INFLUENCES OF MARKET RESPONSE TIME ON SALES PLANNING AND FORECASTING IN THE INDUSTRIAL CONTEXT

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DECLARATION OF INDEPENDENT WORK

I, Alexander Grohmann, student number 210094656, do hereby declare that this research project submitted to the Central University of Technology, Free State, for the Degree DOCTOR TECHNOLOGY: MARKETING, is my own independent work, and complies with the Code of Academic Integrity, as well as other relevant policies, procedures, rules and regulations of the Central University of Technology, Free State, and has not been submitted before to any institution by myself or any other person in fulfilment (or partial fulfilment) of the requirements for the attainment of any qualification.

22 May 2012

Signature of student | Date

DEDICATION

To my future wife Melanie and my family

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Do not worry about anything… ask and pray.

Philippians 4: 6

DECLARATION OF LANGUAGE EDITING

BY A SATI AFFILIATED PRACTITIONER

I, Enése van der Walt, hereby declare that I am affiliated with the South African Translators' Institute. My Membership number is 1002484. I declare that I have edited the document in question, titled "Influences Of Market Response Time On Sales Planning And Forecasting In The Industrial Context" which was written by Mr Alexander Grohmann.

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ABSTRACT OF THIS RESEARCH PROJECT

A reliable sales plan and forecast is the basis for good cash flow management and capacity planning. If the sales figures are below plan, the sales manager will increase the sales efforts in order to compensate these deviations. Usually, it can be expected that these efforts should be at least partly successful in the consumer markets. This situation is expected to be different in the industrial markets, as usually the generation of sales turnover can only be achieved by either new customers or new products sold to existing customers. It is therefore expected not to be possible to immediately compensate a loss of sales turnover within the planning period by increased sales efforts.

This research project investigated whether industrial markets react differently from consumer markets by investigating the sales planning and forecasting process in the Machinery & Equipment Industry, the Automotive Supplier Tier 1 and the Automotive Supplier Tier 2 Industry. It investigated several time aspects of the sales process, displayed as customer-supplier interaction.

The results of the research project showed that in fact sales processes in the investigated industry sectors have such a long duration, that it is not possible for sales managers to immediately compensate low sales figures by increased sales efforts. The sales turnover raise will come in a later period and thus simply too late for the current one. This results in the fact that the reliability of the sales forecast (for the established sales plan) is reduced, if industry characteristics and special time aspects of the sales process are not taken into consideration. These time aspects can be described best by the *Market Response Time* (MRT). The MRT is defined as the time lag between the start of an *increase of sales efforts by the supplier* (first contact) and *the market response* in terms of increased purchase. This is at the time when the customer starts to financially respond, with the result of a *sales turnover increase* at the supplier’s side. If the MRT is long, sales planning and forecasting has increased importance, because sales efforts need to be planned well in advance. For this reason response times are major elements in planning and forecasting, although it was previously not very well recognised in literature and practice.

Based on a qualitative empirical study with the case study methodology, 41 case studies were undertaken within the three industry sectors. The investigated companies showed that these three industry sectors have different MRTs, such as 68 weeks in the Machinery & Equipment Industry, 138 weeks in the Automotive Supplier Tier 1, and 62 weeks in the Automotive Supplier Tier 2 Industry. These different MRTs influence the companies planning and forecasting processes in different ways.

This research project qualitatively showed that if time aspects were taken into consideration in sales planning and forecasting, forecast accuracy could improve. It was furthermore indicated that an adequate sales planning approach could improve forecast accuracy as well. In a second step, it was indicated that these companies, which are aware of the time aspects, have shown a better sales performance in terms of sales force productivity, growth of productivity and market position. Concluding it can be stated that the respect of time aspects, such as MRT, may increase sales performance.

The study's results have some limitations, which are the research context and the research methodology. As the project only investigated the industrial context, namely the Machinery & Equipment and the Automotive Tier 1 Supplier and Tier 2 Supplier Industry, its results can only be applicable to this context. The research methodology of this project is a qualitative one, which means that the sample size is small but deep and statistical generalisations cannot be made. Based on this, further research implications of this project are that its results may further be statistically generalised by quantitative studies. Especially the sales planning and forecasting processes in the detected clusters per industry sector should be investigated on a broad sample. Thirdly, the indicated relation between market knowledge and accuracy should be further investigated. This is because it can be estimated that the forecast accuracy is the highest if the company’s information horizon is equal to the product life cycle time of the products produced. Last of all, as there are only a few research projects done in the industrial context regarding market response models and time aspects, therefore these topics should be further investigated.

ABBREVIATIONS

AR	Autoregressive
ARIMA	Autoregressive integrated moving average
B2B	Business-to-business
B2C	Business-to-consumer
CEO	Chief Executive Officer
CLV	Customer Lifetime Value
CPFR	Collaborative Planning, Forecasting and Replenishment
CRM	Customer Relationship Management
EC	Electronic Commerce
ERP	Enterprise Resource Planning
ETS	Econometric and time-series Analysis
FMTS	Fixed-Model time-series
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Average Percentage Error
MDSS	Market Decision Support System
ME	Mean Error
MEAN	Mean Absolute Percentage Error
MRO	Maintenance, Repair and Overhaul
MRT	Market Response Time
OEM	Original Equipment Manufacturer
OMTS	Open-Model time-series
OR	Operations Research

RfQ	Request for Quotation
R&D	Research & Development
SEO	Sales Executive Officer
SKU	Stock Keeping Unit
S&OP	Sales and Operations Planning
Tier 1	Supplier at the 1st position in the supply chain to the Automotive Original Equipment Manufacturer
Tier 2	Supplier at the 2nd position in the supply chain to the Automotive Original Equipment Manufacturer
Tier 3	Supplier at the 3rd position in the supply chain to the Automotive Original Equipment Manufacturer
Tier 4	Supplier at the 4th position in the supply chain to the Automotive Original Equipment Manufacturer

CHAPTER 1: INTRODUCTION TO THE RESEARCH PROJECT

1.1. INTRODUCTION

This research project investigates the sales planning and forecasting process in the context of time of different industrial companies.

Planning and forecasting are very important for a company's success, it is the primary task of the sales manager (Hanssens, Parsons and Schultz, 2001: 11). The reliable sales plan and forecast is the basis for capacity planning and cash flow management (Jain and Covas, 2010: 5). If the forecast is too high, too much capacity was planned which results in increased cost; if the forecast is too low, too little capacity was planned which results in customer frustration and loss. It is evident that the establishment of a sales plan is a kind of personal commitment of the sales manager, this means that his word stands for the reliability of the plan. Should there be movements that indicate that the forecast of the plan will not be fulfilled, the sales manager will try to increase the sales efforts in order to reach his announced figures. Usually, it can be expected that these efforts should be at least partly successful, as the sales success is linked to the sales power (Goerne, 2009: 1-5). This is true for consumer markets. The products exist, the sales channels exist and work, and customers more or less know the product. Increased sales efforts by putting pressure on the sales channels will instantly lead to increased sales figures (Goerne, 2011: 1-5).

This research project investigates whether industrial markets, also called business-to-business (B2B) markets, react in the same manner. As there is a multitude of industrial markets, three important sectors have been chosen: The Machinery & Equipment Industry, the Automotive Tier 1 Supplier and the Automotive Tier 2 Supplier Industry sector.

Companies acting in the Machinery & Equipment Industry manufacture complex, mainly technological and mostly expensive products to be delivered worldwide (European-Commission, 2003: 36). Such expensive machines need to be financed in advance by the manufacturer until the product is delivered to and paid by the customer. The German Automotive Industry still demands most of these high-end products because of the pressure to gain zero tolerance on production mistakes (Goerne, 2009: 2). For this reason, machines are mainly manufactured in a strong co-operation between customer and supplier with the intention to build up and maintain a long-term relationship. The Machinery & Equipment Industry can be characterised by about one million employees that generated 190 billion Euro in sales in 2010 mostly (87%) through medium-sized companies (headcount less than 250 employees and less than 50 million Euro sales turnover (European-Commission, 2003: 36)) in Germany. It is the second largest industry in Germany in terms of employees (700 000 employees), export quota (>70%) and economic power (190 billion Euro industry sales turnover) (Bundesministerium für Wirtschaft und Technologie, 2010b).

The Automotive Industry is divided into two groups. It is the group of the Original Equipment Manufacturers (OEM) which assemble the components, systems and modules to an automobile, delivered by the second group, the Automotive Suppliers (Woldrich, 2010: 5). The Automotive Supplier Industry is defined as an industry in which all companies produce internal or external manufactured components, systems or modules that are part of the automobile (Volpato, 2004: 1). The investigated Automotive Industry manufactured approximately about 3 583 million automobiles with a sales turnover of about 261 billion Euro with more than 750 000 employees in 2010 (Verband der Automobilindustrie, 2010: 16). It is the most important industry in Germany in terms of number of companies (1 000 companies), export quota (> 80%), and economic power (261 billion Euro industry sales turnover) (Bundesministerium für Wirtschaft und Technologie, 2010a).

Globalisation, market saturation in Europe and the USA, price dumping, market atomisation through endless model offensives by OEMs in every market segment, decreasing product life cycles, and the fast increase of technical and organisational complexity of the product characterise the demand of the Automotive Industry today (Becker, 2006: 1; Verband der Automobilindustrie, 2010). This results in big sales and income challenges for all actors in this context. The increasing pressure on cost, profit and risk is passed on from the OEM to its suppliers. The OEMs are able to exploit their position with regard to the suppliers, because the concentration process is much more advanced at the manufacturer level (limited number of OEM's) than at the supply level (increased use of identical parts for different models, decreasing number of orders to suppliers, increasing order volume to gain economy of scale effects by the OEM, higher capacity risks because high order volumes, increasing project complexity and increasing capital requirements for suppliers). All suppliers must defend and maintain their leading role in costs and technology in order to stay competitive and endure the growing challenge of financing OEM's projects by increased credit security requirements by the banks (Becker, 2006: 37-38). This makes a reliable plan and forecast of future sales turnover most important.

All these challenges in the Automotive Supplier Industry will have varying effects on both the structure of OEM and supplier. The effects of these challenges and changes on the suppliers side depend on the position in the supply chain they occupy (Mentzer and Moon, 2005: 3-8). For this reason, the Automotive Suppliers are also called Automotive Tier 1, Tier 2, Tier 3 and Tier 4 suppliers, for which the number is characterising their position in the supply chain as displayed afterwards.

Figure 1: The automotive supply pyramid

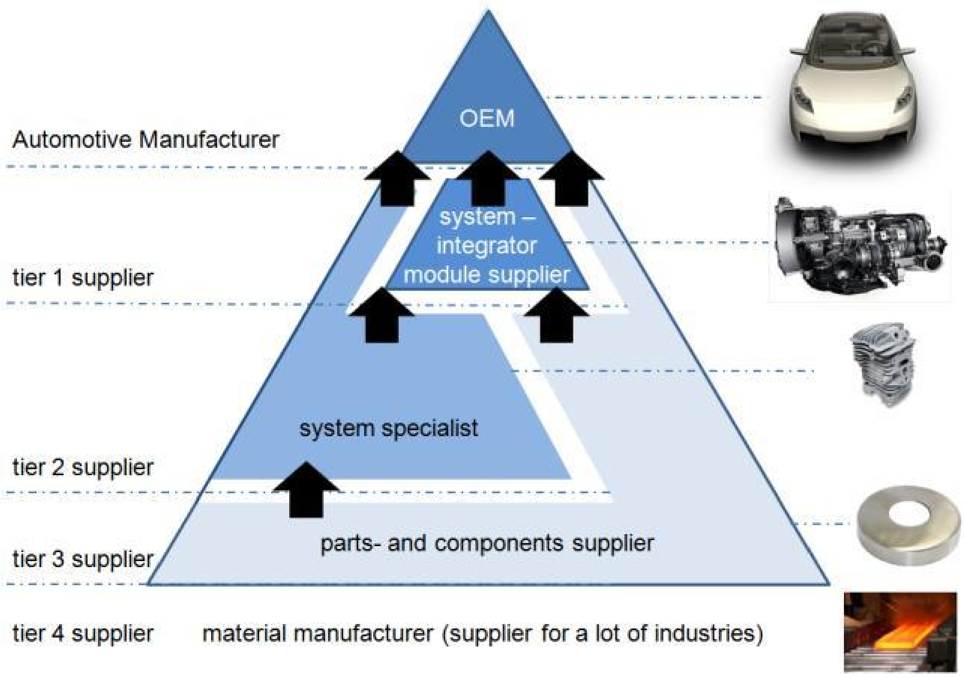


Figure: Adapted from Becker (2006: 164) and Volpato (2004: 1)

The automobile manufacturer is usually a big company or conglomerate, internationally present, and develops and supplies complete automobiles. As there are less than 20 major car manufacturers worldwide, its suppliers have a small number of customers, and a relatively small number of active parts which have a relatively high value per part (Goerne, 2008: 6).

The system integrator, known as a Tier 1 supplier, serves the OEM directly and is at the very top of the supply hierarchy. The Tier 1 supplier is less active in development and more actively involved in assembly of highly complex products (Institut für Wirtschaftsanalyse und Kommunikation, 2004: 425; Becker, 2006: 165). Such complex products can be car seats, axles and gearboxes, or crankcases. This requires a high level of both production competence to join all parts and components from a sub-supplier to ready-to-install modules (in the automobile), and logistic competence to deliver the modules just in time to the OEM (Becker, 2006: 165). According to the limited number of possible customers (OEMs), the Tier 1 supplier is acting in a highly competitive market and is highly dependent on the OEM (Goerne, 2008: 2). Tier 1 companies are mostly big co-operations or groups of companies with a high internationalisation rate, high technological knowledge and economic power with a large number of suppliers.

The system specialist, known as a Tier 2 supplier, is mostly medium-sized with a usually small financial base and fewer employees (Goerne, 2010: 6). The Tier 2 supplier is however defined by high technological development competence and low installation activity (Verband der Automobilindustrie, 2010). By this technical know-how, the Tier 2 supplier is able to manufacture products of high quality with comparable low prices, such as forgings for axles, aluminium die castings or stamping parts for car seats. Tier 2 companies are also able to manufacture several assembly groups or components as a functional compound, but not necessarily as an installation unit to the OEM (Becker, 2006: 164-165). The customer base is usually larger than that of the Tier 1 suppliers, because there are a large number of Tier 1 suppliers.

The parts- and components supplier, known as a Tier 3 supplier, is typically a relatively small company characterised by a small installation activity, little financial background, fewer employees, a low number of products produced and low development activity (Institut für Wirtschaftsanalyse und Kommunikation, 2004). Usually, a Tier 3 supplier produces low-technology but standardised parts according to detailed specifications (by the customer) and acts as a sub-supplier for a superior module supplier or system specialist who put the parts into their intended use within a module or system (Becker, 2006: 164; Goerne, 2008: 3). In some exceptions, the Tier 3 supplier supplies directly to the OEM. An advantage of the Tier 3 supplier is its quite broad customer diversification as the Tier 3 supplier produces parts not only for the Automotive Industry, but for other industries, too.

A typical example for a Tier 4 company is a material manufacturer, who supplies the raw material to the Tier 3 supplier (or others). Tier 4 suppliers are big conglomerates and have a big installation activity. They are acting in a large number of industries as suppliers and determine the prices for the raw materials (Goerne, 2010: 7).

