Building the new forecasting model

In order to improve a forecasting process by introducing a new technique, the "Analyze" phase is perhaps the most important step in the DMAIC approach. In this subsection the new forecasting model will be built and tested against the historical performance of the current model at the case company. The construction of the model will be divided into two phases representing the separate components of the forecasting model: from leading indicators to the sales funnel and from the sales funnel to orders. Finally the new model will be compared to the past accuracy of the current forecasting process in each of the selected countries or regions.

First, however, the data needs to be introduced. Figure 3-2 shows a clear structure of the data needed for the model.

The leading indicators used in this paper are published on a monthly basis by OECD and Markit Economics. The data can be extracted in Excel format. The indicators, respectively, are available at:

- CLI and BCI (http://stats.oecd.org/Index.aspx?DatasetCode=MEI_CLI, visited 14/4/2015)
- MPMI (http://www.tradingeconomics.com/country-list/manufacturing-pmi, 14/4/2015)

The sales funnel data is extracted from the case company's CRM system. As mentioned previously, the system's newness constrains the analysis. This means that any statistical models will not be robust, and as more data becomes available, the model needs to be updated and recalibrated. From the perspective of this thesis, we need the *end* of the sales funnel for analysis. This is because the probability and predictability of closing the deal is highest at the end and because some sales cases only enter at the end of the funnel.

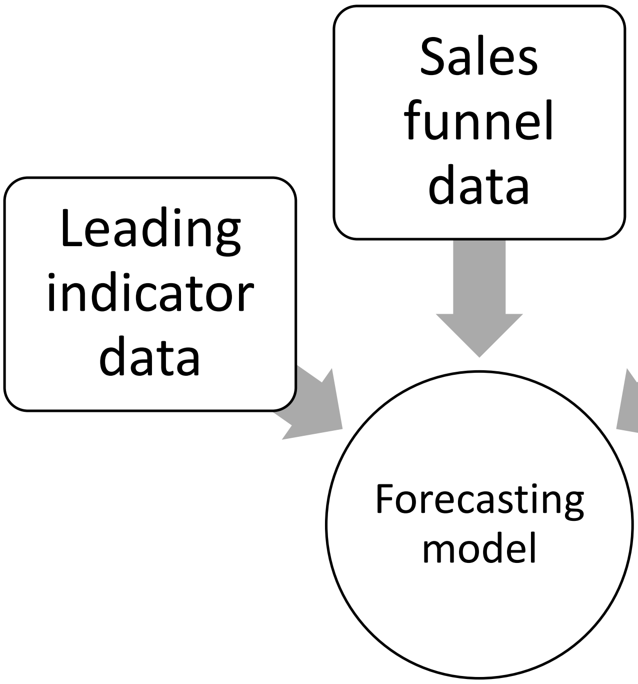


Figure 3-2: Data needed for analysis

In particular, we need the monetary *funnel value* for both offers and hot offers for each country or region. In other words, we must extract the monthly monetary values of all outstanding offers or hot offers. The logic behind using the monetary values is that they contain information of larger, individual sales cases that the unit quantity of e.g. offers would ignore. Moreover, translating a monetary funnel value to a monetary financial order forecast is logical. The data will be extracted for the selected countries for one business line only. Due to confidentiality, all monetary figures will be omitted from this paper. Fortunately doing so does not impair reporting the findings of the analysis.

3.4.1. Leading indicators and the sales funnel

To assess whether an indicator leads the sales funnel, a synchronization process must be applied. This means *lagging* the funnel offers or hot offers so that the graphs line up with the leading indicators. The number of periods, or months in this study, needed to synchronize the two is referred to as lag. Essentially, the leading indicator will lead the funnel by a lag of n periods. To quantify the optimal degree of synchronization, a Pearson's correlation statistic will be calculated for each lag. In theory, once the funnel and the indicator have been synchronized, the correlation will be maximized. In this thesis, a positive correlation statistic of 0 - 0.249 is considered weak, 0.250 – 0.649 neutral, and 0.650 – 1.000 strong. This process will yield several correlation tables for each indicator, funnel variable, amount of lag and all the countries or regions. A high correlation with so little data may not be a sign of strong dependency, but a random occurrence, so human intelligence is required to inspect the graphs to estimate if the funnel is being led by an indicator. Furthermore, this correlation analysis needs to be updated once enough data has accumulated to assess whether the indicators still seem to lead the sales funnel.

Figure 3-3 represents the German CLI and the three month rolling average € of offers in Germany, before and after synchronization.

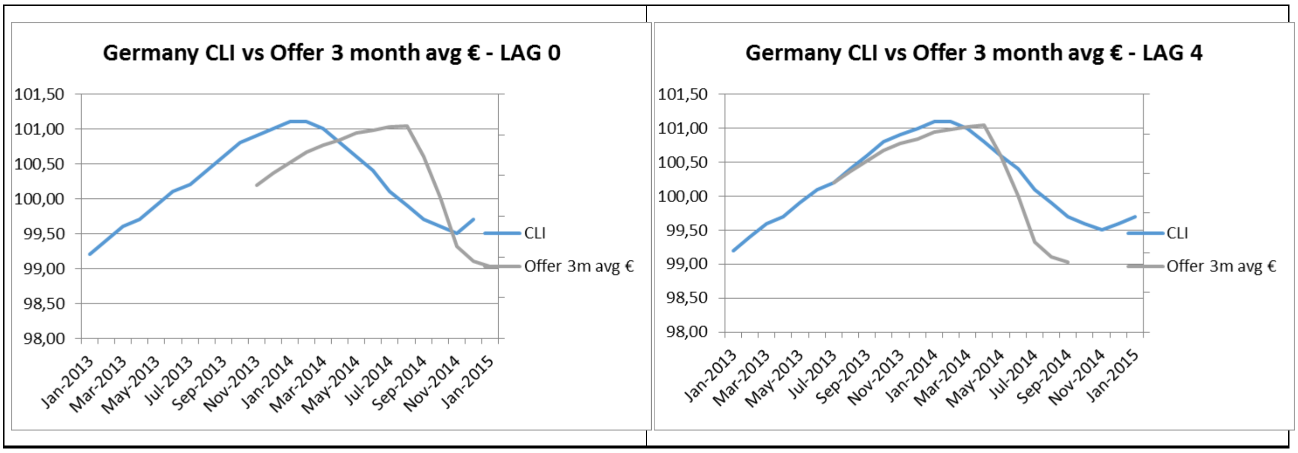


Figure 3-3. Synchronization of funnel and indicator in Germany

As can be observed, the Composite Leading Indicator does indeed seem to lead the German offer base (€) to some degree by roughly four months. The y-axis on the left represents the indicator values, whereas the offer base values on a separate axis are omitted due to confidentiality. After synchronizing the funnel and the CLI, the correlation coefficient between the two variables is 0.948. This is very strong and implies significant dependency between the offer base and the CLI with a lag of 4 months. Graphical inspection of Figure 3-3 does seem to imply the same as the correlation statistic: the relationship of the funnel and the indicator seems to be strong. Theoretically, we should choose the indicator and lag based on the highest correlation, but human intelligence is necessary to inspect the relationship graphically. In this study, the offer or hot offer base will be lagged up to six months for each indicator in each country.

Essentially, the process above was repeated for all of the ten countries and Europe. The other three regions must be excluded from this phase because there are no indicators available that represent these geographic regions. This is because the regions are imaginary aggregate geographical areas combined together for strategic purposes of the case company. These regions will be included for the last phase of the analysis. Appendix 1 is a compilation of the full correlation tables for each country, indicator and lag term, whereas figure Appendix 2 is a graphical representation of the leading indicators and sales funnel for each country where a strong relationship was discovered.

3.4.2 Volatility in the sales funnel

In the course of the correlation analysis, certain observations can be made regarding the applicability of the leading indicators in predicting the sales funnel. It seems that the lower the sales funnel volumes, the more subject the offer or hot offer base is to variation from individual sales cases. Using the rolling averages will alleviate this, but if the variation is bad enough, the indicators or indices are unlikely to correlate very well with the funnel base. Inversely, if the volumes are large enough so that they cannot be distorted by individual cases, they are likely to correlate better with their respective indicators. Figure 3-4 below represents a situation where the funnel variation is too high.

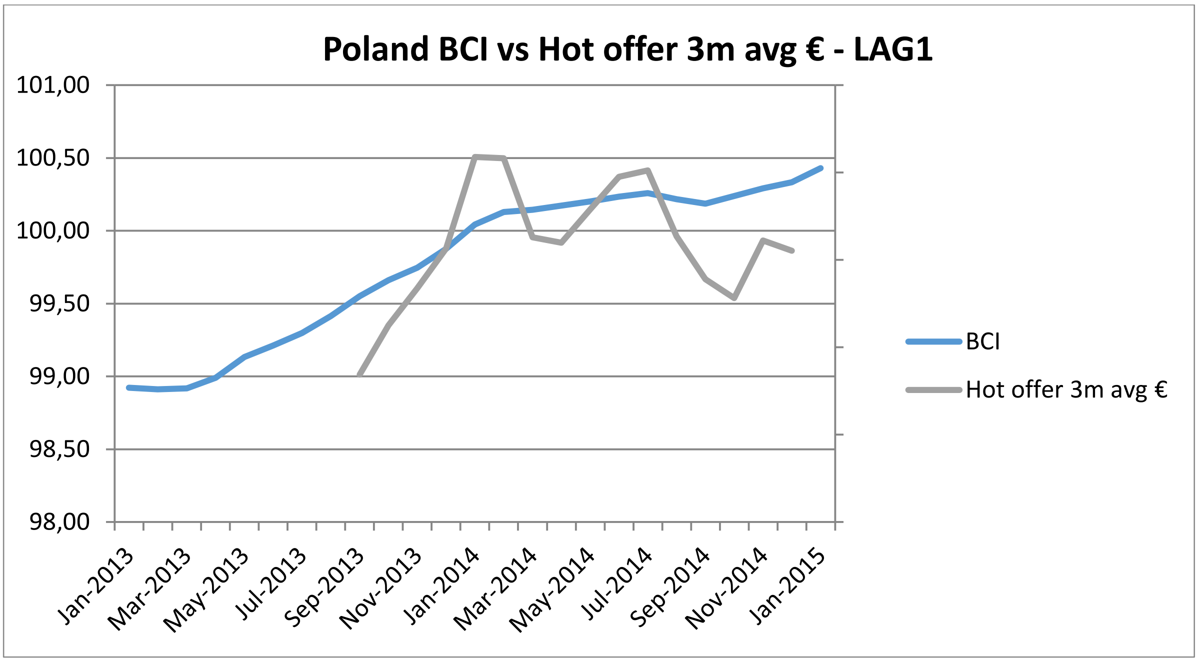


Figure 3-4. Volatility in the sales funnel

Poland was excluded from this study for this very reason, but it serves well as a reminder to pay attention to variation in the funnel base levels. In India the funnel is both volatile and uncorrelated with the indicators, rendering it invalid for leading indicator forecasts. China and Australia exhibit signs of volatility in the sales funnel as well, presented in Appendix 2. An attempt to predict the sales funnel with leading indicators in China and Australia will still be made based on their acceptable correlations with the indicators, to see how the indicator-funnel forecast performs under moderate volatility.

The indicators aim to project economic fluctuation, so it follows that the sales funnel volumes must be high enough to correlate with the indicator and not be distorted by individual larger sales cases. A prime example of stable volumes is observable in the case company's region Europe, where the sales funnel volumes are so high that they are truly led by macroeconomic composite indicators or indices. This is illustrated in Figure 3-5 below, after synchronization.

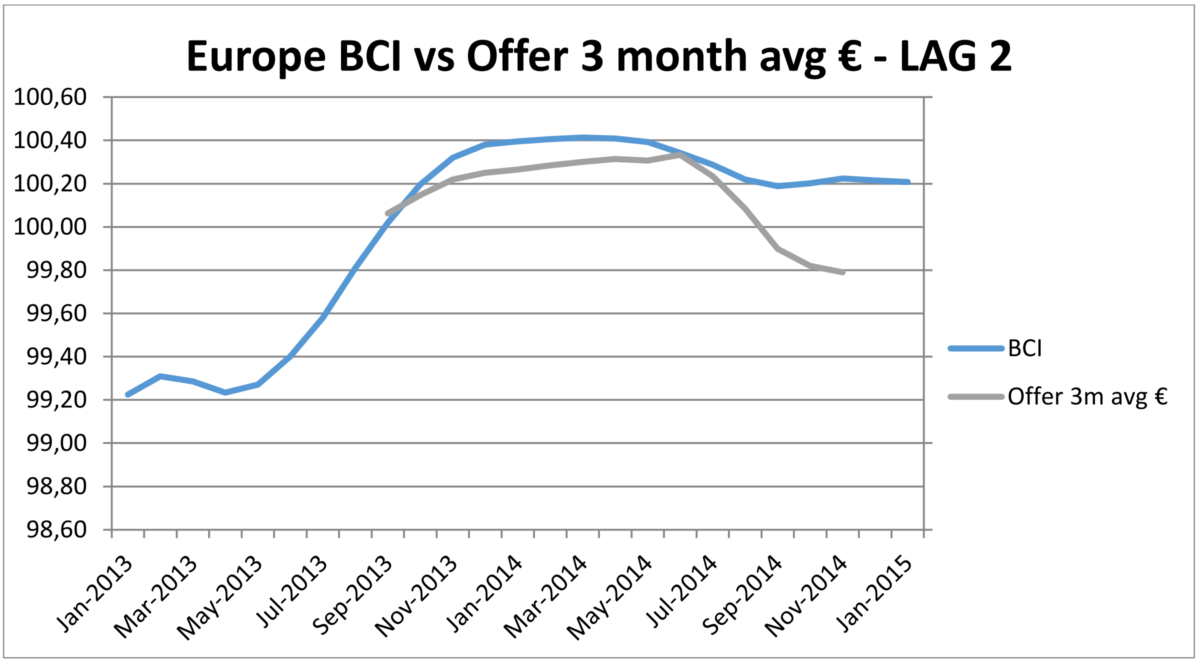


Figure 3-5. High volumes bring stability

3.4.3 Volatility of the indicators

Just as volatility in the sales funnel deteriorates the predictability of the values, the sensitivity of the indicators impacts the forecasting performance of the model. Some indicators are more sensitive than others. In general, the more input the indicator contains, the more stable it is. Larger economies, such as Europe or the United States exhibit more stability in their indicators than e.g. Sweden. Naturally, this stems from the fact that the sample size in the surveys used for the indices is larger and that the variables included in the CLI are more stable.