These afore described market sectors represent a wide span of the industrial business and can be found around the world. It is well known that sales processes in these markets are much longer than in consumer markets. This is the case because the generation of new sales turnover can only be achieved by either new customers or new products sold to existing customers. This results in the fact that it is not possible for sales managers to compensate low sales figures by increased sales efforts within the current planning period. The sales turnover will simply come too late. This means that the reliability of the sales forecast (for the established sales plan) is limited, if industry characteristics and time aspects of the sales process are not taken into consideration (Hult, Cavusgil, Kiyak, Deligonul and Lagerström, 2007: 59-60; Goerne, 2008: 1). Such industry characteristics are obviously determined by the industry itself; and time aspects of the sales process can be described best (among others) by the *Market Response Time* (MRT).

The MRT is defined in the context of this research project as the time lag between the start of an *increase of sales efforts by the supplier* (first contact) seen as a market stimulus and *the market response in terms of increased purchase*, thus at the time the customer starts to financially respond with the result of a *sales turnover increase* at the supplier’s side (MacFarlane, 2003: 103).

If the MRT is zero or very short, there would be less need for sales planning and forecasting because every sales action by the supplier would result in increased sales turnover (if the capacities are available). If the MRT is long, sales planning and forecasting has increasing importance, because sales efforts do not immediately cause increased sales turnover and need to be planned a long time in advance. For this reason, response times are major elements in planning and forecasting, although it is previously not very well recognised (Makridakis, Wheelwright and Hyndman, 1998: 2; Hanssens et al., 2001: 3; Goerne and Grohmann, 2010: 69-79). This research project contributes on a strategic viewpoint to the changing role of sales to a strategic, cross-functional process in the industrial context as the length of the sales process (measured as MRT) is expected to depend on industry characteristics and company functions (Storbacka, Ryals, Davies and Nenonen, 2009: 890-906).

It is expected that different industries have different MRTs. It must be further expected that different MRTs influence (the analysed) planning and forecasting processes in different ways. The research question was to investigate industrial planning and forecasting behaviour in detail and examine the time aspects in planning and forecasting in both literature and industry context. For this reason, this project's approach does not see planning and forecasting as a single task of the sales manager. The interaction with other in-house functions, such as Marketing, Logistics, Production, Research and Development (R&D), and Human Resources as well as industry characteristics, environmental conditions, the position in the supply chain the company occupies and customer-supplier relations are considered. This approach is therefore not part of the mainstream planning and forecasting research, which does only consider planning and forecasting as an isolated task by focusing on models, methods or accuracy (Kerkkänen, 2010: 10).

1.2. RESEARCH GAP

Two relevant research gaps could be stated for this project's investigation. The first gap is about planning and forecasting methods and the second gap about the consideration of time in (industrial) sales management.

A large number of investigations are done and discussed about how sales managers can influence sales by means of better leadership, adjustment of the labour to the desired success, increased advertisements or other actions (Miao, Evans and Zou, 2007: 417-425). Also the knowledge of various planning and forecasting methods is very important for practitioners and academics (Stratis and Powers, 2001: 165). The number and sophistication of such methods available to sales managers have improved and the advancement in technology during the last decades have increased efficiency and effectiveness (for instance through the methods of Efficient Consumer Response, Vendor Managed Inventory or Collaborative Planning, Forecasting and Replenishment) in Sales Management (Safavi, 2006: 7). Given all this, however, some researchers report that companies are less familiar with planning and forecasting methods than was the case 20 years ago, furthermore the accuracy of forecasts decreased (McCarthy, Davis, Golicic and Mentzer, 2006: 303-324). System understanding and use, and satisfaction with methods, systems, and management processes have not improved significantly which is dedicated to the trend that most managers concentrate on selecting forecasting software packages (and not on the process itself) (McCarthy et al., 2006: 303-324). Resulting, advancement in technology helps the organisation to do more with less, but there is still a need for a knowledgeable expert who understands the business, the marketplace, and the methods to generate a repeatable, operational, unbiased plan and forecast (Hanson, 2006: 10).

Despite a large number of calls to include time in management research, there is a great lack in time-based research, especially of knowledge in terms of how time can affect business or dynamic sales models (Ancona, Goodman, Lawrence and Tushman, 2001a: 645-663; Plakoyiannaki and Saren, 2006: 218-219; Quintens and Matthyssens, 2010: 92). It was estimated that focusing on time aspects, new variables can increase the understanding of organisations and set as a reference frame to explain organisational behaviour, management and sales processes (Plakoyiannaki and Saren, 2006: 218-230). Imagine the different aspects of time in consumer versus industrial markets. In consumer markets more effort in marketing, such as campaigns or incentives, can lead to increased sales in a short time. This is different in the industrial markets because of technical and commercial issues, such as the industrial sales process itself, manufactured products, environmental circumstances and company characteristics. Even the investigated industries in the industrial context need to be clearly defined as they vary in a broad manner. Imagine the difference in the sales process of a small-sized company in the Machinery Industry versus the sales process of an international corporate group delivering a big-sized OEM in the Automotive Industry sector. It can be estimated without doubt that there will be a big difference of time in the sales process.

1.3. TERMS AND DEFINITIONS

1.3.1. Sales plan and sales forecast

Planning is often mixed with forecasting, but one activity all businesses do to some degree is to anticipate future sales, regardless if it is a one-man business or a multi-national company (Gilliland, 2003: 7). Both expressions are best distinguished by Armstrong (2001: 2), who explains that planning is concerned about how the sales activities should look like and forecasting is about predicting the outcomes of a specific plan.

Usually a company does not only forecast future sales, but also forecasts strategic business plans, financial plans, capacity plans, advanced procurement plans, production plans, the master production schedule or personnel requirement plans (Wallace and Stahl, 2002: 5). All these forecasts have different requirements on the planning horizon (current weeks, months, quarters or years), the level of detail and the unit of measure (currency or unit) for each type of plan that has to be forecasted (Kerkkänen, 2010: 23). These different requirements lead to a large number of different forecasts that may lead to inconsistent plans. Mentzer and Moon (2005: 205) call this phenomenon an *island of analysis* which describes the fact that different departments within a company perform similar forecasts due to the lack of interfunctional communication between departments and units (Kerkkänen, 2010: 23).

Sales forecasting in the context of this research project and according to Mentzer and Moon (2005: 8-11) is the management of the sales forecasting function. The forecasting function is applied within the context of corporate information systems to manage the process of projection into the future of expected future sales on the basis of a stated set of environmental conditions and assumptions, established in plans. A sales forecast is therefore defined as a projection of expected sales (in each market sector, for each product group, aggregated product, item, as detailed as required) into the future, given a stated set of environmental conditions under a specific *sales plan* or *sales program* (as detailed as the forecast) based on sales potential for a product or service (Spiro, 2003: 343; Mentzer and Moon, 2005: 9; Ingram, 2006: 115). Resulting, the purpose of the sales manager is to make projections of sales given a set of specified external (e.g. environment and competition) and internal (e.g. product portfolio and capacity) assumptions (Gilliland, 2003: 7; Ingram, 2006: 115). In other words, a sales forecast represents the outcome of a sales plan (Hanssens, 2001: 4; Mentzer and Moon, 2005: 9; Ingram, 2006: 115). One of the key measures of forecasting performance is accuracy of the forecast, one of the key methods to explain variances in accuracy is how the environment varied from the one defined (Mentzer and Moon, 2005: 9).

Planning stems from forecasting and one purpose of planning is to allocate company resources in such a manner as to achieve the anticipated sales (Jobber, 2006: 24). If the forecasted outcome is not satisfactory, planners can update the plan, then obtain new forecasts and, if necessary, repeat the process until the predicted outcomes are satisfactory (Armstrong, 2001: 3). Once the plan is established, the sales manager should invest all the efforts into putting this plan into reality by fulfilling the plan (Wallace and Stahl, 2002: 1-2).

The goal of a sales plan is not accuracy but to effectively and efficiently meet the forecast demand. To explain variances by monitoring the plan, the question need to be answered how the environment and assumptions in the sales process varied from the one defined at the time the plan was established (Mentzer and Moon, 2005: 9). As a result, the success of the plan depends on the precision of prediction of the customer-supplier interaction (Goerne, 2009: 2; Goerne, 2010: 1-5).

1.3.2. Time and Market Response Time

Time can be perceived objectively or subjectively. The subjective perception of time is when human beings give time their own interpretation (Quintens and Matthyssens, 2010: 93). This psychological aspect of individual perception has a great influence on the estimation of its length; Just imagine how fast time goes when having *a good time* (George and Jones, 2000: 657-685). In this project, time is (and must be) investigated as objective which is defined as measurable by some metric (Ancona et al., 2001a: 645-663; Ancona, Okhuysen and Perlow, 2001b: 512-529). This metric is the structured sales process itself, thus time is investigated in a linear perspective by focusing on the dimension *duration* of time. Nevertheless, the seven dimensions, such as timing, duration, frequency, pace, divisibility, flow and order are classified separately from each other.

Figure 2: The seven process dimensions of time

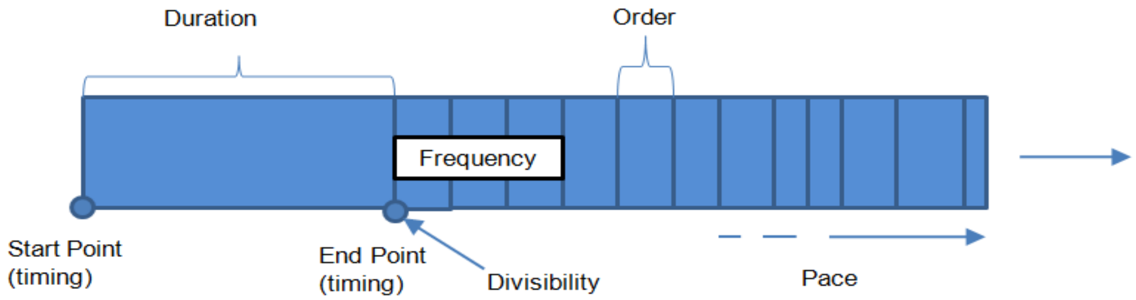


Figure: Adapted from Quintens and Matthyssens (2010: 93) (the dimension *flow* cannot be displayed)

The dimension *timing* is defined as a static reference point in time at which a temporal interval (process) starts or finishes. It is defined by both start and end point. The length of such a temporal interval is defined as *duration*, as measurement of how long a particular process lasts over time. The particular expression *time horizon* is a typical example of this. The measure of repetition of certain sub-processes is called *frequency*. Frequencies can be novel (no or very little repetition), cyclical (many repetitions) or punctuated (intermediate from where novel events are alternated with cyclical events). The speed of the duration of events is indicated by *pace*. Pace can be constant, decrease or increase. The *order* of time is the sequence or arrangement of different events. It can be monochromic (linear; one task is done at a time) or polychromic (circular; tasks are done simultaneously). *Divisibility* of time is either discrete (time can be divided into measurable units) or continuous (time cannot be split up), because other elements are dependent on it. The *flow* of time is a reference point in time, which can be a reference to the past, the present or the future (George and Jones, 2000: 657-684; Mosakowski and Earley, 2000: 796-812; Abbott, 2001: 3-11; Ancona et al., 2001a: 645-663; Quintens and Matthyssens, 2010: 93-95).

Besides the several dimensions of time, there are a large number of terms and expressions regarding time especially in sales. Such terms are the *sales cycle time*, the *length of the sales cycle*, the *customer lead time*, the *product lead time*, the *production lead time* or the *sales/ demand lead time*. Generally spoken, all expressions attempt to measure the length of the sales process, however sometimes the expressions are mixed and the definitions are not clear.

The sales cycle, sales cycle time or length of the sales cycle is defined as the time that elapses between the customer initiating the buying process or as soon as a interested customer is identified, until the point at which a decision is made on which product to buy, thus a contract is signed (Brooks, 2001: 11; Greco, 2007: 38). The customer lead time is defined as the amount of time the customer is willing to wait for a product, and the product lead time is the time how long it takes for suppliers to manufacture the product (Thrift, 2006: 11; Chase, 2009: 22). The production lead time is the stacked lead time for a product including the time from purchasing and arrival of raw material, manufacturing, assembly, delivery, and sometimes the design of the product (Kerkkänen, 2010: 24). The sales or demand lead time has a large number of definitions; the two most common ones are as follows:

- The sales lead time or demand lead time is the time from when the customer places an order until the goods are delivered (Kerkkänen, 2010: 24); and
- The sales lead time is the time from identification of a person or entity that has the interest and authority to purchase a product or service (first stage of the sales cycle is called a *sales lead*) until its qualification as a sales prospect (second step of the sales cycle) (Bibo and Geunes, 2007: 439-452).

The MRT as relevant time measure, is defined in the context of this project as the time lag between the start of an *increase of sales efforts by the supplier* (first contact) seen as a market stimulus and *the market response in terms of increased purchase*, thus when the customer starts to financially respond with the result of a *sales turnover increase* at the supplier’s side (MacFarlane, 2003: 103). It is the time dimension *duration*, determined by a start and an end point, measured by the sales process metric. In simple words, the MRT is the length of the industrial sales process; it is the duration of the customer-supplier interaction for a defined sales transaction. Furthermore it can be estimated that the longer the sales process is, the longer the planning horizon should be, because the more difficult it will be to predict the outcome of the sales efforts.

Figure 3: Market Response Time equals time lag

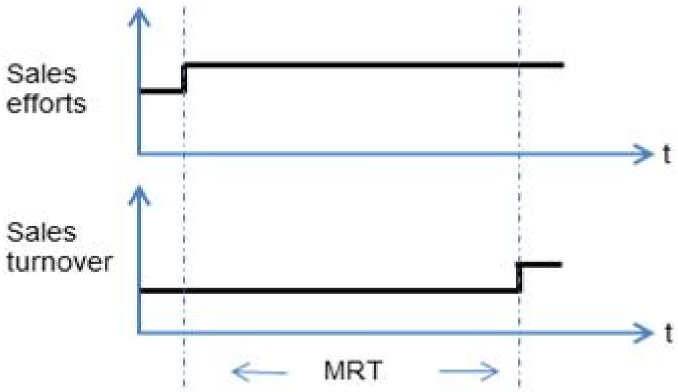


Figure: Developed by the researcher

Summarised, the MRT is the defined time with the widest time span of the sales process, thus from the early beginning, the first customer contact about a special product or project, until the latest end, the sales turnover increase at the supplier's side. The length of the MRT is important and most significant, because as shorter the time is defined, the less significant the expected influence on the sales planning and forecasting process (Maurer, 2011: 16-17).

1.3.3. Market response models

According to Leeflang and Hunneman (2010: 71), market response models are numerically specified relations between a relevant (sales) measure and variables that may explain fluctuations in this measure. The explanatory variables typically are marketing or sales variables thought to produce changes in the response variable, e.g. price and sales promotions. As a result, market response models are most important in the field of marketing and sales, not only because of the value these models can add, but also for other reasons. An example are that under increased scrutiny from Top-management and shareholders, managers feel the need to measure and communicate the impact of their actions on shareholder returns by market response models (Srinivasan, Pauwels, Silva-Risso and Hanssens, 2009: 24-43).

1.3.4. Industrial and consumer markets

According to some researchers, the industrial market consists of all the individuals and organisations that acquire goods and services to be used in the production of other products and services that are sold, rented or supplied to other organisations (Jones, Dixon, Chonko and Cannon, 2005: 183; Kotler, 2006: 374). This business is also known as organisational business (Steward, Morgan, Crosby and Kumar, 2010: 23-40). Typical characteristics of industrial markets are dependent demand, large buying and selling groups (called buying centers and selling centers) and close customer-supplier relations.