The CLI and the BCI appear to be more stable than the MPMI for the countries in this analysis. Two examples of volatility in the MPMI are presented in Figure 3-6. The variation of the MPMI is the most pronounced in the U.S.A and Australia and was observable in the rest of the countries as well. The key implication of indicator volatility is that it will deteriorate forecasting performance, just as sales funnel volatility will. It will manifest as poor correlation with the sales funnel.

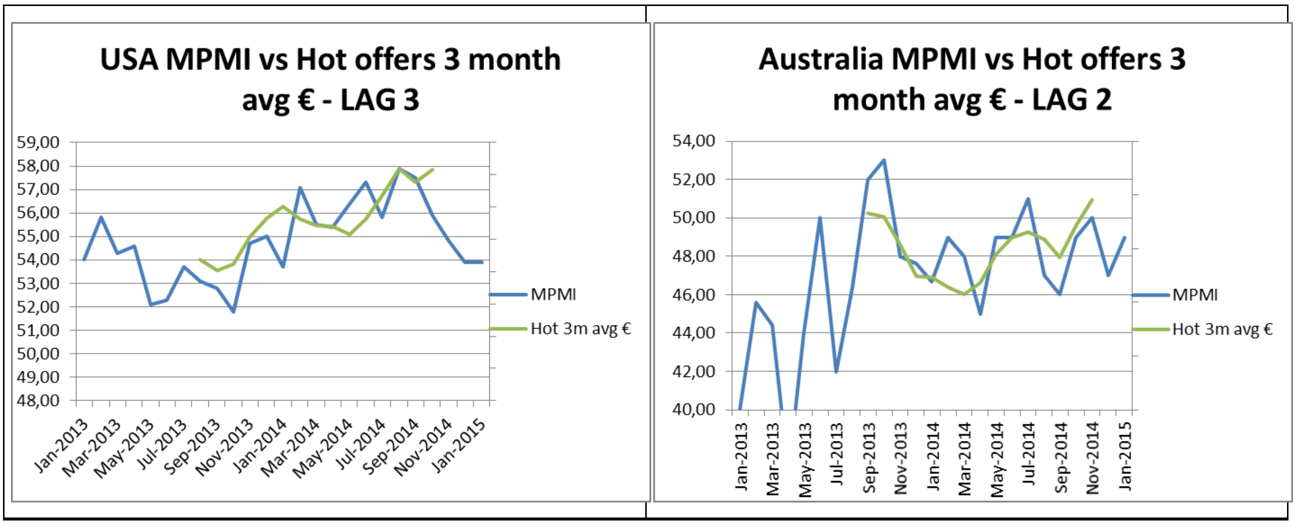


Figure 3-6. MPMI volatility

3.4.5 Regression results

The cross-analysis of each country with its respective indicators and lag terms up to 6 months is presented in Appendix 1. The next step is to select a leading indicator and its respective lag term for each country to be used in actually forecasting the funnel. This is reported in Table 3-3:

Table 3-3: Indicators chosen to forecast the sales funnel

Indicator-funnel relationships

Country	Variable	Indicator	Lag	Correlation
USA	Offer 3m average €	BCI	4	**0.945**
China	Hot offer 3m average €	BCI	1	0.763
Canada	Offer 3m average €	CLI	2	0.881
India	N/A	N/A	N/A	N/A
Germany	Offer 3m average €	CLI	4	**0.948**
UK	Offer 3m average €	BCI	1	0.727
France	Offer 3m average €	BCI	5	**0.947**
Australia	Hot offer 3m average €	BCI	1	**0.911**
Sweden	Offer 3m average €	BCI	1	0.884
Austria	Offer 3m average €	CLI	4	0.846
Europe	Offer 3m average €	BCI	2	0.707

The choice of indicator for each country was based not only on their correlation with the funnel values, but also on whether they graphically seem to lead the funnel to the human eye. It seems that the offer base at the case company is more often led by an indicator than the hot offer base. This is logical in the sense that the offer base represents a much larger volume than the hot offer base, thus capturing economic fluctuation better. As observable, India was excluded from the results due to the volatility of the funnel volumes which severely impairs the predictability with leading indicators. On the other hand, many of the countries exhibit strong correlation with their indicators and show promise with all correlations over 0.7. It also seems that nearly all of the countries with stable funnel volumes correlate the best with a more stable indicator.

As expected, the correlation of the sales funnel and the MPMI was generally low due to the sensitivity of the indicator. It can be stated that the MPMI is not an appropriate indicator for the case company for this very reason. The majority of the countries correlated the best with the BCI, especially France and the U.S.A. In these countries the sales funnel seems to follow the developments of the BCI, implying that these indicators consist of variables that impact the future demand. The CLI yielded highest correlations in Germany and Austria. These indicators are more stable, just as the sales funnel in the countries is too. It is surprising that France and the U.K. had such different lag terms after synchronizing the BCI when the countries' economies are so intertwined. However, the difference is most likely attributable to the sales funnel: the U.K. funnel may simply not be led by a macroeconomic indicator, whereas the France sales funnel seems to be. Different countries have different salesforces, sales processes and market shares. It follows that their sales funnels will behave differently too.

From these results, we may progress to forecasting the historical funnel values using a linear regression model. If a country has a lag of only one period with its leading indicator, it can be argued that the extension of forecast visibility is marginal and that these indicators are almost coinciding rather than clearly leading the funnel. Such is the case in Sweden, Australia in China. The sales funnel in these countries could equally well be projected one period into the future using a simple exponential smoothing model, although exponential smoothing is retrospective and does not account for dynamism in the market. For the countries with longer lag terms, the funnel value can be projected into the future by as many periods as there is lag between the funnel and the leading indicator.

The linear regression model is given below.

Equation 1: Indicator regression model

$$Y_{t+n} = \alpha + \beta IND_t + \varepsilon \qquad (1)$$

Where

Y_{t+n}= Funnel variable in period t + n

α=Intercept , $\beta = Coefficient\ for\ Indicator$

$IND_t = Leading\ Indicator\ in\ t$

$n = optimal\ lag\ between\ variable\ and\ indicator, \varepsilon = error\ term$

In the table below are the results of the regression analysis. The Mean Average Percentage Error (MAPE) describes how well the regression model was able to forecast the funnel's offer or hot offer base *in-sample* compared to the realized historical funnel bases periodically. The MAPE is the average of the absolute percentage errors through the forecasting history. In this study, a MAPE value of under 20% is considered good, 20%-50% satisfactory, and over 50% poor. The accuracy of the forecast is thus 1 – MAPE. In reality, scaling the MAPE from good to poor varies greatly firm to firm, but the scale should reflect the forecasting performance required by the company. The formula for MAPE is given below.

Equation 2: MAPE formula

$$MAPE = \frac{\sum(^{|Yt - Ft|}/_{Yt})}{n} \qquad (2)$$

Table 3-4: Results of forecasting the funnel with linear regression

Country	CRM variable	Indicator	Lag	MAPE	P-value (Ind)	P-value (alfa)	R-Squared
USA	Offers €	BCI	4 months	10%	< 0.001	< 0.001	0.893
Germany	Offers €	CLI	4 months	**9%**	< 0.001	< 0.001	0.899
Europe	Offers €	BCI	2 months	**6%**	0.004	0.003	0.499
Canada	Offers €	CLI	2 months	**5%**	0.002	0.002	0.545
UK	Offers €	BCI	1 month	**3%**	0.029	0.018	0.412
Australia	Hot offers €	BCI	1 month	48%	< 0.001	< 0.001	0.682
China	Hot offers €	BCI	1 month	16%	0.003	0.003	0.566
France	Offers €	BCI	5 months	13%	< 0.001	< 0.001	0.897
Austria	Offers €	CLI	4 months	**8%**	< 0.001	< 0.001	0.716
Sweden	Offers €	BCI	1 month	16%	< 0.001	< 0.001	0.782

Table 3-4 shows the results of the regression analysis. The linear regression model is statistically significant in all of the analyzed countries, but its performance in predicting the historical funnel values varies. On average, the regression model was able to forecast the funnel values with a MAPE value of 13%, or an accuracy of 87%. The regression model performed admirably in predicting the offer or hot offer base for the countries selected, with the exception of Australia. This is attributable to the volatility of the sales funnel in Australia. Appendix 3 illustrates the historical indicator forecasts for the sales funnel in the USA, Germany, Europe, Canada, France and the U.K. The sales funnel volumes in these countries is high enough for the desired level of stability for indicator forecasts.

The forecasting capacity of the regression model using leading indicators should be tested out of sample (Marcellino, 2006). The results *in-sample* are promising and encourage further research once there is sufficient data for out-of-sample testing. It seems like leading indicators can indeed be incorporated into forecasting the sales funnel. What ultimately dictates whether leading indicators can be used for this purpose is the volatility or variation in the funnel base and the leading indicators. If there is much variation, or if the funnel base is so small that individual sales cases can cause a significant peak in the funnel base, leading indicators will not be likely to correlate very well with that funnel. It seems that higher sales funnel volumes bring stability which in turn improves the predictability with leading indicators. Similarly, the more volatile the leading indicator, the more dependent the sales funnel needs to be and the more difficult forecasting becomes.

How can a company translate these sales funnel values to actual order level forecasts then? Next a practical model for this is proposed and tested against actual historical order levels as well as the case company's own historical forecasting performance.

3.4.6 From the sales funnel to orders

To recap, the very end of the sales funnel was selected for this study because the probability of converting these sales cases to orders is the highest. Furthermore, the sales funnel volumes for offers and hot offers were extracted in monetary sums. This is logical because the financial order level forecasts are given in monetary sums as well. Forecasting the historical sales funnel volumes with leading indicators yielded encouraging results. The next step is to translate these sales funnel volumes to order levels.

It is prudent to explain what range of time horizon the sales funnel is able to forecast. In the context of the case company, the sales funnel *cycle time*, i.e. how fast sales cases travel through the funnel, is relatively slow. In the product line chosen for this study, sales cases currently in the offer or hot offer phase are assumed by experts at the company to convert to orders within the next three months. The cycle time of the sales funnel varies by industry and even by firm. Determining how fast sales cases move through the funnel on average is important, as this directly impacts how far we can expect to project an order level forecast from the sales funnel. For the case company, a cycle time of three months from the offer base to orders implies that we can use the sales funnel to forecast the next three months' order intake. From Figure 3-1 (forecast horizon) it is evident that the sales funnel based forecasts should thus be compared against the case company's own 3-month forecasts, i.e. the forecast for the next quarter (Q).

The forecast practitioner could theoretically use either the offer base or the hot offer base to forecast order intake. It is sensible to use the same funnel variable here that was used in the regression model. Thus the practitioner may project the funnel base into the future with leading indicators and then convert that base into order intake for the next three periods. However, if the forecasting horizon of the next three months is sufficient and the leading indicators are excluded from the forecasting model, it is possible to use either of the sales funnel variables at the end of the funnel.

Having determined the conversion time from the end of the funnel to orders to be roughly three months, it is necessary to estimate a *conversion rate* for the offer or hot offer base to the next three months' orders, i.e. what percentage of the funnel base translates to orders. This is in practice the same as the win rate or hit rate of offers. One way of doing this is a simple optimization model, where we compare our *rolling three month forecast* (i.e. period to period) with historical rolling three month order values. We need to find a single parameter, or conversion rate, that translates our current funnel base into the next three months' orders while minimizing the MAPE from this rolling historical comparison.

An example is in order. Our sales funnel's offer base at the end of June should produce the order forecast for July, August and September. This lump sum represents rolling quarterly orders and can be estimated by optimizing a parameter λ that represents the conversion rate of offers to orders. This can be achieved by comparing the forecasts to actual historical rolling quarterly forecasts, calculating the MAPE for each forecast, and minimizing the average of all the MAPE values. The optimal parameter will yield the lowest total MAPE throughout the history. The process is repeated for each country, so each country will have their own parameter. One tool for solving this optimization problem Microsoft Excel's Solver. Using a single parameter for each country is based on the assumption that in the long run, the conversion rate from the funnel to orders is relatively stable and converges to some number. The problem is formulated as:

Equation 3: Sales funnel-based order forecast

$$Orders\ for\ next\ 3\ months = \lambda Y_t \tag{3}$$

Where

$\lambda = optimized\ parameter\ that\ minimizes\ average\ MAPE\ of\ all\ observations$

$Y_t = Current\ sales\ funnel\ base\ value$

It should be noted that this very simple model assumes the conversion rate to be relatively stable. If the rate is actually volatile, this model will not work. However, for the case company, the cycle time and conversion rate from the funnel to orders are believed to be quite stable, so this model is worth testing. The true test, like in the regression model, should be conducted out of sample with more data. Once the case company has accumulated enough data, the conversion from the sales funnel to orders should be attempted with a linear regression model too. However, this regression model will be equally powerless in the event that the conversion rate changes and would need to be recalibrated eventually as well. The benefit of using the *conversion rate* logic is that forecast practitioners may simultaneously monitor the win rates from offers to orders. A substantial drop in the win rate will deteriorate sales funnel-based forecasts, but the change will be noticed immediately.

Now let us examine the results from the sales funnel to orders conversion. Note that this forecast does not yet incorporate leading indicators, but uses actual historical sales funnel values. Was the sales funnel-based forecasting model any better than the current forecasting technique used by the case company? This can be assessed by comparing the realized quarterly orders with both the sales funnel-based forecasts as well as the case company's own next quarter's forecasts. For the regions that did not have a leading indicator and a predefined sales funnel variable, both the offer base and the hot offer base were tested, and the one yielding the best results was selected.

Table 3-5 represents the results of forecasting next quarter from the sales funnel versus the case company's own forecast. In the table, dark green cells represent excellent accuracy (MAPE under 10%), whereas light green cells represent good accuracy (MAPE under 20%). A MAPE of 20-50% is considered neutral and colored yellow, whereas a MAPE of 50% and over is considered poor and colored red.

Table 3-5: Sales funnel-based forecasting performance

Country	Funnel variable	Sales funnel MAPE	Case company MAPE	Case company actual MAPE
USA	Offers €	15%	53%	25%
Germany	Offers €	17%	23%	30%
Europe	Offers €	**7%**	**5%**	11%
Canada	Offers €	22%	13%	32%
UK	Offers €	31%	64%	32%
Australia	Hot offers €	32%	77%	76%
China	Hot offers €	22%	56%	52%
France	Offers €	29%	67%	45%
Austria	Offers €	20%	36%	30%
Sweden	Offers €	28%	17%	41%
Region 2	Offers €	23%	39%	29%
Region 3	Hot offers €	30%	28%	16%
Region 4	Hot offers €	41%	25%	30%
India	Hot offers €	56%	110%	105%
	Average	**27%**	**44%**	**40%**

In forecasting the next quarter's order intake, the sales funnel based forecasting model produced a more accurate forecast in 9 out of 14 cases than the case company in the sample. On average, the sales funnel based forecast performed 17 percentage points more accurately than the current forecasting technique. However, upon inspecting the accuracy of the case company's forecasts from the last 6 years, indicated as *actual MAPE* in the table, we may observe that the sales funnel based forecast was superior 12 out of 14 times. In the countries or regions where the sales funnel could not produce a reliable forecast the order levels tend to be rather volatile. This may be the result of such small order volumes that large sales cases cause a peak, or because the demand in these areas is naturally more volatile. Either way, it seems that the sales funnel based forecast requires a certain degree of stability in both the funnel and the order intake. Figure 3-7 graphically illustrates four exemplary cases where the sales funnel was able to forecast the order levels well. As observable, the funnel forecast is relatively stable, meaning that the funnel volumes and order levels in these countries have relatively little variation.

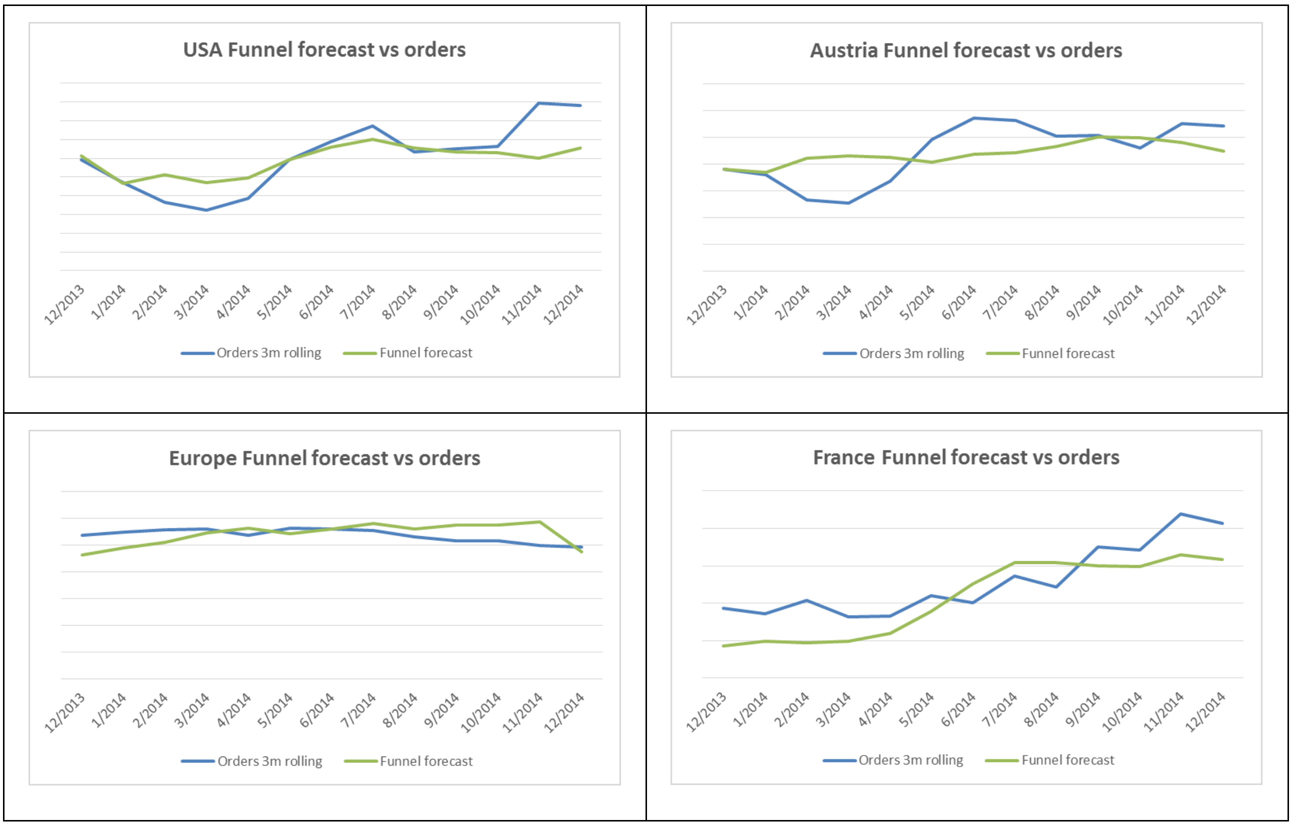


Figure 3-7: Sales funnel based forecasts

With the encouraging results from both the leading indicators predicting the sales funnel, as well as the sales funnel predicting orders, it is time to combine the two into one single model and test its applicability. Thereafter, the results will be summarized and the key considerations in using such a model discussed.

3.4.7 Synthesis

Integrating the leading indicators and the sales funnel together into a single model to forecast orders has two key benefits:

1. Extended visibility. The leading indicators, depending on the lag, will project the sales funnel into the future based on actual market development
2. Improved accuracy. The sales funnel, a source of real time prospective demand, will provide better estimates of actual order intake than models using solely historical data, if the demand is volatile.

Figure 3-8 illustrates the forecasting horizon of the new model. This varies in each country or region, depending on their synchronization lag (n).

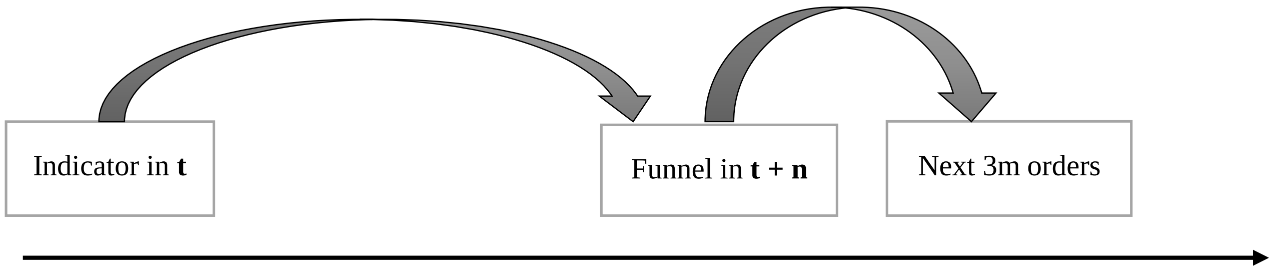


Figure 3-8. Forecasting horizon of the new model

To test the performance of the hybrid model (incorporating both leading indicators and the sales funnel), we may simply predict the historical funnel base using the historical leading indicators for each country using the linear regression model and then use the forecasted sales funnel base to predict order intake with conversion rates. This analysis will exclude the regions that do not have leading indicators. The forecasts produced by the hybrid model will be compared to the Q, i.e. next quarter's forecasts of the case company. The results are presented in Table 3-6:

Table 3-6: Hybrid model forecasting performance

Country	**Hybrid model accuracy**	**Case company MAPE**	**Case company actual MAPE**
USA	26%	53%	25%
Germany	13%	23%	30%
Europe	**7%**	**5%**	11%
Canada	19%	13%	32%
UK	31%	64%	32%
Australia	43%	77%	76%
China	31%	56%	52%
France	19%	67%	45%
Austria	18%	36%	30%
Sweden	21%	17%	41%
Average	**23%**	**44%**	**40%**

The results from predicting the funnel base with leading indicators and further the order intake from the sales funnel are good. Interestingly, the hybrid model performed even better in this sample than the sales funnel component alone with an average MAPE of 23%. The hybrid model beat the case company's forecasting accuracy nine times out of ten in the lifespan of the CRM system, and 10 times out of 10 if comparing with the true historical MAPE of the case company.

Technically, using both the leading indicators and the sales funnel in predicting order levels will subject the forecast to two sources of error, one from each component. However, the hybrid model performed rather well in sample. As for the two components individually, the hybrid model should be tested out of sample with more data to validate the results.

Despite the promising performance of the hybrid model, an analyst at the case company pointed out an important consideration in its applicability. The lag from the leading indicator model, varying for each country or region, makes the model an unstandardized forecasting technique, meaning that each country needs their own indicator and lag. This leads to multiple non-uniform forecasting horizons – a potentially undesirable situation in e.g. a large corporation. Thus it is proposed here that the leading indicator component be treated as a "set of binoculars" in the case company that the forecast practitioners or decision makers may use as a source information, rather than an official forecasting technique. If the constraints of a uniform forecasting model for different countries can be relaxed, or if there is only one country in the analysis, the hybrid model will be fully usable.

3.4.8 Applicability and performance of the forecasting model

The sales funnel based forecast of the next three months' order intake is valuable, but the forecast for the next three months can be used to improve the forecasts for two quarters away as well, i.e. for Q+1. Even though the sales funnel at the case company will not be able to project a forecast so far into the future itself, it can be used to adjust the Q+1 forecasts by a naïve approach explained below.

For example, if our sales funnel-based system forecast for the next 3 months, or the next quarter (Q), is 3MEUR, and the case company forecast for Q+1 is 6MEUR, there is a great discrepancy between the two estimates. Knowing that our system forecast leverages the actual current sales funnel levels, reaching this 6MEUR would require doubling either the funnel value or the funnel win rate. Neither of these is likely to happen in one quarter's time. Thus, by taking a *median* of the system forecast for Q and the company forecast for Q+1, we may adjust the Q+1 forecast to the desired direction. This way we are producing a system forecast for Q and a consensus forecast for Q+1. Figure 3-9 illustrates the mediating role of the sales funnel forecast graphically.

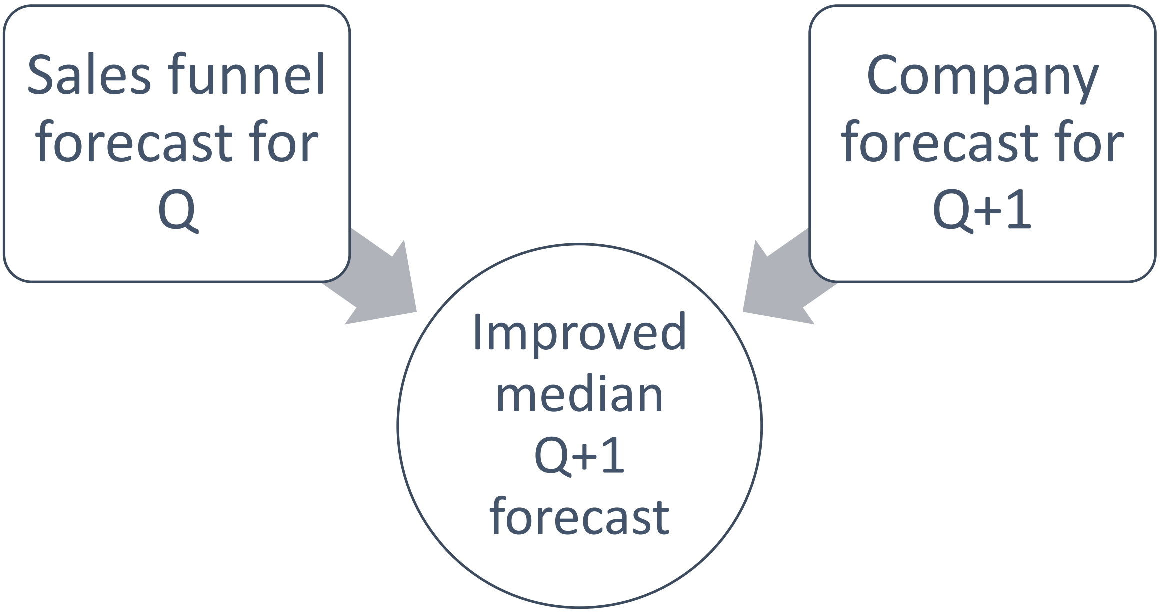


Figure 3-9: Sales funnel improving the Q+1 forecast

Table 3-7 presents the results of forecasting the Q+1 order intake with a median between the Q sales funnel forecast and the Q+1 case company forecast. The accuracy of the median technique is reported in the "Naïve MAPE Q+1" column.

Table 3-7: Sales funnel-based naive forecasting performance for Q+1

Country	Naive MAPE Q+1	Case company MAPE Q+1	Case company actual MAPE Q+1
USA	49%	74%	34%
Germany	22%	47%	43%
Europe	11%	13%	25%
Canada	25%	33%	38%
UK	49%	57%	28%
Australia	38%	61%	112%
China	32%	73%	54%
France	27%	67%	44%
Austria	26%	27%	29%
Sweden	29%	31%	61%
Region 2	26%	38%	28%
Region 3	26%	46%	21%
Region 4	34%	23%	38%
India	29%	94%	162%
Average	**30%**	**49%**	**51%**

The values in the column “Naïve MAPE” represent the mean average percentage errors for each country or region using the median approach. The two other columns represent the case company’s forecast accuracy for the CRM system’s lifespan and the entire history, respectively.