Table 1: Industrial sales vs consumer sales

	Industrial markets	**Consumer markets**
Demand	Dependent	Independent
Customer-supplier relation	Close (series business)	Loose (individual business)
Scale and value of the purchase	Medium to high	Low
Buyer	Powerful	Powerless
Length of negotiation	Long	Small
Buying decision	Organisational	Personal
Product required	Processing	For use

Table: Developed by the researcher, with some definitions from Jobber (2006: 11-12) and Kotler (2006: 374)

This type of selling differs significantly compared to the consumer markets. Differences are in the demand, the customer-supplier relation, the scale and value of the purchase, the power of buyers, the length of negotiation, the nature of the buying decision and the use for which the product is required (Jobber, 2006: 11-12; Kotler, 2006: 374).

1.3.5. Sales performance

Performance measurement is defined as the assessment of the relationship between business activities and business performance (Clark, Abela and Ambler, 2006: 191-

208). This broad definition makes it possible to measure sales performance in a large number of ways, such as *customer engagement*, which is the rational and emotional attachment a customer has to the company, *sales team skills*, which is the process and technical skills of the sales team to satisfy customer needs, or *effective sales communication* (Smith and Rutigliano, 2003: 68; Ariyachandra and Frolick, 2008: 113-120). In this research project, sales performance is measured by a combination between the primary task of a sales manager, which is according to Yu Ha and Florea (2009: 139-156), to generate sales turnover, and the common performance measurement approach *measurement of productivity* by Rust, Lemon and Zeithaml (2004b: 109-127). Thus, sales performance is measured by the consolidated sales turnover per sales employee in 2010 (productivity in Thousand Euro), the consolidated sales turnover per sales employee development from 2008 to 2010 (growth of productivity in percent), and the market position of the investigated company. The performance measure *sales productivity* in Euro (or Dollar), the number of sales employees divided by sales turnover, is a commonly defined operating performance ratio by investopedia.com and used by a large number of companies, such as Cisco, Siemens and Coca-Cola.

1.3.6. Sales plan and forecast horizon, forecast interval, forecast form and forecasting method

The *sales plan horizon* is defined as *how far the plan goes into the future* and the forecast horizon is defined as *how far the forecast goes into the future* (Wallace and Stahl, 2002: 24-26). The forecast horizon should obviously be similar to the plan horizon. This is indicated by the plan and forecast definition in section 1.3.1, as the forecast represents the outcome of the plan. If, for instance, a corporate plan is established for the next two years, a sales forecast for that two-year time horizon should be undertaken.

The *sales forecast interval* generally shows *how often the forecast is updated* (Demetrescu, 2007: 227-238). Usually, forecast intervals can be weekly, monthly, quarterly or yearly. According to Wallace and Stahl (2002: 24), most companies use a monthly forecast interval. If the two-year corporate sales plan must be updated every three months, it can be stated that the forecast horizon is two years and the interval is quarterly.

The *sales forecasting form* is what needs to be forecasted or planned. Some departments need to know what physical units are to be produced, while other functions need to know the currency equivalents of these units and other functions need to plan based upon the weight.

A *sales forecasting method* is a procedure for estimating how much of a given product (or product line) can be sold if a given sales program is implemented (Sanders and Ritzman, 2004: 514-529). Well-managed companies do not rely upon a single sales forecast method but use several. If different methods produce roughly the same sales forecasts, then more confidence is placed in the results. If different methods produce greatly different forecast figures, then the sales situation needs further study (Still, Cundiff and Govoni, 1998: 42).

1.4. RESEARCH PROBLEM

The problem statement of this research project is that MRT is ignored during industrial sales planning and forecasting in different industry sectors leading to inefficient planning (Goerne and Grohmann, 2010: 69-79).

This problem can be described as follows: In order to improve the precision of sales planning and forecasting in industrial markets, it is important to understand the time lags related to actions on the market.

1.5. CASE STUDY RESEARCH METHODOLOGY

It is the aim of this research project to describe special aspects of the planning and forecasting behaviour of companies in three industry sectors and to show the reasons for acting in the detected manner. In order to display this best, the research will be a qualitative study by investigating the Machinery & Equipment and the Automotive Supplier Tier 1 and Tier 2 Industry sectors with the *case study research methodology*.

The case study research methodology is appropriate when answering “how” and “why” questions and the investigation of a contemporary phenomenon in depth and within its real-life context is executed (Yin, 2009: 9-18). As the main research questions are constituted from “how”-questions and since the issue under investigation represented a present-day problem currently faced by numerous companies trying to take advantage of the opportunities enhancing sales planning and forecasting, it is decided that the case study methodology is best suited to the inquiry (Dubois and Gadde, 2002: 753-760). This fact is further discussed in the methodology chapter four (page 91 and following).

There are four basic types of case study designs: The holistic single-case design, the embedded single-case design, the holistic multiple-case design, and the embedded multiple-case design. Which type of case study to choose is dependent on the research purpose, questions, propositions and theoretical context (Rowley, 2002: 19). Holistic case studies examine the case as one unit by focusing on broad issues, such as organisational culture or strategy. On the other hand, embedded designs identify an amount of sub-units, called embedded units of analysis, such as industries or locations (Rowley, 2002: 22). The most appropriate design for this research project is the embedded multiple-case design. The reason for this design is that this project investigates three industry sectors and embedded units of analysis, such as sales and controlling departments. Furthermore, it is the aim of this research project to attain a deep, comprehensive and comparable understanding of the technical and commercial issues affecting a company’s sales planning and forecasting process.

The exploration and description of the cases took place through detailed, in-depth data collection methods, involving multiple sources of information that were rich in context which included interviews, documents and observations. This approach can be used to either predict similar results (literal replication) or predict contrasting results but for predictable reasons (theoretical replication) (Yin, 2009: 47). In case study research, three principles of data collection are relevant to establish the construct validity and reliability of the case study evidence. All of them formed the basis for this research topic. The principles are 1) use multiple sources of evidence, 2) create a case study database, and 3) maintain a chain of evidence (Yin, 2009: 114-124).

In real life context, individual suppliers in the Automotive Industry can be assigned to various positions (Tier 1, Tier 2, Tier 3 or Tier 4) in the supply chain according to how broad their product portfolio is. The expansion in products and supply chain positions can be returned to the increasing crowding-out competition in the Automotive Industry (Becker, 2006: 165). This fact makes it quite important to clearly and purposively choose the participants in the empirical study. For this reason, the purposive sampling method was applied within the case study methodology. This means that the sample was selected with a purpose in mind and consequently a specific predefined group was sought, because it illustrates some process that is of interest for a particular study (Silverman, 2006: 104).

Case study evidence can come from many sources, such as documentation, archival records, interviews or direct observations. The key strength of the case study method lies in the involvement of multiple sources (also indicated by the University of Texas, http://www.ischool.utexas.edu/). The designated data gathering tools were used systematically and properly in collecting the evidence. Throughout the design phase, it was ensured that the study was well constructed to ensure construct validity, internal validity, external validity, and reliability. For the gathered qualitative data, the data collection methods of pattern matching and cross-case synthesis technique were applied (for further details see chapter four) (Patton, 2002: 432; Vos, 2005: 333). The quantitative data from fixed interview-questions was displayed in charts and figures.

1.6. EMPIRICAL STUDY

The process of the empirical study already started with an in-depth literature review about sales planning and forecasting (chapter two) as well as market response research (chapter three) to develop the research objectives. As soon as the research objectives were determined, an interview schedule was designed for the pilot study.

Figure 4: The process of the empirical study

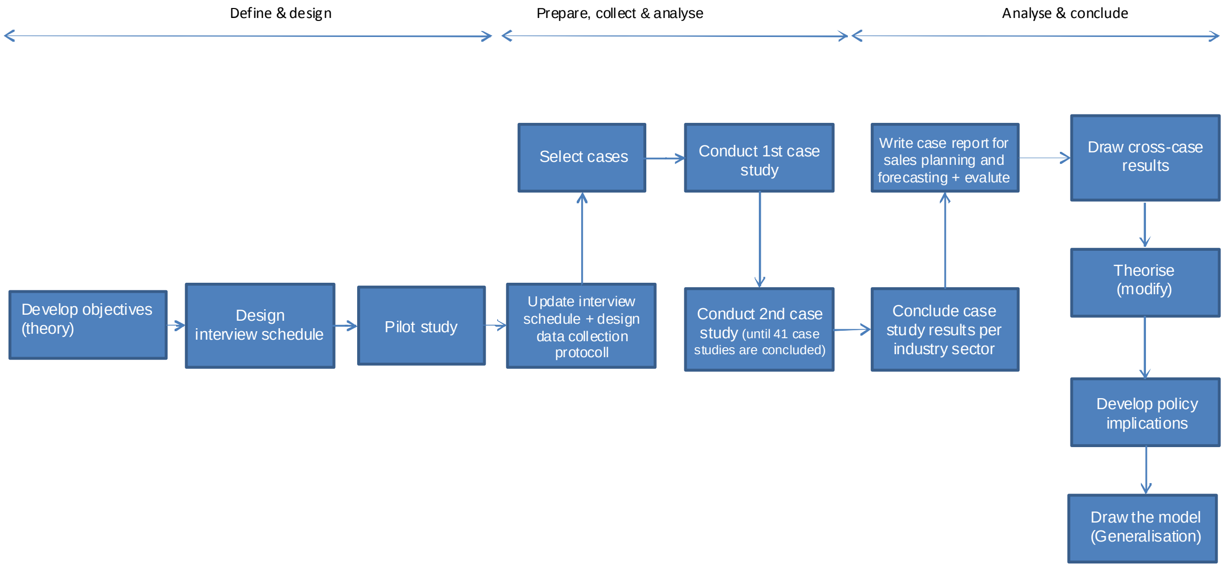


Figure: Adapted from Yin (2009: 57) and Hancock and Algozzine (2006: 7-68), optimised for this project by the researcher

The intention of a pilot study was is to prevent a considerable trial and error in the empirical study as well as to gain a first overview and understanding about the topic, to develop relevant lines of questions, to provide some conceptual clarification for the research design and to help to refine the data collection plans. Furthermore, it is recommended to field-test the interview situation, as well as the wording, ordering of questions and the interview design (Seidman, 1998: 32; Yin, 2009).

Following the pilot study, the cases were selected (purposive sampling) and conducted (internal data by a structured interview schedule). Based on the results of the case studies, case study results per industry sector were conceptually ordered and described in chapter five, afterwards theorised and concluded in chapter six. *Conceptually ordering is* classifying the gathered data into discrete clusters, according to their properties and dimensions structured in the interview schedule including external information. *Describing* is purely presenting the clustered data without conclusions to distinguish those clusters without necessarily relating to each other to form on overarching explanatory scheme. *Theorising* is the act of constructing from data an explanatory scheme, thus a conclusion, that systematically integrates various concepts through statements of relationships (Strauss and Corbin, 1998: 19; Goulding, 2002). In a glance, the research findings move beyond conceptual ordering to theory, displayed in three models for each of the investigated industry sectors (see section 6.1 on page 146 and following).

1.7. LAYOUT OF THE STUDY

1.7.1. Literature section and empirical section

The aims of the literature section were to identify common scientific literature about sales planning and forecasting, as well as investigate literature about market response research, especially modelling market response. The literature review supported the generation of the case study design.

1.7.2. Primary and secondary objectives of the research project

The primary objective (or similarly *aim*) of the research project was to investigate the sales planning and forecasting behaviour in the Machinery & Equipment, the Automotive Tier 1 Supplier and Automotive Tier 2 Supplier Industry sectors.

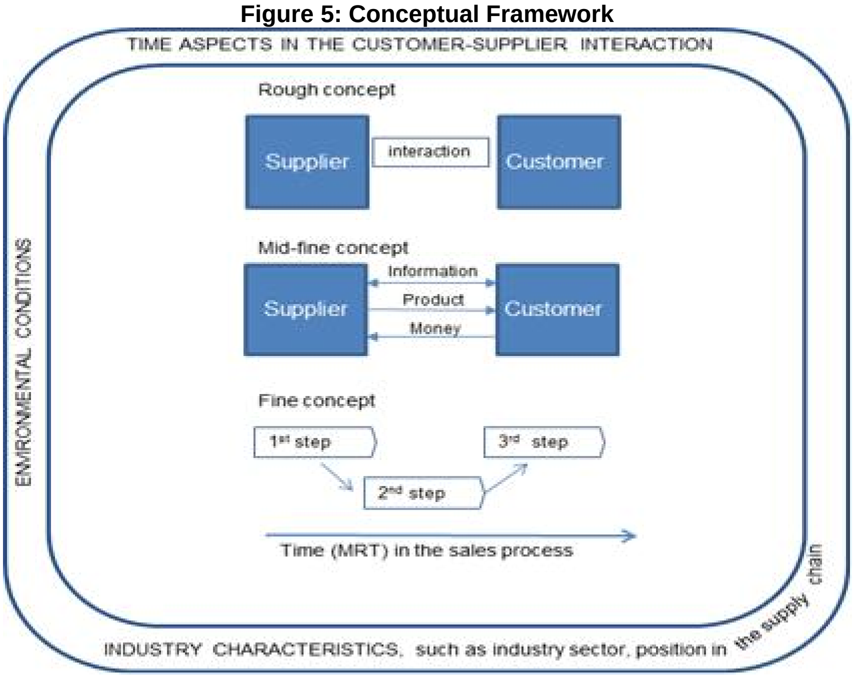
The secondary objectives of the research project were, to:

- Determine the sales process and time frames (aspects, durations) in the three selected industry sectors;
- Determine the state of sales planning and forecasting in the three selected industry sectors;
- Determine the effects of time aspects (MRT) on the planning horizon; and
- Determine the effects of forecast accuracy on sales performance to increase the sales performance by implementing time aspects (MRT) into sales planning and forecasting.

1.7.3. Conceptual framework of the research project

As it is indicated in the literature, the intentions to establish a conceptual framework are many and varied, such as to identify who or what will be included in the project, to describe what relationships may be present in the project based on theory and/ or experience (Baxter and Jack, 2008: 553; Yin, 2009: 85).

Figure 5: Conceptual Framework



Framework: Developed by the researcher

The framework displays from outside to inside the environmental conditions (technical and commercial issues), the industry characteristics (such as the industry sector and the position of the company in the supply chain) as well as the time aspects in the customer-supplier interaction, where the industrial sales process is undertaken. The sales process, which is in fact an interaction between supplier and customer (rough concept), can be displayed finer as the transaction of information, products and money between the customer and supplier (mid-fine concept). The fine concept displays the interaction between the customer and supplier by process steps which are influenced by time aspects (MRT).

1.8. LIMITATIONS

The following aspects indicate the limitations of this research project:

- Research context: This research project only investigates the industrial context, especially the Machinery & Equipment and the Automotive Supplier Tier 1 and Tier 2 Industry sectors. Its results can only be applicable to this industry sectors; and
- Research Methodology: The underlying research methodology of this research project is a qualitative one. The qualitative approach is the only suitable approach for the research context, because the emphasis is placed on collecting individual, detailed, in-depth information and the qualitative rather than the quantitative element of the information is important. For this reason, statistical generalisation cannot be given.

1.9. CHAPTER LAYOUT

The first chapter gives a short and concise introduction to the research project. It includes the focus of the research project, the research gap and defines necessary terms. The problem statement as well as the aims of the project are displayed and a short introduction to the underlying research methodology of this project is given.