It is evident that forecasting performance deteriorates the further you try to predict. However, 13 out of 14 times the naïve approach yielded a better average forecast accuracy than the case company’s current method. This suggests that the sales funnel can give you a *reality check* for forecasts beyond its own horizon. Using the funnel like this permits us to extend the forecast horizon from Q to Q+1, although this technique needs a Q+1 estimate from the current method. Still, using the sales funnel as a measure of discrepancy between these forecasts seems prudent.

Before concluding the “Analyze” phase of the DMAIC approach, it is informative to summarize the findings. First of all, it was established that some of the selected indicators do indeed lead the sales funnel of the case company. Using the indicators and a linear regression model, we were able to forecast the historical offer or hot offer bases at an accuracy of 87%, or with a MAPE value of 13%. From there on, using the optimized parametric conversion rate from the sales funnel to orders for the next quarter resulted in an improvement of 17 percentage points in forecast accuracy. Furthermore, taking the median of that forecast and the case company’s forecast for Q+1 substantially improved the forecast accuracy for Q+1 forecasts by 19 or 21 percentage points, depending on what the time frame was for the measurement of accuracy. Finally, combining the leading indicators and the sales funnel for forecasting order intake improved the historical forecasting accuracy by 21 percentage points. These findings imply that a sales funnel-based forecast is superior to the current forecasting method used by the case company.

What should this forecasting model be used for then? Using the sales funnel will provide good estimates of short-term demand, or the next quarter at the case company. That estimate can be used to adjust the forecasts one quarter further. Using the leading indicators with a regression model will extend the visibility by predicting the sales funnel values n periods in the future.

It is imperative to remember that this forecasting model needs to be complemented by human intelligence. Thus it is a baseline forecast produced by the system. The baseline forecast from the sales funnel needs to be evaluated by experts who have contextual knowledge of their product lines. For example, if the system produces a forecast, a manager may know for a fact that a certain sales case will be won and that it will realize into orders in the next quarter. Thus the manager can adjust the baseline forecast using her contextual knowledge. In this sense, the final component of this forecasting model is *judgmental adjustment*. Figure 3-10 represents the relationship of the individual components, as well as the deteriorating factors that limit the usability of the model introduced earlier.

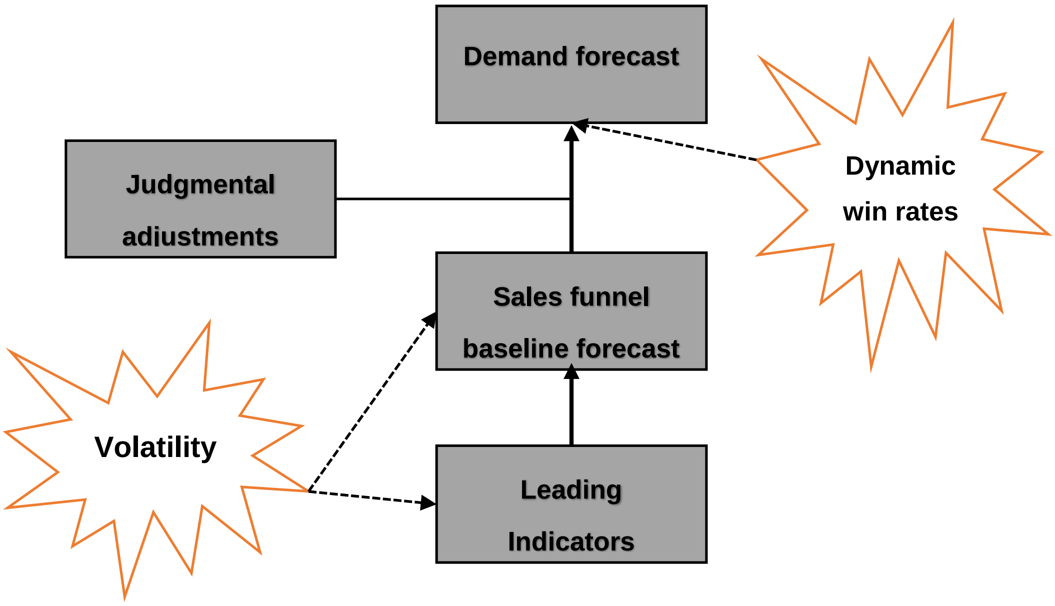


Figure 3-10: Deteriorating factors of forecast performance

The principal considerations in sales funnel-based forecasting are listed and elaborated in Table 3-8 below.

Table 3-8: Considerations in the use of leading indicators and the sales funnel

Attribute	Implication
Size of business / market share	• The sales funnel must be large enough to fluctuate with leading indicators. • The smaller the funnel volume, the bigger the distorting effect of individual larger sales cases in a project-based business.
Sales funnel cycle time	• The sales funnel can only forecast relative to its cycle time. If the cycle time is fast, it may render quarterly forecasts impossible.
Changing market dynamics	• Changes in the market share or win rate of offers necessitates recalibration of model.

Analysis	• Constructing this model requires rather extensive analysis in both the leading indicator and the sales funnel phases.

How should the forecasting process be tailored to benefit and support this type of a forecasting model? Furthermore, what other factors need to be considered when improving forecasting *process* performance? The next subsection identifies areas of improvement in the case company's forecasting process from a more holistic perspective.

3.5 Improve: Enhance the process

Improving a company's forecasting process does not only constitute giving them a turnkey forecasting model. At the case company, the issues in forecasting performance are more profound than model-specific. At the organizational level, forecasting management, accountability and company culture are of utmost importance in developing forecasting performance. Changing these factors can be a massive undertaking, far beyond the scope of this paper. However, recognizing the areas of improvement, as well as the organizational requirements of the newly built forecasting model is valuable to both the case company and the reader. Providing the case company with an assessment of the current state as well as the required level of proficiency in their forecasting management gives them a sense of direction for future improvement.

In this section, the sales funnel-based forecasting model will be assessed from the perspective of the forecasting management rubric by Mentzer et al. (1999). In more detail, each key dimension will be visited with regards to where the case company needs to be in order to successfully implement the new model. By comparing the requirements and the current status of the case company on the rubric, a way forward can be proposed (Moon et al., 2003) in terms of the key dimensions. Table 3-9 is the forecasting management rubric by Mentzer et al. (1999). On the rubric, the orange circles represent the current location of the company, or the *as-is* state, assessed earlier in the "Define" phase. The green circles represent where the company needs to be, or the *as-should-be* state, in order to implement the model and ultimately improve forecasting performance on a procedural level.

Table 3-9: Requirements of improving forecasting performance at the case company

Stage	Functional Integration	Forecasting Approach	Systems	Performance Measurement
1	• Disconnection between areas and lack of accountability	• Naïve forecasts • No real understanding of market environment in forecasting context	• Systems not linked electronically, manual transfer of data • No performance metrics in reports	• Accuracy not measured • Forecast performance not tied to any measure
2	• Coordinated meetings, but dominated by few areas	• Recognition of forecasts' business impact • Intuitive understanding of market environment	• Cross-functional links between systems • Performance measures available	• Accuracy measured • Performance measured based on accuracy
3	• Real consensus between functions • Rewards for accuracy	• Cross-functional forecast input • Strong management support • Advanced forecasting methods that incorporate market intelligence	• System allows for subjective input • Ad-hoc reports available • Systems are developed and respond to evolving needs	• Holistic understanding of the impact of forecast performance
4	• Forecasting is separate functional area • Cross-collaboration • Feedback loops	• Forecast and business plan are developed hand in hand • Top management committed to continuous improvement in forecasting • Continuous training in new methods	• Systems are open, so all internal stakeholders can provide input	• Multidimensional metrics of forecast performance • Forecast error triggers problem-solving process

Functional integration is critical to forecasting performance at the case company. Although the sales funnel-based forecasting model itself does not necessitate cross-functional input, the judgmental adjustments it undergoes do. As previous research on the field of judgmental forecasting suggests, the best way to improve this process is a cross-functional consensus. This has two benefits of paramount importance, alleviation of individual bias and sharing of information. A single manager adjusting forecasts will tend to introduce bias to the forecast, but a consensus forecast in the form of an average from individual point estimates will remedy this problem, as seen at the clothing manufacturer Sport Obermeyer (Fisher et al., 1994). As established earlier, the sales funnel-based forecasting approach should serve as a system-produced baseline forecast that is to be complemented and adjusted by human intelligence. At the case company, the forecasts currently travel from function to function with each department making their own adjustments to them. This is inefficient and does not fix the bias problem. Thus the case company needs to form a forecasting board for their judgmental estimates as regular protocol. The forecasting board should comprise all relevant stakeholders who need the forecasts and can contribute to the adjustments with their own expertise. Essentially, the way forward in the dimension of functional integration is to revamp the forecasting process by including relevant stakeholders to the judgmental adjustment process of the baseline forecast.

The forecasting approach should certainly be changed from the disparate regional practices to a common tool for baseline forecasts, namely the one constructed in this study. The case company has recognized the business impact of forecasting performance and acknowledges that the market environment dictates demand. From this plateau of recognition and understanding the case company needs to jump to the next stage of proficiency, where the judgmental forecasting input is cross-functional and the entire forecasting process is backed up by management support. The sales funnel-based forecasting technique combined with leading indicators can be regarded as an advanced forecasting method that leverages market intelligence in a quantifiable way, meeting the criteria of the next stage of proficiency. The way forward here is to sell the new tool to the management and start using and maintaining it. In the optimal scenario, the case company will start to develop their forecasting techniques on a regular basis, but giving the forecast practitioners access and support in the use of the model built in this study is a big step forward.

Perhaps the biggest area of improvement as well as the most critical requirement of the sales funnel-based forecasting model are the systems used for producing the forecasts. The systems determine how arduous it is to produce the forecast. Fildes and Hastings (1994) state that the more there is manual input, the more there is room for error. Furthermore, they note that the forecast practitioners in their study felt like there was too much manual data collection in the process. Such is the case with sales funnel-based forecasting as well. Extracting the data, analyzing the relationships of leading indicators, the funnel and order levels as well as measuring the case company’s historical forecast accuracy is an extensive task. The data for this study was extracted from three different sources and compiled together manually. In the long run, this is not sustainable. The systems at the case company are not integrated, so the forecast practitioner needs to manually compile and analyze the data. The systems are not developed as a response to the needs of the forecasters at any acceptable pace.

The way forward for the case company is to drive development in these systems to facilitate the extraction and analysis of data. If the systems were developed so that a single platform could store data on the leading indicators, the sales funnel, realized order intake and even the stakeholders' qualitative input for adjustments, maintaining sales funnel-based forecasting with cross-functional, consensus adjustments would be possible. This is by far the biggest requirement for the case company and the first port of call.

Performance measurement is currently acknowledged, but it does not have any significant impact on the forecasting process at the case company. That is, the subpar accuracy of the forecasts is known to have a negative impact on the operations of the company, but there is no official accountability or motivation for better forecasting performance. Forecasting accuracy measures cannot be gauged on a regular basis, as the systems do not currently calculate these metrics. What is needed is not only developing the systems to provide these metrics, but an organizational understanding of why forecasting performance is important and why it should be measured. The way forward is to establish accountability of forecasting performance, create motivators, develop the systems so that the measures are easily attainable and push forecasting performance towards an organizational competence and value. This will be covered in more detail in the "Control" phase of the DMAIC approach.

The preliminary implementation plan for the case company, as a big picture, can be assembled by compiling the *way forward* (Moon et al., 2003) in each *key dimension* (Mentzer et al., 1999) into a single table, given below. These two frameworks complement each other well, and form a logical setting to assess the company's current processes. Despite the case-specific context of the implementation plan in this study, combining the frameworks by Mentzer et al. (1999) and Moon et al. (2003) creates a useful tool that might work well in other contexts as well due to the generic nature of the key dimensions. These two frameworks work well together just for that reason: they are very generic. Moreover, they are a very clear and presentable way to show the management where there is need for improvement and how to progress to that direction. The summarization of these is presented in Table 3-10.

Table 3-10: Applying the frameworks of Mentzer et al. (1999b) and Moon et al. (2003) into the context of the case company

Key dimension (Mentzer et al., 1999b)	**Way forward** (Moon et al., 2003)
Functional integration	• Include relevant stakeholders for consensus-based judgmental adjustments in forecasting process

Forecasting approach	• Use sales funnel-based system forecast as baseline, complemented with consensus forecast adjustments
Systems	• Integrate disparate systems together to facilitate ad hoc analysis and reduce manual work • Provide forecasting performance metrics
Performance measurement	• Establish accountability for forecasting performance • Develop motivation system, e.g. incentives

3.6 Control: It's here to stay

The last phase of the DMAIC problem solving model constitutes controlling and monitoring the improved process. In the event of further need of improvement in the future, the DMAIC checklist can be revisited from whatever perspective it is that needs improvement. The DMAIC approach, like other process improvement approaches, is a reiterative continuum of monitoring, controlling and improving. This is a critical closure for the cyclical process model (CPM) of action research, as the paramount goal is to act upon an issue and *learn* from the solutions (Davison et al., 2004).

At any company, such as the one in this study, using the sales funnel or leading indicators will provide a quantitative baseline forecast produced by the system. If this is all that is needed, the DMAIC process can rest. However, if the issues in forecasting performance are more profound than that, more aspects of the forecasting process need to be considered. At the case company, forecasting performance is acknowledged, but mainly measured on an ad-hoc basis. It is not a key performance indicator (KPI) and calculating the accuracy measures is a manual process, when it should be one of the most readily available figures for all stakeholders in the company.