The second chapter investigates industrial sales planning and forecasting. In the first part, it gives a broad literature based overview about the evolution of sales planning and forecasting and its different approaches and theories in the historical context until today. In the second part, the overall company planning cycle as well as planning and forecasting processes and methods are introduced. Finally, forecast accuracy and proper sales performance measures are discussed.

The third chapter gives an in-depth literature review about the evolution of market response research and market response models. It is the aim to identify any market response model that operates with time or any similar model. In the second half of the chapter, the methodology of marketing modelling as well as other aspects of modelling market response is shortly introduced to set up the literature basis for real lifetime observations in sales planning and forecasting as a function of MRT.

The fourth chapter points out the research methodology for this research project that is the case study methodology. It introduces to the case and research questions, the boundaries for the case, the conceptual framework, the design of the case study, the data collection and sample methods and size and data processing. Finally, the research process for the empirical study is discussed.

The fifth chapter demonstrates the results of the empirical qualitative study as well as some statistical background information to selected questions.

The sixth chapter discusses the empirical results and gives conclusions and recommendations based on the background of the literature review and the gathered empirical data. It states three models and discusses the aims with the results of this research project. At the end, conclusions, recommendations, limitations and further research implications of the project are discussed.

CHAPTER 2: SALES PLANNING AND FORECASTING IN THE INDUSTRIAL CONTEXT

The following chapter introduces planning and forecasting sales and the execution of the planned sales by the sales process. In the first part, the history of planning and forecasting sales is introduced to provide the necessary background information to the topic. Afterwards, the planning and forecasting process is discussed in detail. The main part of this chapter describes the process of executing the plan and the sales forecasting process by the customer-supplier interaction to generate future sales turnover. This execution is discussed for the three investigated industry sectors, followed by a classification and description of methods to forecast sales and the discussion about popularity and usage of these forecasting methods. The chapter concludes with a short part regarding forecast accuracy and sales performance.

2.1. HISTORY OF PLANNING AND FORECASTING

In retrospect, forecasting was often devaluated that it is not a respectable human activity and even not worthwhile beyond the shortest of periods (Drucker, 1973: 124). It had to face a lot of prejudices: One of the earliest was made by the Scottish philosopher David Hume (1777) in his book *An Enquiry Concerning Human Understanding*. Hume was concerned with the problem of induction, the reasoning from particular elements or facts to general conclusions.

This view changed over time. The early seller dominance in the Western World in the 1950s changed to buyer dominated markets in the late 1960s, thus marketing and sales became important tools for the success or failure of a company (Hogarth and Makridakis, 1981: 115-138). In addition, several research studies have shown that companies that plan their product-market strategies and predict the aggregate customer spendings, have a greater chance of achieving commercial success (Brownlie, 1985: 35-63; Fornell, Rust and Dekimpe, 2010: 28-35). It can be thought, that for this reason, much attention has been given to the challenges of planning, forecasting and controlling sales efforts since the 1960s (Alderson, 1964: 180-191; Shuchmann, 1966: 45-56; Grinyer, 1975: 70-97; Brownlie, 1985: 35-63; Fornell et al., 2010: 28-35). For this fact, the use of planning and forecasting has risen to prominence within a few decades and now receives considerable attention from both academics and practitioners (Lapide, 2002: 11).

In the early beginning of planning and forecasting, estimates for customer orders were often overstated to be sure there was enough products allocated to meet the customer needs (Covas, 2006: 6). In the middle 1970s, supply planning was done based on an inflated forecast to build inventories and to meet upside sales potential, but lower volumes were submitted for financial commitments. Sales and marketing was expected to beat their figures and supply planning had to maintain low inventories, low delivery costs, and high service levels. Additionally, demand planning was responsible for stock-keeping unit (SKU) level accuracy, while sales was measured on total volume targets (Covas, 2006: 6; Tribou, 2006: 7).

Since the early 1980s, technology has increased the speed by which forecasts were calculated. This made forecasting more and more popular in practice and in the academic world, as indicated by the introduction of the *Journal for Business Forecasting* in 1981. The internet has enabled companies to integrate forecasting with other internal processes, as well as to collaborate with other customers and suppliers. This has tremendously improved business performance (Safavi, 2006: 8). The personal computer made business forecasting technology available to companies of all sizes, all with a degree of analytical sophistication (Smart, 2006: 11). Prior to the advent of the personal computer, the lack of automated tools and the associated processes limited business forecasting effectiveness and efficiency (Milliken, 2006: 9).

In the 1990s, a proliferation of forecasting software can be stated. Software solution providers realised that forecasts do not exist in a vacuum, indeed they are part of an overall corporate planning process and need to be integrated with other planning systems (Smart, 2006: 11). Solutions whereby the forecasting toolset was integrated with supply side processes for master scheduling and distribution requirement planning or enhanced functionalities, such as automatic forecasting model selection based on forecast error, were highly requested (Milliken, 2006: 9). In line with new technological possibilities, management supported more and more the collaboration among partners both internally and externally in the supply chain. This was not possible in the early 70s due to limited technology (Tribou, 2006: 7). In parallel, Enterprise Resource Planning (ERP) systems appeared at the end of the 1990s. The ERP vendors certified forecasting software partners to provide business forecasting functionality through interfaces. Today, most of the large firms that use ERP systems have a business forecasting module built into their calculations (Milliken, 2006: 9). Milliken (2006: 9) referred to another change in managing future sales during this time: Customers had placed more and more responsibility on vendors to ensure product availability through arrangements such as Vendor Managed Inventory programs and in return, vendors have agreed to make point-of-sale data available to manufacturers which they could use in their forecasting efforts. These Collaborative Planning, Forecasting and Replenishment (CPFR) processes are used extensively in the retail and consumer goods industry.

The increase of forecasting speed influenced both technology and the classical Supply Chain Management. The speed at which forecasts can be altered today with technology also presents a significant risk to the supply chain: It is possible to modify the forecast so often that the supply chain cannot react quickly enough, produces products that are no longer needed (excess) or does not manufacture products that are needed (shortage) (Tribou, 2006: 7). Competitive global markets and high service level requirements have made accurate forecasting more critical (Smart, 2006: 11).

In the past, the focus was on efficiency, lowering costs, and improving asset utilisation. Today it moves from effectively balancing and matching supply with demand to mode demand sensing, demand shaping, and developing a more dynamic, predictable, and profitable manufacturing response (Schlegel, 2006: 12). New technologies such as Radio Frequency Identification and Supply Chain Event Management improve visibility in the supply chain and reduce internal response times to changes in demand (Milliken, 2006: 10). Advanced methodologies are now able to solve intractable problems associated with intermittent slow moving demand which simplifies safety stock management and inventory requirements for organisations in a variety of industries and Maintenance, Repair and Overhaul (MRO) organisations (Smart, 2006: 10).

Since 2000, planning and forecasting have become fundamental management tasks, although they are often given too little time within a busy salesman`s schedule (Gilliland, 2006: 10). Currently, the markets are highly volatile and it is of utmost importance for companies to have some idea of what will happen in the future (Spiro, 2003: 335; Jain and Covas, 2010: 5). As customer lead times (see section 1.3.2, page 11) shrink and product lead times (see section 1.3.2, page 11) increase as a result of global sourcing, the dependence on accurate forecasting is an inevitable consequence (Thrift, 2006: 11; Chase, 2009: 22). The supply chain globalisation with its decreased lead times, global reach across multiple countries, markets, channels, brands, and products, requires a more and more granular forecast (Thrift, 2006: 11; Chase, 2009: 5). Even joint sales planning (of supply chain members) came to mind to increase market share and value (McCarthy and Golicic, 2002: 431-454; Dolpp, 2004: 59). This idea for more CPFR leads to a survey done in 2005 about CPFR (Jain, 2005: 3-7). One of the results was a new call for collaboration, not only within a company but also outside, to achieve basically the same objectives, that is, to improve planning and forecasting, reduce inventory, and improve customer service as well as supply chain performance.

In the late 2000s, companies utilise their Sales & Operations Planning (S&OP) process to align sales estimates to demand planning's unbiased statistical forecasts and the financial commitment. A single forecast is the outcome which is submitted to supply planning. In this process, each (product) group has shared responsibility to forecast accuracies in the annual objectives. Positive effects are driving down inventory and improving customer service. According to Covas (2006: 6), performance metrics will continue to improve as companies make building demand planning capability and cross-functional collaboration a priority.

Changes in sales forecasting has been a highly discussed topic since Mentzer and Cox (1984a: 27-36) in the 1980s, continued by Mentzer and Kahn in the 1990s (1995: 465-476) and in the 2000s (McCarthy et al., 2006: 303-324). The newest findings in this research question about forecasting practices revealed both discrepancies and similarities between today’s sales forecasting practices and those of ten and twenty years ago. The number and sophistication of methods available to sales forecasters have improved and the change in computers during this time span has increased efficiency and effectiveness in forecasting (McCarthy et al., 2006: 322). Given all this, some researcher report that accuracy, technique and systems understanding and use, and satisfaction with techniques, systems, and management processes have not improved, though the familiarity and usage of various sophisticated sales forecasting techniques have increased (McCarthy et al., 2006: 303-324). Companies now leverage predictive analytics to detect patterns in selling behaviour. This sense demand by detecting behaviour patterns by data mining technology, measure the effectiveness of market strategies and optimise marketing expenditures across the product portfolio (Chase, 2009: 1). Resulting sales methods and applications have changed to proactively drive, rather than to react to, sales. This is essential because the days of customer loyalty and limited market offers seem to have gone.

While all these developments in the broad field of forecasting have helped the organisation do more with less, there is still a need for a knowledgeable expert who understands the business, the marketplace, and the techniques to generate a repeatable, operational, unbiased forecast plan (Hanson, 2006: 10). It has been proven that sales planning is important and maximises sales success as the business environment has changed dramatically over the past twenty years (Johnson, 2008: 64-70). Increasing globalisation, widespread adoption of information technology, and the advent of e-business were important milestones. Factors stemming from these environmental changes such as time-based competition (McCarthy and Golicic, 2002; McCarthy et al., 2006: 303-324) and product proliferation (Bayus and Putsis Jr, 1999: 137-154) have a direct impact on planning and forecasting practices and processes (Moon, Mentzer and Smith, 2003: 21-26).

The highly volatile markets create a large number of challenges and difficulties for the companies in terms of reliable plans for future sales turnover. Results for non meeting, thus unreliable plans, can be missed customer deliveries, loss of credibility with customers, loss of customers, expediting, higher manufacturing costs, reduced flexibility and responsiveness and reduced financial performance (Singh, 2009: 10). Unreliability can be caused by many factors. Most of the literature dedicates unreliable plans to the fact that sales plans usually are based on data about markets, industry conditions and on aspects of strategic goals and environmental appraisals

(Hult et al., 2007: 60). Unreliability can cause, most dramatically, unplanned loss of sales turnover which endangers the survival of the company on the market (Morlidge and Player, 2010: 1). This reliability of the sales plan in the industrial context depends on two factors i) the precision of prediction of customer relations (because this is the basis for future sales turnover) and ii) the precision of the forecasts of the economic environment (Goerne, 2009: 2).

2.2. OVERALL COMPANY PLANNING CYCLE

The overall company planning cycle determines the budgeted operating result of the company for the upcoming planning period which usually is one year. It is calculated as the difference between the total revenue and the total expenditures for the year summarised for every cost center (departmental budget) (Goerne, 2011: 3). The sales plan is the task of the sales manager (sales department), who is the only one that plans revenues for the company; all other managers (departments) do plan expenditures or resources.

The company planning cycle usually starts top-down (from the Top-management side) by setting profitability targets and the operating result for the upcoming period. The Top-management further budget for investments for specific departments, such as the Production Department or the R&D Department which should be intensely discussed between the Management and the Head of Department beforehand. If the legal form of the company requires a Board of Directors to control the Board of Management, the targets need to be approved by the Board of Directors at the end of each planning cycle. This administrative board meeting is typically held in October or November (for the three selected industry sectors that form part of this research) to set the targets for the new fiscal year (that usually is equal to the annual year) (Wallace and Stahl, 2002: 25; Goerne, 2011: 3).

Figure 6: The overall company planning cycle

Figure: Developed by the researcher according to the lecture notes of Goerne (2011: 3)

As soon as the profitability targets are set, the Marketing Department needs to define the specific industries and markets of activity as well as the marketing budget to invest for the following year. Based on these figures, the Sales Department plans the sales turnover and sales amount for the upcoming year. This sales plan usually is customer specific and item specific. The sales amount is then forwarded to the Production Department. Based on the top-down investment for the production and the total sales amount, the production plan is set in terms of personnel requirements (working hours), machine requirements and total amount of production material. These figures are forwarded to the Procurement and Human Resources Department. The Procurement Department calculates all the expenditures in terms of procurement costs and the Human Resources Department calculates the personnel expenses both based on the production plan. The Controlling Department takes all the plans into account to calculate the variable as well as fixed cost for the upcoming planning period. The profit and loss statement is then simulated and thereof the operating result is derived. An actual-nominal calculation is provided to the Top-management which itself can then compare the planned and simulated targets. If the planned figures are satisfactory, the plan can be established, if not, the cycle can start again. This project and the following chapters are all about the *sales planning and forecasting* as a step in the above mentioned process.

2.3. SALES PLANNING AND FORECASTING PROCESS

The process of planning and forecasting (by the sales manager), executing (by the sales force) and monitoring the execution of sales figures (by the sales manager), such as sales turnover and amount, is often called a sales system, sales control loop, Sales Management or S&OP (Wallace and Stahl, 2002: 67; Backhaus and Voeth, 2007: 327-598; Goerne, 2009: 2; Wilkinson, 2009: 79-95). (This step in the process is surrounded by a frame in figure 6, page 29).

Figure 7: Sales planning and forecasting process

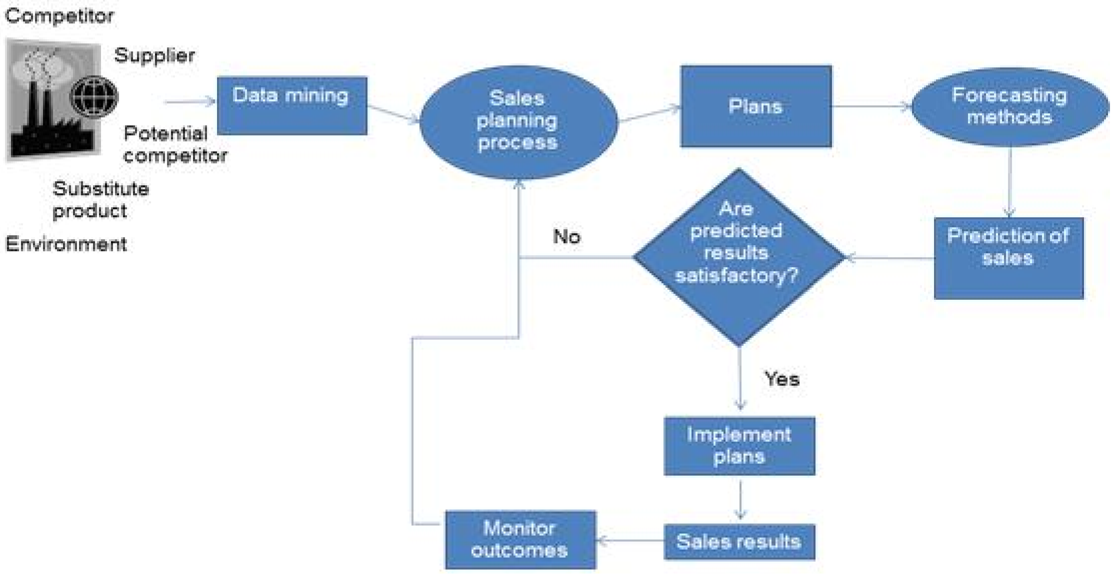


Figure: Adapted from Armstrong (2001: 3) and Goerne (2009: 7)

The sales planning process is mainly based on a large number of external and internal data. External data (also known as market data), such as data about competitors, about potential competitors, information from suppliers or environmental data, is generated by data mining. Data mining provides the sales manager with exactly that data which is needed, thus relevant for the company planning and forecasting process. The sales plan can be done by the specific sales approach of choice; this can be top-down, bottom-up or mixed planning (the sales planning approach will be discussed later on in section 2.4, pages 34-36). Having the sales plan and the prepared external data available, the next step within the sales planning process is to compare if this external data fit into the objectives of the sales plan. The result can be that the sales plan is too ambitious. This is the case, for example if the sales plan is to grow ten percent, but the economic data only predicts an economic growth of one percent and there is no reason why sales should grow more. On the other side, the sales plan can be too conservative; this is if the economic growth is much higher than the planned sales growth. If the sales plan fits into the current environmental situation, specific strategies and operational plans for sales need to be prepared. This part of the process should give prove that the objectives in sales can be reached, e.g. if the power of the sales force is strong enough to support growth (Fildes, 2010: 2-6).

The next step is to establish a sales forecast to represent and predict the outcome of the established sales plan (in terms of sales turnover and amount) undertaken by the forecast method of choice (see figure 10, page 44) (Hanssens et al., 2001: 4).

The process of forecasting sales is usually a monthly computer-based calculation cycle to review and monitor sales plans and their execution. This is done for customer expectations and internal operations for its accuracy, process accountability, lessons learned, future risk management and additionally give updated input to the Production Department (Sheldon, 2006: 2). This forecasting process is mainly based on information developed from data collection, or influences from the market or from the sales and marketing team, information about competitor actions or environmental fluctuations (Sheldon, 2006: 3). The overall sales forecasting process is normally divided into three phases. It is the input phase (usually from a variety of sources), the conversion phase (the forecasting process and its methodology) and the outcome phase as displayed in figure 8 (Wallace and Stahl, 2002: 14).

Figure 8: Forecasting process

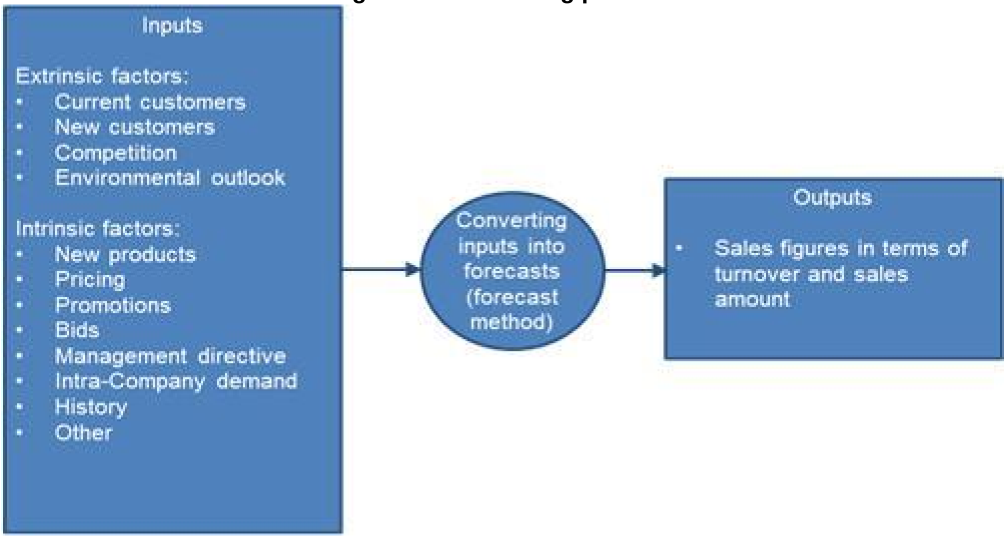


Figure: Adapted from Wallace and Stahl (2002: 14)

The impact of extrinsic factors, such as current customers, new customers, competition and environmental outlook, are difficult to predict, primarily because they are outside of the company and cannot be influenced. The same applies to intrinsic factors. Imagine the impact of new products and new technology on future sales for existing products (Wallace and Stahl, 2002: 16-20). To minimise the impact of unforeseen influences, Klatch (2007: 28) recommends different forecast levels on which the forecast should be executed, such as the strategic forecast level, the tactical and the operational forecast level. The first level in this approach is to execute the strategic (general) forecast of economic and business conditions as well as competitive activities. The second level on the tactical level is to estimate the total level of sales or possible demand based on the number of customers and their purchasing ability as well as internal capacity. The last level on the operational forecasting level is to forecast the product or product group sales per market segment and finite capacity calculations (Klatch, 2007: 28). On the contrary, Ingram (2006: 115) recommend to refer to three factors that should be defined to forecast: the product level (industry sales, company sales, product group sales, product item sales), the geographic area (word, country, region, territory, customer), and the lead time (short, medium, long). Both approaches attend to minimise the relevant factors which affect the outcome of the forecast.

The second phase in the forecasting process is the conversion phase. It is the conversion of inputs by the forecasting method into an output (phase 3). People give their input in terms of the forecasting frequency, forecast interval and forecast horizon. For this input it is most important what kind of forecast, e.g. sales forecast, a financial forecast or a production forecast, is undertaken (see section 1.3.1 and the term “island of analysis” on page 8). For effective financial planning it is, for instance, highly recommended to have a horizon of minimum 12 months related to the fiscal year (Wallace and Stahl, 2002: 25).

The underlying process of any forecast is its methodology, today mostly executed by forecasting software. The methodology, however, is the heart of any forecast. It determines the forecast input, thus all methods use input factors, the historic pattern and the output of the plan. In other words it can be said that the forecast methodology determines the intelligence of the sales manager (department). The methodology must be structured to calculate reproducible and transparent results to build a company’s outlook in terms of sales amount and sales turnover (Wallace and Stahl, 2002: 28-32). As a result, forecasting is a necessary tool (measured by the Key Performance Indicator *accuracy* (please refer to section 2.7, pages 58-62)) and the key for effective and efficient planning (Jain and Covas, 2010: 6).

If the forecast outcome is not satisfactory, e.g. too low in terms of sales turnover or amount, planners need to update the plan and then obtain new forecasts based on the new plans. This process can, theoretically, be repeated many times, until the predicted outcomes are satisfactory. However, the time schedule of the planning process in the industrial context is usually very tough; this results that plans usually will be only one or two times updated before they are finalised (Goerne, 2009: 3).

Afterwards, if the outcome of the forecast is satisfactory, the plans are established and implemented into the overall company systems (to be continued in the overall company planning cycle). Such a sales plan can be, for example, very detailed per product group, market sector and / or country. The grade of detail is dependent on the grade of accuracy which has to be gained by the management.

The last step in the sales system is to continuously monitor the sales results as outcome of the sales plan (Mentzer and Moon, 2005: 1112). As indicated in section

1.3.1 (page 9), the success of the sales plan depends on the precision of prediction of the customer-supplier interaction (Goerne, 2009: 2; Goerne, 2010: 1-5).

2.4. SALES PLANNING APPROACH

Industrial planning is increasingly characterised by the need to plan worldwide future sales for a large number of items in a highly volatile economic environment (Kahn, 1998: 14-19; Lapide, 2006: 14-16). Product and worldwide customer knowledge is as important as to adequately set future sales goals by plans. Three approaches are available to set future goals; it is *top-down planning*, *bottom-up planning* and *mixed planning*.

The top-down strategy plans an aggregate total and distributes it to individual items or units proportionally by the sales manager (Goerne, 2011: 6). This plan is then forwarded as sales target top-down to the sales force. This kind of planning seems useful for improving the accuracy of detailed plans (in addition to bottom-up), because aggregated demand is less volatile than its individual items, due to the phenomenon of compensating errors where random errors and variations tend to cancel each other (Lapide, 2006: 14-15). In 2010, Rieg (2010: 17) proved this statement for the Automotive Industry sector at an example of a German car manufacturer. He concludes that high family forecast accuracy often comes from balancing low and high item forecasts. The overall plan can be used for any type of demand, such as aggregation across products, sales channels, geographies, and even time itself (Lapide, 2006: 15). The top-down approach is the older, more recognized approach in the industrial context.

Top-down models typically do a poor job of planning lower forecast levels, e.g. at the item per location level, because the aggregated data at the top-level is an artificial representation of the true nature of the business by levelling out peaks and valleys (Rieg, 2010: 17). For this reason, top-down planning only makes sense when a top-level aggregated group is made up of items that have similar patterns of variation (Lapide, 2006: 15).

On the other side, the bottom-up strategy combines the estimates of each product group or single items separately to compute the estimate for the entire company (Tichenor and Davis, 2009: 184-189). This is mostly done by the sales force. The sales plan (or estimated turnover) is then forwarded bottom-up to the sales manager or board of sales management. This approach is better for situations where the individual items have different patterns of variation, e.g. high level of country versions of a product (Lapide, 2006: 15). In B2C, almost everything is planned bottom-up (Yoskovitz, 2009: 1-4).

Proponents of the bottom-up strategy point to the fact that one can achieve a better mean absolute percentage error (MAPE) value at the lower level, because the lower level models reflect the actual nature of the business, planned by people acting daily in this business (Williams and Waller, 2011: 17-26). However, bottom-up planning often has a bad accuracy at higher forecast levels, maybe as a result of accumulating data (Kahn, 1998: 14).

The question of accuracy of top-down versus bottom-up planning in forecasts can mathematically be answered by a simple equation with the result that neither bottom-up nor top-down execute better figures based on the underlying methodology of exponential smoothing (This is in theory, please refer to some results of this project e.g. table 5, page 165). In top-down forecasting an aggregate forecast is broken down into item forecasts using popularity percentages based on historical data. If the aggregate forecast, sometimes called a family forecast (FF_t), is generated by an exponential smoothing model, the individual item forecasts i ($FI_{i,t}$) are generated using a modification of the same smoothing model as follows (Snyder, Koehler, Hyndman and Ord, 2004: 444-455):

$$\text{Family Forecast: } FF_t = FF_{t-1} + \alpha(F_{t-1} - FF_{t-1}) \quad ;$$

$$\text{Item Forecast: } FI_{i,t} = \rho_{i,t}\, FF_1 = \rho_{i,t}\,[FF_{t-1} + \alpha(F_{t-1} - FF_{t-1})$$

where

FF_t	family forecast for period t;
$FI_{i,t}$	item i´s forecast for period t;
$\rho_{i,t}$	popularity percentage forecast for item i at time t;
$\Sigma \rho_{i,t} = 1$	for each time period t for n different items in the family;
α	smoothing constant that ranges from 0 to 1;
F_{t-1}	observed family demand in period t-1.

Latest research results by Williams and Waller (2011: 17-26) pointed out that the superiority of the top-down or bottom-up forecasting as the more accurate forecast method depends on whether shared Point-of-Sale data are used.

In 1998, Kahn (1998: 19) came up with the idea of a mixture between the bottom-up and top-down approach, called a *mixed-planning* approach. The advantage of this approach is that the bottom-up plan can be improved by comparing it with a top-down plan. Therefore the individual bottom-up item plans can be improved by adjusting correction factors derived from looking at the aggregated group's bottom-up versus its top-down plans (Lapide, 2006: 15). Based on this, it is obvious that the combination of both methods is recommended for adequate planning (however no investigation could be found about the planning approach and performance) (Amdam, 2010: 1805-1819).

2.5. SALES PROCESS

The execution of plans in the industrial context can be described best by the sales process, which is in fact a customer-supplier interaction and the reliability of plans depends on the outcome of this interaction (Goerne, 2010: 1-4).

2.5.1. Reliability of the sales plan

The literature review indicates that the industrial market is a complex environment and differs significantly from the consumer market (table 1, page 13). Literature furthermore advises that this difference is most important, if improvements in the planning and forecasting process as well as the sales process are of value for the company or not (Kerkkänen, 2010: 15). Taking this into consideration, it is obvious that it is important that each planning and forecasting process fits into the special characteristics of the company's environment, future sales and needs. This indicates that a clear definition and understanding of the company’s characteristics as well as the sales process is essential, which is disregarded in most scientific literature.

Most of the literature dedicates unreliable plans to the fact that sales plans are usually based on volatile data about markets, industry conditions and on aspects of strategic goals and environmental appraisals (Hult et al., 2007: 60). Unreliability can result, most dramatically, in an unplanned loss of sales turnover or increased costs which endangers the survival of the company on the market (Morlidge and Player, 2010: 1). Even a sudden rise in sales turnover can cause losses due to smaller capacity, thus less output to satisfy customer needs, which results in customer’s frustration and loss (Goerne, 2009: 2). Therefore, it is most important for the company's success (even survival in volatile times) to carefully plan its future business; it is the primary task of the sales manager (Hanssens et al., 2001: 11). Once the plan is established, the sales department should invest all the efforts into putting this plan into reality by fulfilling the forecast of the plan (Wallace and Stahl, 2002: 1-2).

The reliability of plans depends, according to Goerne (2010: 1-4) on the outcome (in terms of sales turnover and amount) of the customer-supplier interaction, which is the underlying investigation in this research project. Its reliability is measured by forecast accuracy. For this reason, a sales plan and sales forecast does plan and forecast the sales turnover as the function of the customer-supplier interaction. This customer-supplier interaction is defined by the industry it is applied in. In general, it can be classified into several main steps, such as:

(1) Establish a first contact to the potential customer, e.g. at a fair or by direct contact, the potential customer sends afterwards an Request for Quotation (RfQ) to the potential supplier;
(2) The potential supplier receives the RfQ and establishes an offer; It is possible that this offer needs to be updated several times during the negotiation phase;
(3) If the potential customer and supplier finally agree, the supplier sends out a final offer to the customer and the customer responds with an order;

(4) The order is received by the supplier and the production process starts until the final product is sent out to the customer / or installed at the customer site and the customer pays according to the invoice and payment terms; and
(5) The supplier receives the payment and its sales turnover increases.

2.5.2. Customer-supplier interaction in the Machinery & Equipment Industry (based on the Pilot Study)

The simplified customer-supplier interaction in the Machinery & Equipment Industry sector is, according to Goerne (2008: 4), defined by complex products that mostly need to be defined and manufactured according to specific customer requirements. This customer-supplier interaction can be roughly divided into five steps.

(1) First contact: The first step of every sales process, independent of the industry it is applied in, is the first contact between the potential supplier and the potential customer. This is the defined starting point of the sales process in this research project. In the Machinery & Equipment Industry sector, the response to this first contact is the RfQ by the interested customer which is sent out to the potential supplier. Such an RfQ depends on whether it is a customer defined or a supplier defined product. If it is a customer defined product, the RfQ is usually a technical drawing with detailed specifications and requirements, known as a specification document. If it is a supplier defined product, a single order number can be sufficient (as the product is already defined by the supplier in its product portfolio).