The main issue at the case company lies in the organizational culture and the forecasting process itself. The forecasts travel through several stakeholders and are adjusted by each one according to their needs. At the country level, this can result in biased estimates that the finance department, production and supply need to mark down based on their own predictions. This is not an efficient process. If the forecast practitioners were to adopt the sales funnel-based system forecast as a baseline and make consensus adjustments to it, the bias would be significantly reduced. Furthermore, in some areas sales forecasts and sales targets are systematically mixed up, causing a scenario where a manager will tell the forecaster that “their forecast is not enough”. The sales target should be 100% of the *sales forecast*, not vice versa. Otherwise the usually optimistic targets themselves introduce bias into the forecasts, resulting in deteriorated forecast performance and multiple coexisting forecasts for various stakeholders.

What comes to organizational culture in forecasting, the case company needs to promote two things: accountability and motivation. Although the two are intertwined, they can be pursued quite differently. As Davis and Mentzer (2007) and Fildes & Hastings (1994) suggest, accountability is critical to forecasting performance. If there is no feedback from the management back to those who produce the forecasts, it is unlikely they will ever be inclined to improve their forecasting methods. Accountability goes hand in hand with rewarding. If the forecast performance is excellent, the forecasters should be rewarded for their efforts. After all, improvements in forecasting performance were estimated to result in substantial direct and indirect cost savings, as well as facilitated operations for many functions by the stakeholders. Thus incentivizing forecasting performance can arguably yield more cost savings than incur costs.

Management feedback, accountability and reward systems can be considered as *extrinsic motivators* (Ryan & Deci, 2000) to forecasting performance. In addition to these, *intrinsic motivators* can play a role in the performance. For example, when forecasting performance is initially adopted as an incentivized KPI for the company with honest, constructive and continuous feedback from the management, it will slowly take root and become a *core competence*, assuming the company has the proper methods to produce the forecasts in the first place. It must be understood that forecasting performance is actually a cost saver that is of strategic value to the company. In the long run, provided that the methods are continuously improved and the management stays active in demanding and rewarding forecasting performance, the stakeholder functions of the forecasting process can start to regard it as a *core value* (Mi Dahlgaard-Park et al., 2006). This can be considered as the long-term objective in forecasting.

In the context of the case company, the lack of accountability and performance measurement are the first short-term things to fix. The forecasters currently producing judgmental estimates may not even know how accurately they are predicting demand, unless they are doing extremely poorly. Developing the systems to automatically provide calculations of various error and accuracy metrics would provide this information to whomever needs it. This should be emphasized when integrating the currently disparate systems in the future. In the optimal scenario, the forecasters would understand the value of consulting the sales funnel-based forecast in light of their own historical forecasting performance. This forecasting performance needs to be reported regularly and monitored as a KPI.

Since the forecasts are currently adjusted by each function according to their best estimates, there is a lack of accountability in the process. Furthermore, the interviewed stakeholders of the forecasting process unanimously stated that there needs to be more accountability for the forecasts, indicating that the matter is understood but not acted upon in the case company. In each country, the relevant stakeholders need to be identified because they can contribute to adjusting the forecasts. If these adjustments are done on a consensus basis, i.e. an average of the point estimates is used to adjust the sales funnel-based forecast, the process will be more streamlined *and* more accurate. The consensus board is then accountable for the forecasting performance and can be rewarded as an incentive to maintain it if they are doing well. Moreover, the management can give the consensus board feedback on a regular basis without having to contact the ones making adjustments individually.

Essentially, once the case company has successfully implemented the sales funnel-based forecasting model in one region and the subsequent countries and understands the requirements of the model in terms of training, accountability and systems development, they can import the new practices to other regions on a global scale. This is prudent, since simultaneous training of numerous forecasters in multiple countries is inefficient and will not lead to a uniform understanding of what can be done with the new model or how forecasts should be produced in the future. Having an internal benchmark region will facilitate the distribution of knowledge inside the firm. Moreover, if top management supports the transition to the new forecasting approach in one central region, management support can be secured more easily in other areas as well.

Finally, it is vital to understand the continuity in forecasting improvement. As mentioned earlier, the DMAIC model is not meant to provide a final, definitive solution to any problem, but is rather structured in a way that necessitates reiteration when improvement is needed. Drawing from this logic, the case company needs to monitor forecasting performance constantly and allocate resources to investigating any significant drops in performance. These can be caused by a number of things, such as changes in market share, win rates or demand variation, alerting the company to recalibrate the quantitative sales funnel-based forecasting model. Moreover, the forecasting process itself should satisfy the needs of all stakeholders and should be revisited from the DMAIC perspective in the event that it does not. Pursuing continuous improvement is a major step towards making forecasting performance a core competence and value.

3.7 Limitations and applicability

The findings of this study are based on a single industry-specific case study and are not fully generalizable or transferrable as such. The forecasting technique proposed in this thesis requires a sales funnel with a relatively slow cycle time and sufficient volume to correlate with indicators on an economic scale. Consequently, the market cover of the company in any country must be substantial enough to follow economic fluctuation. For example, a smaller company from the same industry as the case company in this thesis may not be able to use the same leading indicators, since its demand can be too volatile and greatly influenced by individual sales cases. This will deteriorate the forecasting performance of leading indicators. However, regardless of company size, the sales funnel itself is still a relevant source of information for demand forecasting. It is the forecasting horizon and technical method used to convert the funnel to orders that change firm to firm.

Company size also plays an important role in the generic improvement of the forecasting process. The forecasting management framework adapted from Mentzer et al. (1999) is targeted for medium to large-sized companies that:

1. Have a distinct forecasting process and systems
2. Have separate organizational functions that use the forecasts (e.g. production and sales)
3. Have capital-intensive decisions linked to forecasts

For companies that meet these criteria, industry is not necessarily a constraint in using leading indicators and the sales funnel. An example of this is the construction business that has a clear, project-based sales funnel. This funnel has a relatively slow cycle time and can be assumed to be led by some indicators. In this sense, as long as the aforementioned criteria are met, it is irrelevant whether the company is a manufacturer or provider of services. If the sales funnel’s cycle time is rapid, its role in forecasting is very different, but then so is the entire forecasting process. The capacity planning in an industry with rapid order fulfillment is more difficult because a safety buffer in capacity has an emphasized role. Moreover, using market intelligence for forecast visibility is more difficult from a faster sales funnel since the company would have to react very fast to market signals.

Ultimately, the formulation and testing of a sales funnel-based forecasting model requires a lot of data. In testing the dependencies of the sales funnel and leading indicators, the longer the historical time frame, the better. If the time frame is very short, good correlation with the sales funnel and some indicator may be random, or just a lucky coincidence. The amount of historical data in this case study was not sufficient to say for certain whether the indicators are truly leading the funnel. Moreover, the testing of the model was done in-sample. Even though the data was sufficient for building the generic model, it needs to be tested out-of-sample and once enough data has accumulated, the case company must perform the necessary recalibrations to the model.

The DMAIC approach for forecasting does not necessarily impose company-specific limitations. It is an applicable method for identifying areas of improvement in forecasting performance as long as there is a distinct and routine process for forecasting. Forecasting process improvement fits in well with DMAIC because it requires structure and logic due to its extensive nature. The DMAIC framework proposed in this study is best suited for medium to large-sized companies, just as the sales funnel-based forecasting technique, but it can be adapted to the contexts of smaller enterprises as well due to its logical structure and the generic nature of its steps.

4. Discussion

From the literature, the most important contributions of this study is the combination of the frameworks by Mentzer et al. (1999) and Moon et al. (1998) for evaluating the current state of forecasting management at a company and a way forward to improve it, the best practices of judgmental forecasting and the justification to use market intelligence in a forecasting model. Additionally, the DMAIC approach known from Six Sigma process improvement was tailored to a forecasting process improvement context. These findings formed the theoretical framework for improving the forecasting performance of a company in the case study. The case study, in turn, provided this thesis with the necessary tools to test the applicability of leading indicators and the sales funnel in demand forecasting. This forecasting model would then be embedded to a wider objective of improving the case company's forecasting process in general, introducing characteristics of *action research* to the paper.

In this section the case study will be summarized with regards to the DMAIC approach. Important findings and implications will be discussed and compiled into one coherent subsection. Thereafter, the research question and the objectives will be addressed to assess whether they could be met or not.

4.1 DMAIC and the case study

In the previous section, the forecasting process at the case company was examined with the DMAIC approach with hopes to identify areas of improvement in forecasting performance. Due to the extensive yet structured nature of the problem, the DMAIC approach appears to be a valid tool for improving the forecasting process while retaining sufficient focus.

The first step in this approach is to define and chart the forecasting process. It is important to identify the stakeholders of the forecasts, the time horizon of the forecasts and what they are fundamentally used for. Understanding the relationships of the various stakeholders is vital in determining who to talk to in a company. In this study, the forecasting process was charted by interviewing the key functions that use the forecasts. In the industrial manufacturing context that this study focused on, the key stakeholders at the case company were Sales, Production, Supply, Demand and Supply Balancing and Finance. Each of these functions has a distinct role in the operative planning of the company and has special insight on demand forecasting. The stakeholders expressed their frustration at the lack of accountability in the forecasting process, since the initial frontline order forecast would travel through the organization and undergo multiple adjustments before being used for planning. The fundamental reason behind so many adjustments was that the frontline forecasts are so unreliable that each function needs to adjust them or pay for the consequences.

Even before quantitative analysis, identifying the stakeholders gives you a clear picture of who should be present in the formulation of the forecasts. A consensus approach in forecasting will make the forecasting approach more efficient, less biased and more accurate, if the stakeholders' insight is consulted before making the forecasts rather than after. This way the forecasts would not have to travel through the organization, since the adjustments could be agreed upon jointly. Cross-organizational collaboration is not only a best practice of forecasting management (Mentzer et al., 1999), but a key guiding principle of demand planning (Cecere, 2013; Hoover Jr et al., 2002).

It is equally valuable to gauge the current perceptions of the forecasting process in the company in the "Measure" phase of the DMAIC approach. The key stakeholders at the case company were unanimously dissatisfied with the current forecasting performance, but not a single one could provide any accurate estimates. This revealed a fundamental lack of performance measurement practices in the case company's forecasting process. The reason for this information gap became evident in the interviews: the current systems do not allow for automated analysis or monitoring of forecasting performance and that producing these figures is a manual process. This is a situation that needs to be fixed regardless of whether a better quantitative forecasting model is available or not. After presenting the actual figures of historical forecasting performance in the countries and regions of this study, the stakeholders were surprised to see the degree of inaccuracy in the forecasts, the average MAPE for the next quarter's forecasts at 40%, and the average MAPE for Q+1 forecasts at 51%.

Additionally, in the "Measure" phase it is important to produce tangible estimates of the business impact of forecasting performance. At the case company, the biggest direct costs of dissatisfactory forecasting performance will be incurred by Supply and Production, but the indirect consequences will impede efficient operations throughout the stakeholders. Finance, for instance, needs communicate the forecasts to shareholders and Supply to the supply chain. Measuring the tangible impact of forecasting performance is difficult, but even so, the annual cost savings of a 10% improvement in forecasting performance was estimated to amount to over 10MEUR globally from supply, procurement and production costs.

In the "Analyze" phase, a new forecasting tool was developed for the firm using macroeconomic leading indicators and the case company's sales funnel. The motivation for this was to create an improved method for producing system baseline forecasts, with hopes to increase the accuracy of the forecasts and make them more market-responsive. Moreover, a better quantitative baseline forecast would facilitate the judgmental adjustments of the consensus-based forecasting approach. Regression analysis was used to predict the sales funnel volumes with leading indicators with high accuracy. The sales funnel's offer or hot offer base, depending on the country or region, was converted to the next quarter's orders with an optimization model. Using the forecast for the next quarter as a reality check for the Q+1 forecasts by the case company improved the Q+1 accuracy substantially. This was achieved by simply taking the median of the baseline Q forecast and the Q+1 company forecast.

The in-sample results of the forecasting model are promising. Using the sales funnel alone, the forecasting performance for the next quarter (Q) was improved by 17 percentage points, and by 21 percentage points for Q+1. When forecasting the sales funnel with leading indicators, and further predicting orders from those estimates, the forecasting performance was improved by 21 percentage points compared to the case company's historical performance. These results are motivating and encourage the practitioner to test the model out of sample.

Results of the "Analyze" phase provide an answer to the research question: *"Can we construct a feasible demand forecasting model using leading indicators and sales funnel data?"*. We may conclude that leading indicators and the sales funnel can be integrated together to produce rather accurate demand forecasts. At the case company, this technique was superior to previous methods in historical comparison. The sales funnel at the case company seems to follow the developments of leading indicators, making it an idea worth testing in other companies as well. Although the model yielded promising results, it comes with certain considerations regarding its applicability. These will be addressed in more detail momentarily by revisiting the research objectives of this study.

Regarding the implementation of the model and the overall improvement of the forecasting process, the key dimensions of Mentzer et al. (1999) were consulted: functional integration, forecasting approach, systems and performance measurement. It was established that a consensus approach should be implemented at the case company, pursuing cross-functional collaboration in the forecasting process. The forecasting approach should be the market-responsive, sales funnel-based baseline forecast complemented by consensus adjustments. The systems at the company need to be integrated together and developed so that monitoring of performance is possible. This is a requirement for sales funnel-based forecasting at the case company, as compiling the data is a highly manual process at the moment. Finally, performance measurement needs to be pushed toward the direction of a key performance indicator. One method of doing this is incentivizing forecasting performance, but the first step is to explain why the performance matters to the forecasters.

The final phase of the DMAIC approach is “Control”. This refers to constant monitoring of the process to make sure it performs well. In a forecasting context, good performance is ultimately only attainable by making people care. This makes it a matter of organizational culture. An important step for the case company is to establish accountability in the forecasting process and motivate the practitioners to good performance. This can only be achieved if the management demands and rewards for it. In the long run, forecasting performance needs to be a core value at the company, so that it can be a core competence in the future.