(2) RfQ income: As soon as the RfQ is received by the potential supplier, the sales back office prepares a specific offer, based on the customer specifications or on the order number. If the offer is established, it is sent out to the potential customer, who then has to decline or accept it. Usually, if large buying volumes are discussed, one or more negotiation meetings are undertaken.

(3) Final offer sent out: As soon as the negotiation (process) is successful, a final offer is sent out by the potential supplier to the potential customer, who then accepts it and sent it back as an order to the supplier.

(4) Order income: As soon as the order is received by the supplier, raw material is procured (if it is not in stock), the production means are established (tools,

machines, devices) until the product is manufactured, assembled, delivered (or installed at the customers' site) and invoiced to the customer.

(5) Sales turnover increase: The final step in the customer-supplier interaction and the defined end point in the sales process in this research project is the payment (depending on the payment terms) of the customer and therefore the sales turnover increase at the supplier's side.

2.5.3. Customer-supplier interaction in the Automotive Tier 1 Supplier Industry (based on the Pilot Study)

The simplified customer-supplier interaction in the Automotive Tier 1 Supplier Industry sector is, according to Goerne (2008: 6), defined by framework agreements to produce complex products or aggregated products that need to be manufactured after request by the customer and delivered just-in-time to the Automotive OEM customer. This is the most common sales process and therefore discussed in this project. The customer-supplier interaction can be roughly divided into five steps.

(1) First contact: The first step in the sales process is the first contact between the potential supplier and the potential customer. In the Automotive Tier 1 Supplier Industry sector, the response to this first contact is the RfQ and invitation to a tender by the interested customer. However, before the RfQ is sent out to the potential supplier, the supplier has to indicate its reputation as "reliable" company in terms of references and available technology (process knowledge) (please refer to section 1.1 (page 2) and the necessity for zero-tolerance production). Such a RfQ that is then sent out to the potential supplier is mostly a customer defined product (that needs to fit into the automobile produced by the Automotive OEM), defined by a specification document. There are, however, several other possibilities that will be mentioned, but not further discussed; such other co-operation between an Automotive OEM and the Tier 1 supplier can be a) a "research & development relationship" to together develop specific products or aggregates that are already in mind of the Automotive OEM, or b) a "concept developments relationship" to ask the potential supplier for a concept about a specific technical problem without any ideas and requirements by the Automotive OEM.

(2) RfQ income: The second step in the defined customer-supplier interaction is that as soon as the RfQ or invitation to a tender is received by the potential supplier, the sales back office prepares a specific offer for the tender, based on the customer specifications. If the offer is established, it is sent out to the potential customer / or presented at a meeting scheduled by the potential customer. On that meeting, the potential customer has to decline it, accept it or invite the presenters again. During the negotiation process, in this context also called a bidding process, the potential supplier had to update the offer several times, especially in terms of technical solutions and price (please refer to section 1.1 (page 2-3) and the power of the Automotive OEMs).

(3) Final offer sent out: As soon as the negotiation process was successful, a final offer is sent out to the potential customer who accepts it by submitting a framework agreement which is signed by both parties. The framework agreement includes the technical specifications, prices, quantities and sometimes even descriptions of the production process, by which the product had to be manufactured. As soon as the framework agreement is established, raw material is procured (if it is not in stock), the production means are established (tools, machines, devices) until the first request, known as a *call*, is done by the OEM.

(4) “Order” / Call income: As soon as the first call is done by the OEM customer, the supplier produces the requested amount of products and delivers them on the requested time (just-in-time) and place (sometimes even directly to the assembly line) (just-in-sequence). For this reason, the supplier has to store all the capacity, raw material and production means for the indicated amount of products as defined in the framework agreement to be able to deliver after request just-in-time and just-in-sequence. This state lasts as long as indicated in the framework agreement.

(5) Sales turnover increase: The final step in the customer-supplier interaction is the payment (depending on the payment terms established in the framework agreement) of the customer and the sales turnover increase at the supplier’s side. The payment is usually done after every call depending on the requested quantity of the products.

2.5.4. Customer-supplier interaction in the Automotive Tier 2 Supplier Industry (based on the Pilot Study

The simplified customer-supplier interaction in the Automotive Tier 2 Supplier Industry sector is, according to Goerne (2008: 8), defined by framework agreements to manufacture products that need to be manufactured after request of the Tier 1 supplier. The customer-supplier interaction can be roughly divided into five steps.

(1) First contact: The first step is the first contact between the potential supplier and the potential customer. In the Automotive Tier 2 Supplier Industry sector, the response to this first contact is the RfQ by the interested customer. Such a RfQ is mostly a customer defined product (that needs to fit into an aggregate of the Tier 1 supplier). Therefore, the RfQ is usually a specification document that is sent out to the potential supplier.

(2) RfQ income: As soon as the RfQ is received by the potential supplier, the sales back office prepares a specific offer, based on the customer specifications. If the offer is established, it is sent out to the potential customer who had to decline or accept it, usually during a negotiation process. This process is similar to the negotiation process of the Tier 1 supplier as described in section 2.5.3 (page 40).

(3) Final offer sent out: As soon as the negotiation phase was successful, the final offer is sent out to the potential customer who accepts it by submitting a framework agreement which is signed by both parties (similar to the agreement as described in section 2.5.3, page 40). As soon as the framework agreement is established, raw material is procured (if it is not in stock), the production means are established (tools, machines, devices) until the first call is made by the Tier 1 customer.

(4) “Order” / Call income: As soon as the first call is done by the customer, the supplier produces the requested amount of products and delivers them just-in-time and / or just-in-sequence. For this reason, the supplier had to store all the capacity, raw material and production means for the indicated amount of products as defined in the framework agreement to be able to deliver after request just-in-time. This state lasts as long as indicated in the framework agreement.

(5) Sales turnover increase: The final step in the customer-supplier interaction is the payment (depending on the payment terms established in the framework agreement) of the customer and the sales turnover increase at the supplier's side.

2.6. SALES FORECASTING METHODS

The following paragraphs about sales forecasting methods discuss the origin intention of forecasting, classification of forecasting methods as well as the methods itself.

2.6.1. Forecasting model and scenario

A forecast model is a simple representation of reality to make predictions based on what the model imitates about the reality. Because the model can never represent the reality perfectly, a forecast can never produce a perfect prediction. A model can only transform a set of assumptions (input such as environmental factors) into a forecast (output) (Morlidge and Player, 2010: 91-93). For the research context of this project it is important to know what kind of forecasting models and methods are available, how they are selected to be the model of choice, and which methods are used in reality (in the defined industrial context). These explanations will indicate that time aspects, which are not used in sales planning, are not used in sales forecasting, too.

The forecast scenario, thus the underlying theoretical structure for the forecasting model, is as follows: The forecaster starts at a certain point (a), called a *point of reference*, to look backward over past observations (b) and forward into the future (c). At a further stage, a forecasting method needs to be chosen and to fit to the known data and (d) the fitted values need to be obtained by the model. By testing the MAPE (e), the values of chosen parameters can be optimised to downsize forecasting errors (f). Finally, the forecasting method is appraised as to its suitability for various kinds of patterns.

Figure 9: Forecasting scenario

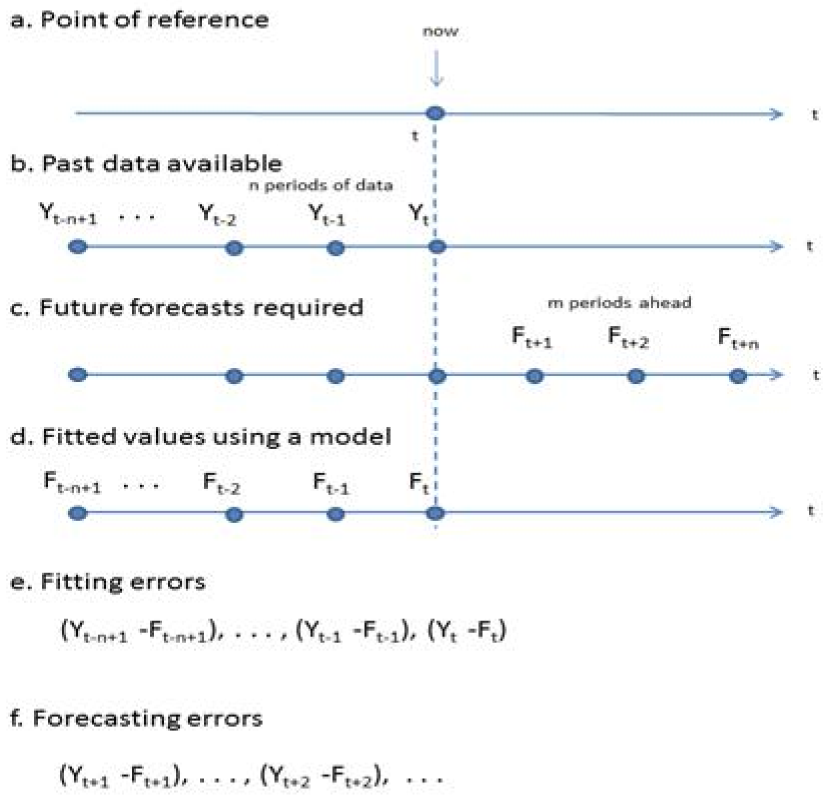


Figure: Adapted from Makridakis and Wheelwright (1998: 139), optimised for this research project

Chase (2009: 101) however points out that a good fitted model error does not necessarily mean a good forecast, it only determines that the model can predict past sales patterns well.

2.6.2. Classification of forecasting methods

It often seems that too many forecasting methods are used in reality, e.g. over 70 time-series methods. This often results in information overload (Mentzer and Moon, 2005: 16-17). Even a large number of methods are available in literature; hence, a large number of different classifications and frameworks for these methods have been available since the 1970s (Kerkkänen, 2010: 26): Makridakis and Wheelwright (1977: 24-38) suggested two criteria for the classification of forecasting methods, such as the *type of information available* (qualitative or quantitative) and basic assumptions about the *type of demand pattern* (history itself). Noonan (1998: 191-201) classified it in two forecasting levels such as the *macro and micro forecast level* and furthermore in *forecasting future* and *current demand*. Another classification is defined in three general categories which are *survey methods, mathematical methods and operational methods* that is in principle similar to the classification of Morlidge and Player (2010: 87-124). They classified it into judgmental methods, mathematical models and a combination of both, called statistical models (Morlidge and Player, 2010: 87-124). Mentzer and Moon (2005: 73-170) classified forecasting into *time-series forecasting, regression analysis and qualitative sales forecasting.* The most common classification of forecasting methods is the one that classifies it into judgmental (*qualitative) and accountable (quantitative) forecasting,* which is the underlying classification for this research project (Armstrong, 2001: 9).

Figure 10: Classification of the forecasting methods

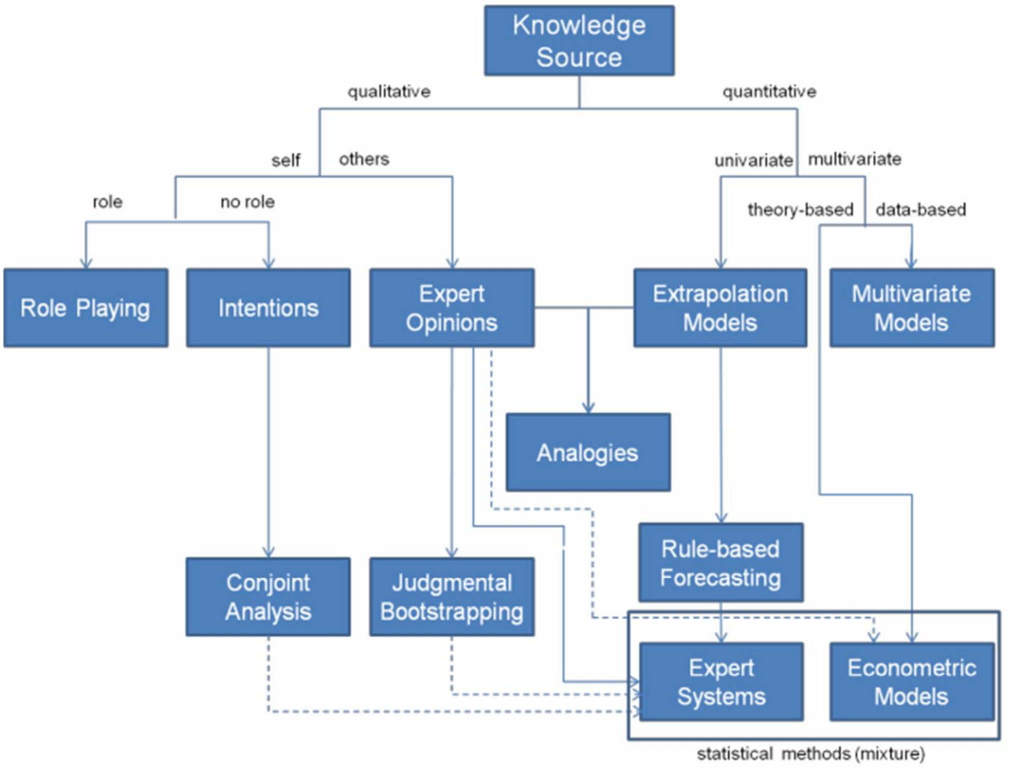


Figure: Adapted from Armstrong (2001: 9)

As displayed in figure 10, there is also a combination of the qualitative and quantitative methods, such as Expert Systems and Econometric Models, called as statistical methods. Quantitative methods are based on accessible statistical records that will form a company basis for estimates and forecasts, mainly be compiled using appropriate computer programs and spreadsheets (Arnold, Chapman and Clive, 2008: 16). In fact, it is not that difficult to predict the continuation of an established pattern. The difficulty is forecasting changes related to a specific pattern or relationship, the timing of change, and the magnitude of the change (Chase, 2009:

53). Qualitative methods rely heavily upon the judgment of the forecaster, either of the person who is forecasting himself, or on other forecasting experts.

2.6.3. Approaches to select forecasting methods

In the industrial context, the decision for a single forecasting method or a group of combined methods and even for qualitative or quantitative forecasting is a management one. However, the use of special forecasting methods must produce benefit by accuracy and by time, and must be understood to produce better decisions (Hanke and Wichern, 2008: 505-506). Only in the case of portfolio expansion by new products and attempting to forecast the future demand, and if no historical data or other sufficient data is available, expert opinions are the only choice and widely applied. Such experts may be internal experts, e.g. executives, key account managers, the sales force, or external experts, e.g. an industry survey (Armstrong, 2001: 57-58). In all other cases, the answer to the question *which forecast method fits best* and *what impact has the forecasting method on the outcome* is not given yet (or only partially), although several approaches since 1981 have faced this question (Daniells, 1981: 52; Georgoff and Murdick, 1986: 110-120; Yokum and Armstrong, 1995: 591-597; Armstrong, 2001: 365-386; Hussain, Shome and Lee, 2012: 413-420). Latest research even points out that there are a large number of well-established and widely-adopted forecasting methods available, however, their performance is far from perfect and it is especially true when the sales pattern is highly volatile (Choi, Yu and Au, 2011: 130-140).

Other detailed approaches to select forecasting methods lacked according to a clear definition of the criterion chosen, such as forecast accuracy, product to be forecasted (e.g. spare parts) or data availability and consistency of the data (Yokum and Armstrong, 1995: 591-597; Romeijnders, Teunter and van Jaarsveld, 2012: 386-393). Other few available research papers about *how to select the best suitable forecasting method* lack in a general approach as they are very specific, such as for direct marketing (Lu, Song, Liu and Wu, 2011: 1627-1636) and for share price data (Fildes, Madden and Tan, 2007: 1251-1264). In addition, a large number of investigations about the popularity of several forecasting methods were done over time with the intention to determine what methods are used by which kind of people and organisations (to solve the question the other way around) (Mentzer and Cox Jr, 1984a: 27-36; Dalrymple, 1987: 379-391; Yokum and Armstrong, 1995: 591-597; Tokle and Krumwiede, 2006: 97-105). They all failed in establishing a system to connect forecasting needs and available data with forecasting methods, for some reasons: In most cases, the investigated forecasting methods using surveys were not clearly defined (compare for instance (Lu et al., 2011: 1627-1636)), the conditions were not defined (e.g. industrial vs consumer goods) and in some cases what was done does not agree with experts' belief about what should be done (Armstrong, 2001: 366-371). The latest serious (and scientifically accepted) approach to select forecasting methods was done by Armstrong (2001: 365-386).

Figure 11: Selection tree of the forecasting method(s)

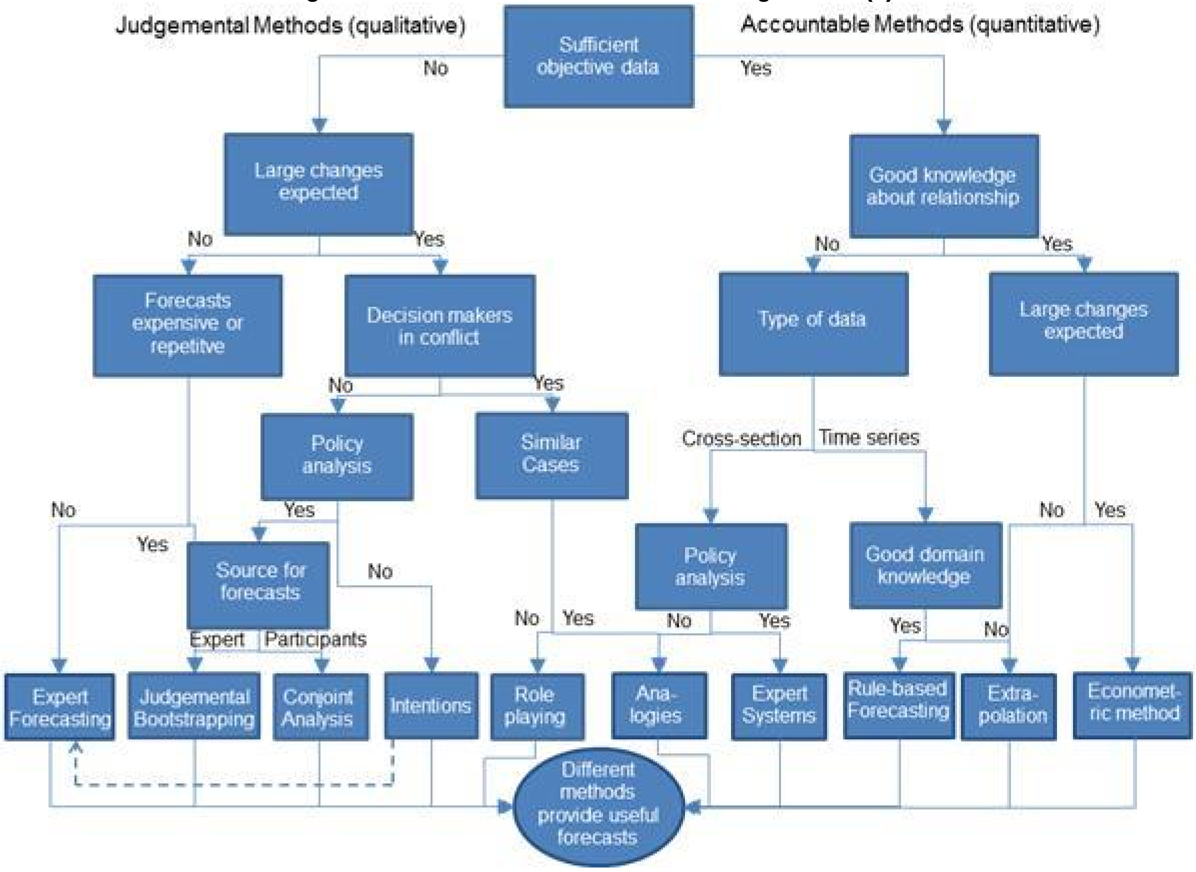


Figure: Adapted from Armstrong (2001: 376)

The author described six ways of selecting, such as convenience, market popularity, structured judgment, statistical criteria, relative track records, and guidelines from prior research. This *selection tree* provides the opportunity to come to the most suitable forecast methodology by answering different questions with yes or no as displayed in figure 11. However, using this selection process requires answering some questions about the forecasting environment, but no guideline to answer these questions is given until today (Kerkkänen, 2010: 29).

2.6.4. Quantitative forecasting methods

Quantitative methods generate forecasts based on established patterns or interrelationships with other factors according to changes in past historical sales or future sales (Chase, 2009: 52). Quantitative forecasting methods are classified into extrapolation and multivariate, also called econometric, models (Armstrong, 2001: 376).

2.6.4.1. Extrapolation Models

Extrapolation models or endogenous techniques do analyse what has happened in the past (historical data) and predict it into the future (Dommert and Getzen, 2005: 106-112). They are based on values of the variable to be forecasted (Mentzer and Moon, 2005: 74). Armstrong (2001: 217-243) differentiates between extrapolation for time-series data and for cross-sectional data. Most literature, however, only discusses time-series extrapolation, also called univariate time-series forecasting, where data is measured over time (Choi et al., 2011: 130-140).

All extrapolation methods (in all scientific areas) examine only four basic time-series types of variation. These variations are trend (T), cycle (C), seasonality (S), and noise (N) (Verbesselt, Hyndman, Newnham and Culvenor, 2010: 106-115). It is not possible to forecast irregular components as they cannot be projected into the future because they cannot be foreseen. Based on these assumptions, a mathematical model define the past behaviour of the series, such as

$$Y_t = f\ (T_t, C_t, S_t, N_t)$$

For this model it is most relevant to obtain only data that really mimic the pattern to be forecasted as well as to use all relevant data. Recent data is more relevant than old data and more data is preferable than less data (Armstrong, 2001: 220-221). If an intermittent series (non-negative series that contains zeros) occurs, the time-series interval can either be aggregated so that it is long enough to rule out intermittent values (if a daily series contains zeros it can be aggregated to a week; if a weekly series contains zeros, it can be aggregated to a month or to replace zero observations with local average values (Armstrong, 2003: 197)). Finally, it is important to remove data of special historical events, e.g. price reductions, in order not to forecast such time-series effects into the future.

If there is no trend and seasonality associated with past sales, the moving average method can be recommended, because this method only allows forecasting the trend, cycle and irregular components by using a smoothing technique, such as simple average, moving average, centred moving average, double moving average or weighted moving average to reduce (to smooth) the random variables (Salcedo, 2003: 64) . In principle, moving averaging is sales observation (weekly, monthly, quarterly, yearly, etc.) and taking the average of all historical periods to provide estimates for the investigated period (Chase, 2009: 110). The method of simple *averaging* is to add up all observed data for a special product or product group for each period (to be investigated) divided by the number of periods (Salcedo, 2003: 64).

The term *moving average* is used to describe the procedure of taking each average by dropping the oldest observation and including the latest as it becomes available, the average moves simply through the time-series until the trend-cycle is computed which can be mathematically displayed as

$$F_{t+1} = (1/k)\sum_{i=t-k+1}^{t} Y_i$$

with k = order.

Moving average transform is very useful in finding the trend of time-series data by reducing the effect of noise, and has been used in many areas such as econometrics (Moon and Kim, 2007: 5415-5431). As simple and cheap to develop and easily systematised this method is, it also has some disadvantages. It is the inability to handle trends and seasonality very well as they can only predict one period ahead with any degree of accuracy. Furthermore they are unable to predict sudden shifts in demand within a reasonable amount of time and to shape future sales using explanatory variables (Chase, 2009: 126-127).

To forecast trends and seasonal effects of time-series, smoothing methods were created to address this option (as moving average methods are not able to handle trends and seasonality) (Billah, King, Snyder and Koehler, 2006: 239). Exponential smoothing is often used to forecast lead-time demand for inventory control (Snyder et al., 2004: 444-455). The most well-known models are single exponential smoothing, Holt's two parameter method, Holt's-Winters three parameter method and Pegel's classification (Makridakis, Hogarth and Gaba, 2010: 137-184). This methods work very well for identifying and forecasting trends and cycles and unexplained error (Chase, 2009: 115):

$$F_t = F_t + \alpha(Y_t - F_t)$$

with

F_t	future demand forecast for period t;
Y_t	actual demand period at time t;
$Y_t - F_t$	forecast error at time t;
α	smoothing constant that ranges from 0 to 1.

Each forecast is simply the old forecast plus an adjustment for the error that occurred from the last forecast. The closer the α value is to 1, the more reactive the future forecast will be, based on past sales (Chase, 2009: 116). When the α value is close to 0, the forecast will include very little adjustment, making it less sensitive to past swings in future sales (Chase, 2009: 116).

In 1957, Charles C. Holt expanded the single exponential smoothing by including a linear trend component, enabling the ability to forecast data with trends (Holt, 2004:5). Holt uses two smoothing constants, α and β (with values between 0 and 1), and two equations. In the special case where α equals β, the method is equivalent to *Brown's double exponential smoothing* (Brown and Meyer, 1961: 673-685). The first equation of Holt is to identify the trend of the previous period by adding the last smoothed value (to eliminate lags), and the second equation to update the trend which is the difference between the last two smoothed values, displayed as follows (Holt, 2004: 1-5):

1 A $$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1})$$

1 B $$b_t = \beta(L_t - L_{t-1}) + (1-\beta)\, b_{t-1}$$

2 $$F = L_t + b_t m$$

with

L_t = estimate of the level of the series at time t;

b_t = estimate of the slope of the data series at time t.

m = number of periods to be forecast.

Equation 1A adjusts L_t directly for the trend of the previous period, b_{t-1}, by adding it to the last smoothed value L_{t-1}. This helps to eliminate the lag. Afterwards, equation 1B updates the trend, expressed by the difference between the last two smoothed values. Since there may be some randomness remaining, the trend is modified by smoothing with β the trend in the last period L_t-L_{t-1} and adding that to the previous estimate of the trend multiplied by 1-β. Finally, equation 2 is used to forecast by multiplying the trend b_t with the number of periods ahead to be forecasted, m, and adding it to the base value.

According to research of Chase (2009: 120-121) and initially by Kirby (1966: 202-210) about the value of mean error (ME), mean absolute error (MAE) and mean absolute percentage error (MEAN), Holt's two parameter exponential smoothing outperforms the single exponential smoothing in every error metric. In 1960, Peter R. Winter expanded Holt's method by adding a seasonal component to forecast not only trend-cycles and errors but also seasonal patterns of data (proved at latest by the case of natural rubber in India (Chawla and Jha, 2009: 39-55)). It is quite similar to Holt's method but with the addition of a third equation to account for seasonal patterns.

$$\text{Level: } L_t = \alpha\,(Y_t / S_{t-s}) + (1-\alpha)\,(L_{t-1} + b_{t-1})$$
$$\text{Trend: } b_t = \beta(L_t - L_{t-1}) + (1-\beta)\,b_{t-1}$$
$$\text{Seasonal: } S_t = \gamma\,(Y_t / L_t) + (1-\gamma) S_{t-s}$$
$$\text{Forecast: } F = (L_t + b_t\,m)\,S_{t-s+m}$$

with

L_t	level of the series at time t;
s	lenght of seasonality (e. g. numer of weeks);
b_t	trend at time t;
S_t	seasonal component;
F	forecast for m periods ahead.

Most demand forecast software solutions automatically find the optimal α, β and γ based on the criteria chosen. Strengths of exponential smoothing methods are the simplicity of development, the good prediction of trends and cycles, faster reaction to fluctuations in demand than a moving average method as well as the easy systematization. On the other hand, it is difficult to find the optimal value for the smoothing weight α, the methods are unable to handle seasonality very well, to predict sudden shifts in demand within a reasonable amount of time as well as to shape demand using explanatory variables (Chase, 2009: 126-127).

If the historical sales data set has no trend or seasonality, the best method is either moving average or single exponential smoothing, but if the data set exhibits a trend, then Holt's two parameter exponential smoothing method is appropriate. However, if it is an indication of seasonality, Holt's-Winters three parameter method of 1960 is useful by adding a seasonal component because a significant improvement in the fitted ME and MAE can be stated (Makridakis et al., 2010: 137-184).

The weakness of time-series analysis in general is that it treats sales only as a function of time, taking no account of any other influencing factors that affect sales, such as the effects of price, the introduction of new technologies, product varieties or competitors (Noonan, 1998: 200). In contrary, the basic premise of *causal methods* is that future sales of a particular product is closely associated with changes in some other variable(s). Chase (2009: 99) explains that for example changes in future sales can be related to variations in price, advertising, sales promotions as well as economic and other related factors. In principle, it is a quantitative method for investigating the cause-and-effect relationships between two or more variables, known as *explanatory method* or *regression analysis method* (Makridakis et al., 1998: 186; Still et al., 1998: 50-51).

Regression analyses are statistical processes and, as used in sales forecasting in this project's context, determine and measure the association between two or more variables, such as company sales and response time (Ekren and Heragu, 2010: 6257-6274). It involves fitting an equation to explain sales fluctuations in terms of related and presumably causal variables. The easiest model in this field is *simple regression*, which refers to a regression of a single variable Y (the *dependent variable* or *variable being forecasted* or *forecast variable*) on a single variable X (the *explanatory* or *independent variable*), e.g. a linear relationship between Y and X, given by

$$Y = \alpha + bX$$

with

α intercept;

b slope of a line;

Y the best fit line that is formed when performing linear regression on a data set.

According to multiple regression methodology, it is possible to rebuild past demand with fit error of 0% (MAPE), because there is one variable to be predicted (e.g. sales), but there are two or more explanatory variables which leads to the general form of:

$$F = \beta_o + \beta\ _1X_1 + \beta_2X_2 + \dots + \beta_kX_k + e$$

with

F dependent variable to be forecasted;

β constant;

β_n parameter estimates;

X_k explanatory or independent variables.

Multiple regression analysis is a powerful method and the most commonly used approach to model a company's forecast (Makridakis et al., 1998: 298; Chase, 2009: 136).

The line of best fit is chosen based on the smallest value for the sum of squared errors through calculating the *correlation coefficient*, also known as ordinary *least squares estimate*. It is the relative measure of the linear association between two (simple regression) or more (multiple regression) numerical variables, varying from 0 (no correlation) to +/- 1 (correlation) (Intriligator, Bodkin and Hsiao, 1996: 136)

$$R^2 = \frac{\Sigma (F_i - Y)^2}{\Sigma (F_i - Y)^2}$$

This idea of minimising the sum of squared errors is the most widely accepted statistical estimate of goodness to fit (Makridakis and Taleb, 2009: 716-733). If the data are measured over time, such as the two examples afore, then this method will be called *time-series regression*, if the data measurement are all taken at the same time, it will be referred to a *cross-sectional regression* (Armstrong, 2001: 217-243). Systems of linear equations involving several independent variables, e.g. more than one multiple regression equation, are called *econometric models*. A forecast made through regression assumes that past relations will continue similar to time-series forecasting. This, called *lead-lag* association, in which deviations regularly occur in related independent variables prior to a change in company sales, is an ideal situation, but it rarely holds except over short periods. Lead-lag relationships are common, but associations between the lead variables and sales in which the intervening time intervals remain stable are uncommon. Periods not only contract or expand erratically; they vary greatly during different phases of the business and sales cycle (Still et al., 1998: 50-51).