4.2 Revisiting the research objectives

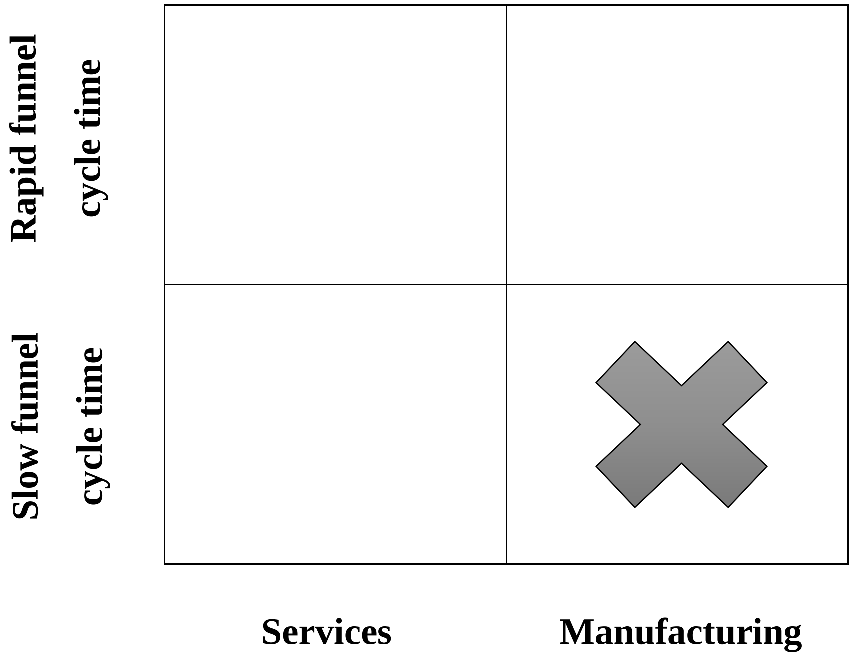
To address the research objectives of this paper:

1. *Describe the most important considerations in the development of the forecasting model (generic)*
2. *Describe the applicability of the model in the business context (generic)*
3. *Develop an implementation plan of the forecasting model for the case company to improve the forecasting process on the whole (case-specific)*

The first objective was accomplished in the “Analyze” phase of the case study. The principal considerations relating to the development of a sales funnel-based forecasting model with leading indicators pertain to volatility, sales funnel cycle time and type of business. It was earlier established that the variation of demand in the sales funnel will deteriorate the predictability with leading indicators. Similarly, the volatility of the indicator will deteriorate the forecasting performance of the model. The optimal scenario for the use of this model is a stable sales funnel and a stable indicator. It would seem that higher sales funnel volumes smooth the influence of individual sales cases and reflect the economic situation better.

With regards to the sales funnel cycle time and type of business, the analysis in this paper focused on an industrial manufacturer with a relatively slow sales funnel cycle time. In this segment at least, it can be argued that the sales funnel and leading indicators can be applied to forecasting. Table 4-1 illustrates the focus of this study. In a business with much faster cycle times, e.g retail or rapidly moving consumer goods, leading indicators may be more difficult to identify. However, in a business with a relatively stable sales funnel and a slower cycle time, industry may not be a limitation. For example, the construction business uses a very similar sales funnel as was presented in this study, despite being a service. Leading indicators are likely available for this industry, so sales funnel-based forecasting is a valid approach for this segment.

Table 4-1: Research focus



The second research objective was accomplished in the "Analyze" phase (subsection 3.4.8), where it was established that the sales funnel-based forecasting model should be used as a short-term baseline forecast, complemented by judgmental adjustments formed by a cross-functional forecasting board. Leading indicators can be used to extend the visibility of the forecasts. The sales funnel itself was found to produce best estimates of the next quarter's order intake, in accordance with the assumed cycle time of the funnel. The forecast for the next quarter (Q) can improve the Q+1 forecast by taking a median of the two. The components of the model are presented below.

The third research objective was thoroughly examined in the "Improve" and "Control" phases of the DMAIC approach in the case study. Adapting the framework by Mentzer et al. (1999) and extending it with the framework by Moon et al. (2003) creates a useful tool for measuring where the company stands now in forecasting management proficiency and where it should go from there. In the context of this study, the sales funnel-based forecasting model necessitates a certain level of proficiency in forecasting systems, due to the fact that it compiles data from multiple sources. The sales funnel-based model itself is an advancement in the dimension of forecasting approach, as it integrates market intelligence into the forecasting process. What comes to improving the forecasting process at the case company as a whole, key areas of improvement are performance measurement, to promote accountability in the process, and functional integration, to ensure efficiency in the process and establish a consensus approach to formulating the final forecasts. Making forecasting performance a core value in the firm is of paramount importance and the key to this accountability and motivation.

Essentially, the forecasting model developed in this study gives regional and country-level forecast practitioners a real-time source of potential demand from the sales funnel, and the tools to use it in forecasting order intake. This quantitative baseline forecast is meant to support their decision making, make their job easier and ultimately improve forecasting performance. Furthermore, the availability of leading indicators gives the company a chance to plan their future operations based on how the economy is fluctuating, constituting a big step toward proactivity.

4.3 Lessons learned at the case company

Having seen the forecasting potential of their sales funnel, the case company is motivated to implement this forecasting model fully in the Europe region, and distribute it as a “ready concept” from there to the rest of the organization. They are currently investigating how to include the most relevant stakeholders into the forecasting process, pursuant of consensus forecasting. The firm is already talking to suppliers of systems solutions with the hopes of integrating their platforms and facilitating not only forecasting, but operative planning as a whole. Performance measurement and accountability will be instilled into the forecasting process by changing reporting relationships and establishing a constant feedback loop. Reward systems may be considered in the future.

The DMAIC approach gave the case company a clearer picture of what the problematic areas are in their forecasting process. Talking to the key stakeholders of the forecasting process and compiling the information from these interviews was key to defining to forecasting process and collecting valuable, cross-organizational insight. Using this information, the case company now understands that expertise from other functions should be leveraged in forecasting. All in all, the case company was satisfied with the end results, stating that an outsider’s perspective was needed for tackling this problem. If an insider had made an attempt at the same project, it might have yielded biased results or even fallen apart due to organizational inefficiency or resistance.

5. Conclusions

Demand forecasting is becoming increasingly difficult due to complex market dynamics, especially for multinational companies. For manufacturing companies, demand forecasting is tied to capital-intensive decision making in operative planning: capacity and resource allocation, procurement and supply chain management. Cost-efficiency in these areas has a direct link to profitability, so forecasting performance can either be a pain point or a core competence of strategic advantage.

The financial performance of many firms is tied to the generic economic situation in their industry. This economic situation fluctuates at varying volatility, rendering traditional quantitative forecasting models ineffective in anticipating change. This implies the need for forecasting practitioners to incorporate market intelligence into their forecasting techniques, in the pursuit of making the forecasts more responsive and ultimately pushing the company toward proactive planning. However, identifying the right information and figuring out a way to use it may not be so straightforward.

The aim of this study was to formulate a practical, yet market-responsive forecasting technique as part of a wider objective that was to improve the forecasting process at a company. The components that enhance responsiveness in our model are the sales funnel and leading indicators. The logic behind this is that the sales funnel, when representing large enough volume, is led by macroeconomic leading indicators. The sales funnel itself is a reservoir of prospective demand and capable of producing good forecasts if the win rate of offers remains fairly constant. Using these components incorporates market intelligence into the forecasting model and makes the forecasting technique more responsive to market developments. Furthermore, leading indicators are a good source of market intelligence because they are objective and a good quantitative model cannot misinterpret these variables. Innovative managers should look for leading indicators of their business: their sales funnel may be more predictable than they think.

The principal success factor of forecasting is selecting the right methods and implementing them correctly. Needless to say, macroeconomic indicators are useless if your demand does not follow their development whatsoever. The strength of the relationship between your business and market indicators determines how they can be used. Even under highly variant demand, leading indicators can be used as qualitative hints as to where the market is going. Sales funnel-based forecasting, in turn, is worth examining at any company where the sales funnel cycle time and forecasting horizon match.

5.1 Key findings

Using this approach for forecasting improved the forecasting accuracy of the case company's order levels by roughly 20 percentage points. Such an improvement in forecasting and planning accuracy is estimated to yield cost savings of over 10MEUR annually, primarily from supply, production and procurement expenses. On a strategic level, the case company can now get more value out of their CRM system by using the sales funnel. Moreover, if their forecasting process is market-responsive, their operational planning is more proactive.

Improving forecasting performance is an extensive task which makes the DMAIC approach useful due to its logical structure and reiterative nature. The steps proposed in this study for DMAIC in a forecasting context applied well to improving the forecasting performance at the case company, ranging from process description, and analysis to improvement and control. In forecasting, improving process performance can be complex because the problem might exist anywhere from forecasting techniques to corporate culture. This is precisely why it is valuable to chart the forecasting process as a whole and talk to the key stakeholders of the forecasting process. In this study, the forecasting management dimensions suggested by Mentzer et al. (1999) formed a helpful framework for identifying the areas where the case company needed to improve in order to not only implement the forecasting technique proposed in this thesis, but to improve its forecasting process as a whole.

An important lesson from this study is the role of cross-organizational collaboration in forecasting. From a theoretical perspective, it is not a novel finding and has strong evidence from previous research such as Sport Obermeyer (Fisher et al., 1994) and sales & operations planning literature. At the case company, cross-organizational collaboration in forecasting will not only mitigate the risks of biased forecasts, but improve the efficiency of the forecasting process by incorporating department-specific insight. This will save the company precious time in operative planning, as forecasts no longer need to travel across the organization for adjustments.

Interestingly, many of the problem areas were acknowledged by one or a few forecasting stakeholders at the case company, but there was no consensus on what to do with that information. It was only after sharing concrete information such as financial estimates of the business impact of forecasting performance and actual historical forecasting accuracy that the stakeholders realized the importance of what was being done. This is undoubtedly the case in many other companies as well. Bringing the forecasting stakeholders and practitioners together, sharing information to identify problem areas and stressing the importance of forecasting performance with tangible measures is a key learning for managers in all firms. This is a good way of setting the stage to implement more market-responsive forecasting techniques such as the one proposed in this thesis.

In the long run, continuous improvement in forecasting is a matter of organizational culture. This is a vast area of research in itself, but the findings of this case study, i.e. establishing performance measurement and accountability in the forecasting process are of paramount importance in making forecasting performance a core value in any organization.

5.2 Areas of future research

The dichotomy of sales funnel cycle time and industry forms four distinct segments of research direction. The focus of this study was on an industrial manufacturer with a slow sales funnel cycle time. Although replicating this study in the same segment is necessary to validate the results and applicability of the findings in this thesis, a particularly interesting area of future research is testing the sales funnel and leading indicators in services, e.g. in the construction business. In services, forecasting demand levels is vital, since service capacity cannot generally be stored as inventory. This emphasizes the role of responsiveness in forecasting and the need for proactivity in operations planning.

As discussed earlier, industry is not a constraint for the model proposed in this thesis as long as the sales funnel cycle time is slow, market cover is large enough and leading indicators of demand are available. An expert from the field of logistics services and road haulage commented on the findings of this study in the following way: "*Our demand is closely related to the market conditions in the construction and infrastructure business. Leading indicators of these fields might well be used for increasing our forecast visibility through the sales funnel".* In this case, the sales funnel is relatively slow and leading indicators are assumed to be available, making the model proposed in this thesis a valid approach and an interesting topic for further research.

Companies with rapid sales funnel cycle times were omitted from earlier discussion, manufacturer or service provider. A faster cycle time will shorten the forecasting horizon of the sales funnel, but leading indicators can theoretically forecast the demand in such cases regardless of industry. The formulation of such forecasting models is likely to differ significantly from the methods of this study. For such companies, the sales funnel may not be as useful in forecasting. These companies should find leading indicators to forecast their sales, since the sales volumes may be aggregated enough to fluctuate with economy. Investigating the potential in the segments omitted from this study would add value not only to the findings of this paper, but to the research area of forecasting in general. Table 5-1 illustrates the research focus of this study (marked with an X), along with two proposed research areas for service industries with slow sales funnel cycle times. Future researchers can use this matrix for segmenting their studies in this field to juxtapose their findings with those of this paper.

Research that merely identifies economic leading indicators of demand for various industries is of great value to companies aspiring toward market-responsive forecasting and ultimately more proactive planning. Further studies could focus on finding leading indicators for different fields of business with a large sample of companies. Using the method introduced in this thesis for examining the relationship between the indicator and a company's demand is recommended.

Table 5-1: Future research directions

	Services	**Manufacturing**
Rapid funnel cycle time	?	?
Slow funnel cycle time	• Construction business • Project-based logistics services	X

For future researchers in the field of forecasting, the DMAIC process improvement proposed in this study can serve as a backbone for improving forecasting performance in case companies, and if the size of the company is sufficient, the forecasting management rubric by Mentzer et al. (1999) can be useful. Ultimately, the field of demand forecasting in businesses is unlikely to become less popular in the future given its direct link to profitability in many companies. To that end, exploring other methods of market-responsive forecasting is warmly suggested, along with complementing the procedural improvement methods of forecasting such as the DMAIC.

References

Akintoye, A., Bowen, P., & Hardcastle, C. (1998). Macro-economic leading indicators of construction contract prices. *Construction Management & Economics, 16*(2), 159-175.

Armstrong, J. S. (2001). Selecting forecasting methods. *Principles of forecasting* (pp. 365-386) Springer.

Auerbach, A. J. (1982). The index of leading indicators:" Measurement without theory," twenty-five years later. *The Review of Economics and Statistics, Vol. 64, no. 4, Pp. 589-595.,*

Berk, J. M., & Bikker, J. A. (1995). International interdependence of business cycles in the manufacturing industry: The use of leading indicators for forecasting and analysis. *Journal of Forecasting, 14*(1), 1-23.

Camba-Mendez, G., KapetanioS, G., Weale, M. R., & Smith, R. J. (1999). *The forecasting performance of the OECD composite leading indicators for france, germany, italy and the UK* National Institute of Economic and Social Research.

Cecere, L. (2013). A practioners guide to demand planning. *Supply Chain Management Review,* , 40-46.

Chakravorty, S. S. (2009). Six sigma programs: An implementation model. *International Journal of Production Economics, 119*(1), 1-16.

Cho, V. (2001). Tourism forecasting and its relationship with leading economic indicators. *Journal of Hospitality & Tourism Research, 25*(4), 399-420.

Cooper, M. J., & Budd, C. S. (2007). Tying the pieces together: A normative framework for integrating sales and project operations. *Industrial Marketing Management, 36*(2), 173-182.

Cox, J. E. (1989). Approaches for improving salespersons' forecasts. *Industrial Marketing Management, 18*(4), 307-311.

Dalrymple, D. J. (1975). Sales forecasting methods and accuracy. *Business Horizons, 18*(6), 69-73.

Dalrymple, D. J. (1987). Sales forecasting practices: Results from a united states survey. *International Journal of Forecasting, 3*(3), 379-391.

Danese, P., & Kalchschmidt, M. (2011). The impact of forecasting on companies’ performance: Analysis in a multivariate setting. *International Journal of Production Economics, 133*(1), 458-469.

Davidson, E. J. (2002). Technology frames and framing: A socio-cognitive investigation of requirements determination. *Mis Quarterly,* , 329-358.

Davis, D. F., & Mentzer, J. T. (2007). Organizational factors in sales forecasting management. *International Journal of Forecasting, 23*(3), 475-495.

Davison, R., Martinsons, M. G., & Kock, N. (2004). Principles of canonical action research. *Information Systems Journal, 14*(1), 65-86.

De Mast, J., & Lokkerbol, J. (2012). An analysis of the six sigma DMAIC method from the perspective of problem solving. *International Journal of Production Economics, 139*(2), 604-614.

Diebold, F. X., & Rudebusch, G. D. (1989). Scoring the leading indicators. *Journal of Business, ,* 369-391.

Diebold, F. X., & Rudebusch, G. D. (1991). Forecasting output with the composite leading index: A real-time analysis. *Journal of the American Statistical Association, 86*(415), 603-610.

Dong, S. (2010). Value creation from CRM systems: Resources and processes. *Proceedings of the 1st International Conference on E-Business Intelligence (ICEBI2010),*

Dreger, C., & Schumacher, C. (2005). Out-of-sample performance of leading indicators for the german business cycle. *Journal of Business Cycle Measurement and Analysis, 2005*(1), 71-87.

Edmundson, B., Lawrence, M., & O'Connor, M. (1988). The use of non-time series information in sales forecasting: A case study. *Journal of Forecasting, 7*(3), 201-211.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review, 14*(4), 532-550.

Fildes, R., Goodwin, P., Lawrence, M., & Nikolopoulos, K. (2009). Effective forecasting and judgmental adjustments: An empirical evaluation and strategies for improvement in supply-chain planning. *International Journal of Forecasting, 25*(1), 3-23.

Fildes, R., & Hastings, R. (1994). The organization and improvement of market forecasting. *Journal of the Operational Research Society, ,* 1-16.

Fisher, M. L., Hammond, J. H., Obermeyer, W. R., & Raman, A. (1994). *Making supply meet demand in an uncertain world* Graduate School of Business Administration, Harvard University.

Gill, P., Stewart, K., Treasure, E., & Chadwick, B. (2008). Methods of data collection in qualitative research: Interviews and focus groups. *British Dental Journal, 204*(6), 291-295.

Graefe, A., & Armstrong, J. S. (2011). Comparing face-to-face meetings, nominal groups, delphi and prediction markets on an estimation task. *International Journal of Forecasting, 27*(1), 183-195.

Harris, R. (2003). What is a customer relationship management (CRM) system. *Even if You Think You Know the Answer, the Question has Changed.[Online] Available: Http://Www.Matr.Net/Print-9070.Html (March 05, 2012),* Heiman, S. E., Sanchez, D., & Tuleja, T. (1998). *The new strategic selling* Nightingale-Conant Corporation.

Helms, M. M., Ettkin, L. P., & Chapman, S. (2000). Supply chain forecasting-collaborative forecasting supports supply chain management. *Business Process Management Journal, 6*(5), 392-407.

Hoover Jr, W. E., Eloranta, E., Holmström, J., & Huttunen, K. (2002). *Managing the demand-supply chain: Value innovations for customer satisfaction* John Wiley & Sons.

Koch, P. D., & Rasche, R. H. (1988). An examination of the commerce department leading-lndicator approach. *Journal of Business & Economic Statistics, 6*(2), 167-187.

Kotler, P., Rackham, N., & Krishnaswamy, S. (2006). Ending the war between sales and marketing. *Harvard Business Review, 84*(7/8), 68.

Lackman, C., Saban, K., & Lanasa, J. (2000). The contribution of market intelligence to tactical and strategic business decisions. *Marketing Intelligence & Planning, 18*(1), 6-9.

Leading Indicator Definition Investopedia. (2003). Leading indicator definiton | investopedia. Retrieved from http://www.investopedia.com/terms/l/leadingindicator.asp

Lee, A. S. (1989). A scientific methodology for MIS case studies. *MIS Quarterly,* , 33-50.

Luxhøj, J. T., Riis, J. O., & Stensballe, B. (1996). A hybrid econometric—neural network modeling approach for sales forecasting. *International Journal of Production Economics, 43*(2), 175-192.

Lynch, D. P., Bertolino, S., & Cloutier, E. (2003). How to scope DMAIC projects. *Quality Progress, 36*(1), 37-41.

Marcellino, M. (2006). Leading indicators. *Handbook of Economic Forecasting, 1*, 879-960.

Mathews, B. P., & Diamantopoulos, A. (1986). Managerial intervention in forecasting. an empirical investigation of forecast manipulation. *International Journal of Research in Marketing, 3*(1), 3-10.

Mathews, B. P., & Diamantopoulous, A. (1990). Judgemental revision of sales forecasts: Effectiveness of forecast selection. *Journal of Forecasting, 9*(4), 407-415.

McAdam, R., & Lafferty, B. (2004). A multilevel case study critique of six sigma: Statistical control or strategic change? *International Journal of Operations & Production Management, 24*(5), 530-549.

McCarthy, T. M., Davis, D. F., Golicic, S. L., & Mentzer, J. T. (2006). The evolution of sales forecasting management: A 20-year longitudinal study of forecasting practices. *Journal of Forecasting, 25*(5), 303-324.

Mentzer, J. T. (1999). The impact of forecasting on return on shareholder's value. *Journal of Business Forecasting Methods and Systems, 18*, 8-12.

Mentzer, J. T., Bienstock, C. C., & Kahn, K. B. (1999). Benchmarking sales forecasting management. *Business Horizons, 42*(3), 48-56.

Mentzer, J. T., & Cox, J. E. (1984). Familiarity, application, and performance of sales forecasting techniques. *Journal of Forecasting, 3*(1), 27-36.

Mi Dahlgaard-Park, S., Dahlgaard, J. J., & Mi Dahlgaard-Park, S. (2006). Lean production, six sigma quality, TQM and company culture. *The TQM Magazine, 18*(3), 263-281.

Moon, M. A., Mentzer, J. T., & Smith, C. D. (2003). Conducting a sales forecasting audit. *International Journal of Forecasting, 19*(1), 5-25.

Moon, M. A., Mentzer, J. T., Smith, C. D., & Garver, M. S. (1998). Seven keys to better forecasting. *Business Horizons, 41*(5), 44-52.

Munda, G., & Nardo, M. (2009). Noncompensatory/nonlinear composite indicators for ranking countries: A defensible setting. *Applied Economics, 41*(12), 1513-1523.

OECD. (2015). Business confidence index (BCI) (indicator).

Parmenter, D. (2010). *Key performance indicators (KPI): Developing, implementing, and using winning KPIs* John Wiley & Sons.

Rigby, D. K., & Ledingham, D. (2004). CRM done right. *Harvard Business Review, 82*(11), 118-130.

Riis, J. O., & Neergaard, C. (1995). Managing technology projects: An organizational learning approach. *System Sciences, 1995. Proceedings of the Twenty-Eighth Hawaii International Conference On, , 3* 514-522.

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology, 25*(1), 54-67.

Sagar, N. (2010). Delivering the plan: The CPFR and S&OP continuum. *The Journal of Business Forecasting, 29*(4), 14.

Sanders, N. R., & Manrodt, K. B. (2003). The efficacy of using judgmental versus quantitative forecasting methods in practice. *Omega, 31*(6), 511-522.

Silverman, D. (2013). *Doing qualitative research: A practical handbook* SAGE Publications Limited.

Söhnchen, F., & Albers, S. (2010). Pipeline management for the acquisition of industrial projects. *Industrial Marketing Management, 39*(8), 1356-1364.

Song, H., & Li, G. (2008). Tourism demand modelling and forecasting—A review of recent research. *Tourism Management, 29*(2), 203-220.

Stewart, T. R., & Lusk, C. M. (1994). Seven components of judgmental forecasting skill: Implications for research and the improvement of forecasts. *Journal of Forecasting, 13*(7), 579-599.

Storbacka, K., Polsa, P., & Sääksjärvi, M. (2011). Management practices in solution sales—a multilevel and cross-functional framework. *Journal of Personal Selling & Sales Management, 31*(1), 35-54.

Taylor, K., & McNabb, R. (2007). Business cycles and the role of confidence: Evidence for europe*. *Oxford Bulletin of Economics and Statistics, 69*(2), 185-208.

Winters, P. R. (1960). Forecasting sales by exponentially weighted moving averages. *Management Science*, *6*(3), 324-342.

Yin, R. K. (2013). *Case study research: Design and methods* Sage publications.

Appendices

Appendix 1: Correlation tables of leading indicators and the sales funnel

CLI vs Hot offer rolling 3-month average €

	Lag-0	**Lag-1**	**Lag-2**	**Lag-3**	**Lag-4**	**Lag-5**	**Lag-6**
USA	0.396	0.135	-0.017	-0.026	0.071	0.253	0.312
China	-0.260	-0.556	-0.708	-0.794	-0.810	-0.783	-0.722
Canada	0.330	0.194	-0.008	-0.071	-0.082	-0.088	-0.070
Germany	0.643	0.769	0.826	0.826	0.739	0.531	0.180
UK	0.077	0.068	-0.048	-0.291	-0.632	-0.789	-0.853
France	0.172	0.335	0.590	0.658	0.648	0.625	0.548
India	-0.234	-0.301	-0.322	-0.343	-0.410	-0.405	-0.373
Australia	0.572	0.584	0.346	-0.014	-0.273	-0.374	-0.285
Sweden	-0.693	-0.753	-0.742	-0.590	-0.516	-0.761	-0.621
Austria	0.699	0.739	0.699	0.558	0.322	-0.006	-0.136
Europe	0.240	-0.030	-0.284	-0.466	-0.603	-0.652	-0.512

BCI vs Hot offer rolling 3-month average €

	Lag-0	**Lag-1**	**Lag-2**	**Lag-3**	**Lag-4**	**Lag-5**	**Lag-6**
USA	0.222	0.318	0.325	0.367	0.467	0.593	0.649
China	0.297	0.844	0.762	0.105	-0.187	-0.374	-0.455
Canada	0.080	-0.614	-0.569	-0.041	-0.004	0.470	0.328
Germany	0.757	0.864	0.817	0.487	0.064	-0.203	-0.284
UK	-0.086	0.117	0.062	-0.346	-0.393	-0.660	-0.836
France	-0.320	0.058	0.464	0.776	0.901	0.848	0.718
India	0.120	0.145	0.209	0.154	0.003	-0.123	-0.424
Australia	0.911	0.826	0.506	0.187	-0.273	-0.374	-0.450
Sweden	-0.644	-0.814	-0.871	-0.786	-0.667	-0.634	-0.332
Austria	0.744	0.733	0.454	0.029	-0.256	-0.390	-0.458
Europe	0.778	0.599	0.190	-0.176	-0.423	-0.545	-0.672

MPMI vs Hot offer rolling 3-month average €

	Lag-0	**Lag-1**	**Lag-2**	**Lag-3**	**Lag-4**	**Lag-5**	**Lag-6**
USA	-0.175	0.255	0.604	0.740	0.737	0.716	0.602
China	0.277	0.357	0.284	0.145	-0.219	-0.247	-0.438
Canada	0.119	-0.353	-0.311	0.021	0.055	0.109	0.023
Germany	0.569	0.559	0.515	0.424	0.393	0.179	0.100
UK	0.237	0.187	0.184	0.226	0.234	0.301	0.174
France	0.378	0.533	0.442	0.263	0.162	0.189	0.176
India	-0.361	-0.426	-0.199	-0.076	0.089	0.100	0.076
Australia	-0.079	0.322	0.669	0.212	-0.175	-0.435	-0.430
Sweden	0.172	0.100	0.368	0.328	0.211	0.188	0.073
Austria	0.686	0.566	0.462	0.495	0.420	0.219	0.144
Europe	0.713	0.882	0.548	0.423	0.176	0.108	0.224

CLI vs Offer rolling 3-month average €

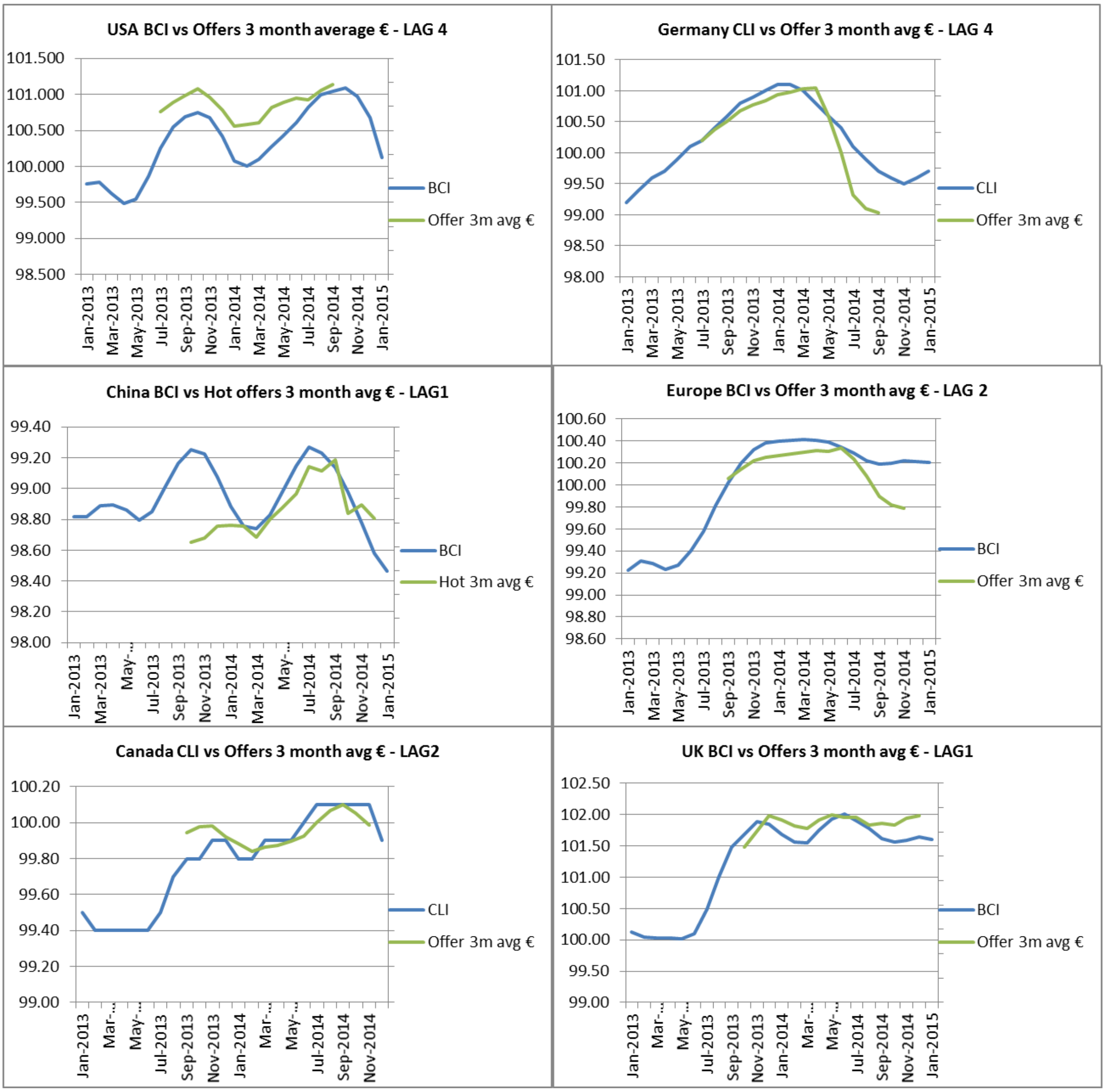
	Lag-0	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5	Lag-6
USA	-0.505	-0.120	0.321	0.726	0.872	0.747	0.401
China	-0.356	-0.636	-0.839	-0.948	-0.985	-0.968	-0.919
Canada	0.306	0.610	0.738	0.686	0.643	0.360	0.085
Germany	0.451	0.680	0.831	0.926	0.948	0.834	0.719
UK	-0.161	-0.134	0.017	0.271	0.560	0.677	0.578
France	0.217	0.391	0.662	0.811	0.859	0.869	0.837
India	-0.150	-0.125	0.016	0.253	0.333	0.195	0.039
Australia	-0.242	-0.203	0.058	0.232	0.247	0.112	-0.213
Sweden	0.821	0.870	0.856	0.794	0.668	0.533	0.475
Austria	0.274	0.567	0.705	0.820	0.846	0.692	0.518
Europe	0.601	0.540	0.414	0.267	0.114	0.006	-0.159

BCI vs Offer rolling 3-month average €

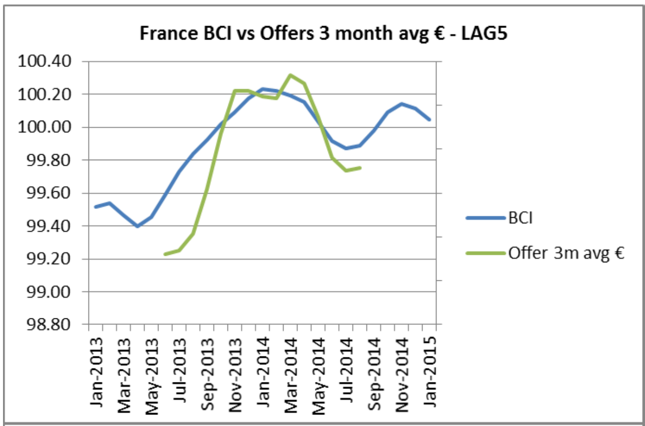
	Lag-0	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5	Lag-6
USA	-0.296	0.161	0.563	0.847	0.945	0.712	0.252
China	0.105	0.067	-0.056	-0.193	-0.230	-0.177	-0.084
Canada	0.220	0.082	0.098	-0.029	-0.147	-0.282	-0.521
Germany	0.599	0.779	0.900	0.790	0.482	0.226	0.321
UK	-0.114	0.352	0.469	0.564	0.630	0.636	0.602
France	-0.642	-0.383	0.045	0.496	0.821	0.947	0.943
India	0.332	0.236	0.400	0.005	-0.179	-0.218	-0.732
Australia	-0.256	0.079	0.251	0.310	0.411	0.119	0.083
Sweden	0.763	0.884	0.882	0.723	0.600	0.528	0.501
Austria	0.485	0.622	0.708	0.658	0.497	0.314	0.154
Europe	0.540	0.723	0.707	0.522	0.311	0.315	0.223

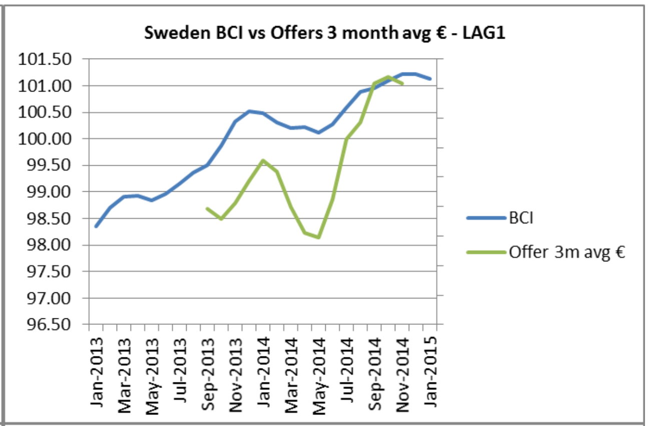
MPMI vs Offer rolling 3-month average €

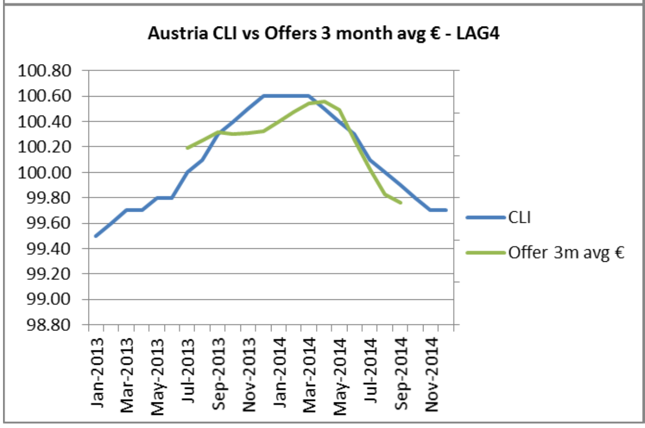
	Lag-0	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5	Lag-6
USA	-0.423	-0.227	-0.086	-0.028	0.058	0.063	0.189
China	0.126	0.081	-0.070	-0.216	-0.211	-0.117	-0.066
Canada	0.336	0.586	0.634	0.538	0.443	0.395	0.220
Germany	0.413	0.574	0.710	0.680	0.669	0.445	0.332
UK	-0.343	-0.061	0.009	-0.255	-0.235	-0.013	0.099
France	-0.041	0.112	0.116	0.166	0.222	0.363	0.293
India	-0.185	-0.356	-0.104	0.024	0.092	0.044	-0.101
Australia	-0.298	0.024	0.208	0.310	0.301	0.297	0.165
Sweden	-0.074	-0.307	-0.481	-0.221	-0.128	-0.025	0.017
Austria	0.247	0.435	0.602	0.580	0.501	0.420	0.364
Europe	0.499	0.710	0.810	0.790	0.699	0.573	0.477

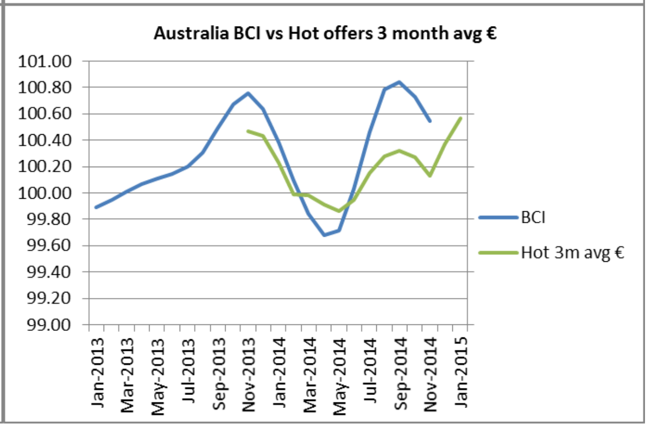


Appendix 2: Synchronized indicators and the funnel

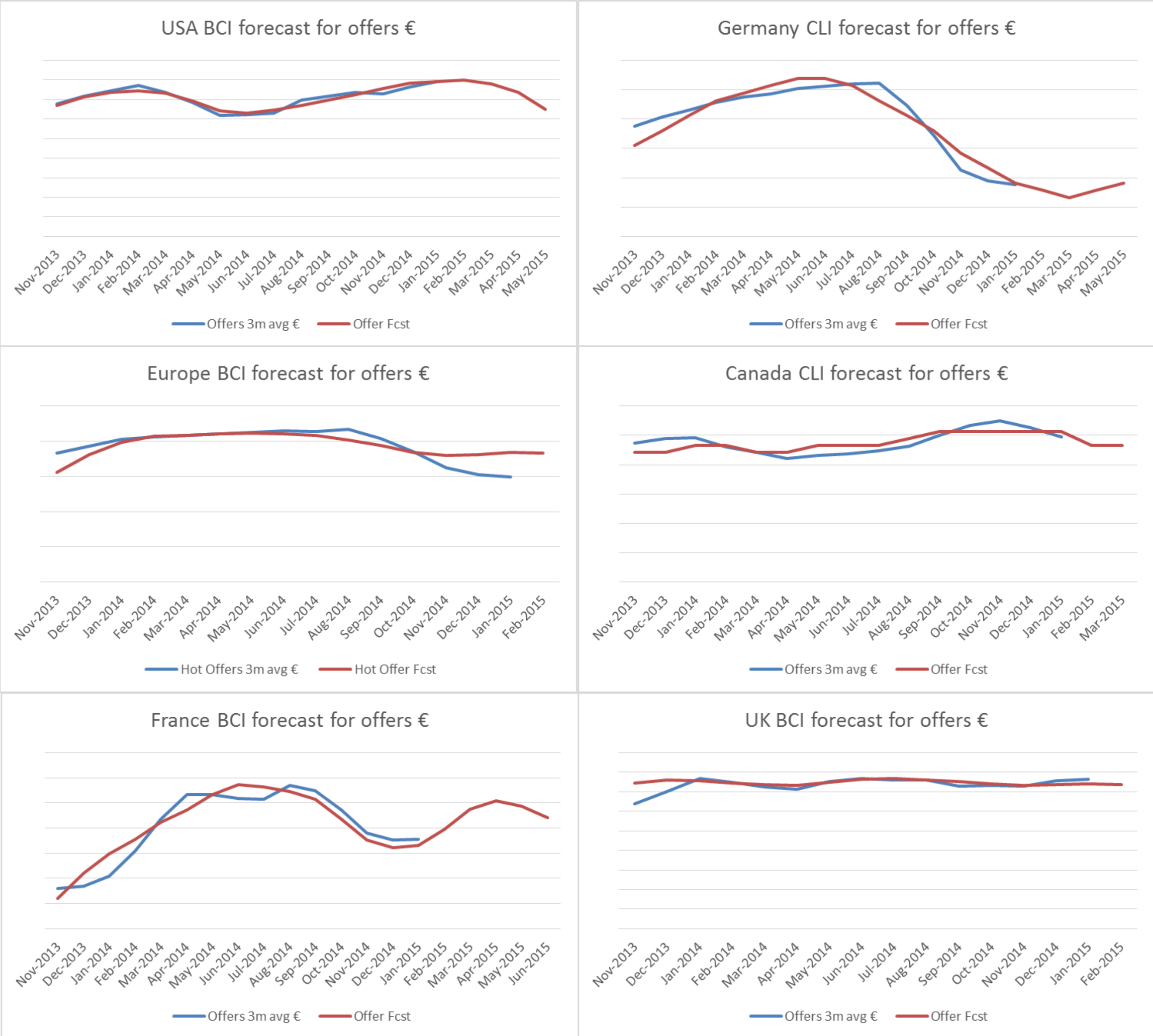








Appendix 2 continued



Appendix 3: Indicators forecasting the funnel