Some of the strengths of regression methods are the good prediction of trends, cycles, seasonality as well as other factors influencing future sales and they are generally more accurate. On the other hand, the methods are difficult to develop because they require statistical and domain knowledge as well as a large amount of data. Therefore, they are hard to systematise or automate (Chase, 2009: 185).

Autoregressive integrated moving average (ARIMA) models were popularised by Box, Jenkins and Reinsel (2008: 746) in the early 1970s. They formalised their theory and methodology of ARIMA models by developing a three-phase process to select the best model from a group of models. This process is divided into an autoregressive (AR), an integrated (Trend = I) and a moving average (MA) phase (Chase, 2009: 163). This approach is more complicated than other time-series methods mentioned afore, but they can handle almost any type of historic pattern with a strong track record and can realise the highest forecast accuracy. Nevertheless, ARIMA models are not applied very often to forecast future sales because of the complexity of developing this models and the difficulty to understand it with no statistical knowledge as well as the necessity of huge data storage (Gilbert, 2005: 305-310; Chase, 2009: 173-174).

Structural models, also called unobserved components models, are recently receiving a growing interest in practice because of the desire to test a variety of theories with market data (Chintagunta, Erdem, Rossi and Wedel, 2006: 604-616). In addition, these models can decompose the response series (actual demand history) into a structure or component, such as trend, seasonality, cycles (Chase, 2009: 177). Such structures or components are intended to capture key features of a time-series that are useful in predicting future and explaining past sales patterns. Structural models are, in principle, an update of ARIMA models or a generalisation of regression models, where the regression coefficient can vary over time. These models attempt to capture the versatility of the ARIMA models while possessing the interpretability of the smoothing models (Harvey, 2006: 327-408). The general equation can be written as

$$F_t = \mu + \gamma_t + \psi_t + r_t \sum_{i=1}^{p} \varphi_i Y_{i-t} + \sum_{j=1}^{m} \beta_j X_{jt} + e_t$$

where

μ, γ, Ψ	trend, seasonal, cyclical;
r	autoregressive component;
$\sum_{j=1}^{m} \beta_j X_{jt} + e_t$	regression term;
$\sum_{j=1}^{m} \varphi_i Y_{i-t}$	regression term including lags of the dependent variable (similar to ARIMA models);
e_t	irregular component (Gaussian white noise).

Structural models have the same advantages and disadvantages as ARIMA models, however, they are relatively new in practice (Chase, 2009: 185).

2.6.4.2. Multivariate and Econometric Models

Econometric methods give good forecasts, if the causal relationship can be estimated accurately, the causal variables change substantially over time, and the change in causal variables can be forecasted accurately (Armstrong, 2001: 339). The econometric approach is complex. It uses a system of equations to represent a set of relationships among sales and different demand-determining independent variables. Then, by inserting values (or estimates) for each independent variable (that is, by “simulating” the total situation), figures (sales) are forecasted (Peña and Sánchez, 2007: 886-909). An econometric model (unlike a regression model) is based upon an underlying theory about relationships among a set of variables, and parameters are estimated by statistical analysis of past data (Jobber, 2006: 32).

2.6.5. Qualitative forecasting methods

An often used synonym for qualitative forecasting is the term *judgmental forecasting*. Qualitative forecasts are projections based on judgment, intuition, and informed opinions; they are subjective by nature and they are difficult to categorise (Kerkkänen, 2010: 26). The range of qualitative methods over time goes from personal intuitions, team work methods, market research to structured decision making models by experts, defined by forecasts made wholly on the basis of subjective assessments and “soft” information (Sanders and Ritzman, 2004: 514-529).

In most industrial businesses, sales forecasts are based on judgment of an individual or a group of individuals, rather than on mathematical or statistical equations. In contrast to quantitative methods, there are no economies of scale effects and they are obviously dependent on the expertise of the modeller (Morlidge and Player, 2010: 95). This expertise is further impacted by cognitive bias, such as the tendency to overestimate, to misestimate, to ignore sample size, to expect random phenomena to look random or the tendency to ignore cumulative probabilities (Bazerman, 2006: 198). Qualitative forecasting methods are namely *role playing*, *intentions* and *conjoint analysis*, *expert opinions* and *judgmental bootstrapping* (Armstrong, 2001: 9).

2.6.5.1. Role Playing

Role Playing takes several roles into account to afterwards predict outcomes by people or groups. This approach is common especially for complex situations, such as market entry strategies or competitor responses to sales and marketing strategies. One of the main advantages is that it is inexpensive with a high possibility to generate new ideas. The methodology is that predictions and new ideas are generated by interacting with each other (Armstrong, 2001: 15-32). These interactions influence each other. Therefore it is important to match the actual situation. Usually, role playing will not be used to forecast sales and is mostly combined with expert opinion, experimentation, intentions, extrapolation or game theory (which makes it less interesting for this research project).

2.6.5.2. Intentions and Conjoint Analysis

Intentions are measures of individuals' expectations or plans about how they will act in the future regarding a specific topic (Armstrong, 2001: 33). The research in this field, e.g. on purchase intentions of customers, has been conducted from the 1950s until today. However, a lot of questions still remain unanswered, such as the validity of intention data, and research findings are even contradictory. For example, Lee et al. (1997: 127-135) concludes that for existing products simple extrapolations of past sales data provided more accuracy than intentions. In a similar study, Armstrong, Morwitz and Kumar (2000: 383-397) found the opposite that intentions contain predictive information beyond that derived from past sales.

A Conjoint Analysis is purely an analysis about what interest customers have and would buy in future in terms of benefits, features, prices etc. of the investigated product. Its methodology covers the design of questions, administration, and analysis of responses with the aim to quantify customer preferences for multiattribute alternatives (Armstrong, 2001: 145). One of the main advantages are the obviously external validity of the method and the grade of the predictive accuracy (Armstrong, 2001: 165).

2.6.5.3. Expert Opinions and Judgmental Bootstrapping

Expert Opinions are sometimes called the Jury Method, where experts are consulted to examine the industry (Jobber, 2006: 29). It may be used when adequate sales and market statistics are missing, or when these figures have not been put into the form required for more sophisticated forecasting methods. The weak point in this method is that the jury of experts is sometimes influenced by current business conditions in their territories and there is a difficulty in allocating the forecast out amongst individual products and sales territories (Jobber, 2006: 29).

Judgmental Bootstrapping is a special type of an expert system that only uses data generated by experts which is then transformed into a quantitative model by regression analysis (Armstrong, 2001: 188). It is appropriate for complex situations, where judgments are unreliable, but where experts' judgments have some validity. Breaking down its methodology, it can be seen as part of econometric modelling.

2.6.6. The popularity and usage of forecasting methods

In order to better understand the research results in terms of which forecasting method the research sample used, this chapter provides literature background about the most common methods. However, results of surveys about the popularity of the forecast are quite difficult to interpret and not easy to compare. Several scientific reasons can be mentioned: The different phrasing of questions, the absent concise definition of forecasting methods in the survey, the mostly absent description of conditions the studies are undertaken and the absent underlying assumptions of the surveys (Diamantopoulos and Winklhofer, 2003: 46). Additionally, the success of the used methods, the satisfaction and the kind of application are not evaluated, the studies measured only usage, and as Armstrong (2001: 368) adds, the studies measured only perceived usage reported by people who would like to be regarded as good managers.

Despite all scientific gaps in comparing studies that investigate the popularity and usage of different forecasting methods, literature often compares such studies. The most concise and comprehensive review of past studies is given by Armstrong (2001: 365-388) and Mentzer and Moon (2005: 214-224). Armstrong (2001: 365-388) presented some selected studies without any recognisable recurring theme, neither historical nor thematic. The approach by Mentzer and Moon (2005: 214-224) was, in contrary, to classify most existing studies, such as the studies of Reichard (1965: 34-48), Wheelwright and Clarke (1976), Pan and Nichols and Joy (1977: 72-77), Mentzer and Cox (1984b: 27-36), Fildes and Lusk (1984: 427-435), Lowenhar (1984: 11-14), Sparkes and McHugh (1984: 37-42), Davidson (1987: 17-19), Armstrong (1988: 449-465), Dalrymple (1987: 379-391), Wilson and Daubek (1989: 19-22) and Drury (1990: 317-329), into four phases. Phase one was examining the relation between forecasting and familiarity, satisfaction, usage and application in the early 1980s. Phase two examined additional issues associated with forecasting, such as forecasting performance across business functions, the influence of forecasters and software support in the middle of the 1990s. Phase three and four are in-depth analyses of several (about 20) companies. The general messages that the cumulated surveys give, are according to the findings of Kerkkänen (2010: 31-32):

- Simple methods, such as moving average (grade of familiarity 92%), exponential smoothing (90%), and sales force composite (71%) are more familiar than complex methods, such as Box-Jenkins (38%), expert systems and neural networks (19%);
- Moving averages are the most popular method (92%) followed by exponential smoothing (90%);
- Satisfaction with forecasting methods does not correlate with their familiarity, hence the most satisfying methods are exponential smoothing (grade of satisfaction 72%) and regression (66%) versus moving average (40%) and sales force composite (34%);
- Most of the respondents use forecast methods for a time period of three months to two years (exponential smoothing was 92 % and both jury of executive opinion and sales force composite were 77 %);
- Forecasting knowledge is mostly distributed by books and colleagues (both 65%), conferences and journals (both 59%) and consultants (46%); and
- Qualitative methods, namely judgmental methods, are widely used in the industrial context.

This indicates that it is still not clear how to evaluate the best suited forecasting method.

2.7. SALES FORECAST ACCURACY

A large number of scientific articles discuss forecast accuracy and emphases it as one of the most important elements of the sales system (Diamantopoulos and Winklhofer, 2003: 45-54; Mentzer and Moon, 2005: 43-72; McCarthy et al., 2006: 316-318; Davis and Mentzer, 2007: 475-495; Kerkkänen, 2010: 32-33). The reasons for the increasing relevance and importance of forecast accuracy in literature as well as practice can be explained by the fact that companies realised in the 1990s that the performance of profit and growth needed to be measured and forecasted (Seth and Sisodia, 1995: 8-23). Furthermore, new concepts of overall business performance measurement, such as the Balanced Scorecard in 1992, have attracted attention to how and which marketing and sales measures should be included in overall performance measurement (Clark, Abela and Ambler, 2005: 241-259).

Forecast accuracy is defined as the deviation of predicted sales and real sales (Goerne, 2009: 1). Such deviations result from forecasters being unable to predict the future or using inadequate instruments or processes (Makridakis et al., 2010: 83-90). Several methods are used in calculating forecasting errors and which method to choose depends largely on the specific characteristics of the data and the questions one wishes to answer. A large number of studies however, discuss forecast accuracy only in the context of how well the prediction of the actual occurrence is. The purposes of forecast accuracy are:

- To measure the deviation of predicted and real sales;
- To compare different methods to determine which one fits best to the sales history of the SKU, product or aggregated product; and
- To estimate the forecast error because any contingency plan must account for such an error (Chopra and Meindl, 2001: 156; Chase, 2009: 80; Kerkkänen, Korpela and Huiskonen, 2009: 43-48).

Significant progress had been made in developing sales forecasting methods over the past three decades (Davis and Mentzer, 2007: 475-495). Despite the large number of studies investigating forecast accuracy, it is impossible to significantly compare their results because of the usage of different measures the studies applied (McCarthy et al., 2006: 304). Scientifically, only the studies which used similar measures to determine forecast accuracy and performance can be compared and transferred to the evolution of forecast accuracy over time. Three studies can be compared: This is the latest one by McCarthy et al. (2006: 303-324) in 2006 about the evolution of sales forecasting management, the study by Mentzer and Kahn (1995: 465-476) and the investigation in 1984 (Mentzer and Cox Jr, 1984a: 27-36). They measured forecast accuracy, defined as one minus the MAPE experienced on different horizons (short-term < three months, mid-term four months to two years and long-term > 2 years) and levels (Industry, corporate, product line, SKU and SKU by location). Some results and explanations of the three studies are listed below:

- The weighted average as overall degree of forecast accuracy was 85% in the study of 1984, 84% in the study of 1995 and 76% in the study of 2006;
- Accuracy decreased over the years for the lower forecast levels (product line, SKU and SKU by location) across all horizons;
- The reduction in accuracy was greater for the mid-term and long-term horizons than for the short-term;
  - It appears that familiarity with forecasting methods have decreased and the methods have not been used properly; and
  - Product proliferation increased which increases forecast complexity to the process;
- Trend from short-term (< three months) to mid- (four months to two years) and long-term (> 2 years) forecasting;
  - The most logical explanation is the increasing volatility of the markets combined with emphasis on more sustainable strategies by the industry;
- The MAPE to measure forecast accuracy is still the measure of choice, the calculation of the percentage error increased from 3% in 1995 to 45% usage in 2006; and
- Accuracy and credibility are still the top criteria for evaluating sales forecasting effectiveness (Mentzer and Cox Jr, 1984a: 27-36; Mentzer and Kahn, 1995: 465-476; McCarthy et al., 2006: 303-324).

In reality, practitioners are judged solely on forecast error (Chase, 2009: 80). Kerkkänen (2010: 33) refers to Mentzer and Moon (2005: 45) and their classification of several error measures into three groups:

- Actual measures of forecast accuracy;
- Accuracy measures relative to a perfect forecast; and
- Accuracy measures relative to a perfect forecasting method (Mentzer and Moon, 2005: 45-59).

The group of actual measures of forecast accuracy describes the actual difference between current sales in a given period and the forecast to be the sales for that similar period predicted at some previous date. All actual measures are based on the calculation of:

$$Error_t = Forecast_t - Sales_t$$

with t = time period in which the sales occurred.

Such an error value is always associated with an observation for which there is both an actual and a predicted value (Chase, 2009: 81). Based on this, the following actual measures for forecast accuracy are assigned to the group of actual measures (Makridakis et al., 1998: 41-45; Mentzer and Moon, 2005: 46-49; Chase, 2009: 81-92):

- $\text{Mean Error} = \Sigma \ \frac{E}{N}$; with E = Error and N = Number of periods for which the error have been tracked;
    - o The Mean Error determines of how much the forecast has been off in the past;
- $\text{Mean Absolute Error} = \Sigma \ \frac{|E|}{N}$; with |E| = absolute value of the error and N = Number of periods for which the error have been tracked;
    - o The Mean Absolute Error, or Mean Absolute Deviation, determines how much the forecast has deviated on average in the calculated number of periods;
- $\text{Sum of Squared Errors} = \Sigma \ E^2$; with E^2 = Squared error;
    - o The Sum of Squared Errors determines an overall measure of how much the forecast has deviated with the premise that the closer the results gets to zero, the better the forecast; and
- $\text{Mean Squared Error} = \Sigma \ \frac{E^2}{N}$;
    - o The Mean Squared Error determines an overall measure of how much the forecast has deviated for each period.

Accuracy measures relative to a perfect forecast do calculate the difference between a perfect forecast (forecast error would be zero) and the actual measure for a given period (Kerkkänen, 2010: 33). According to Mentzer and Moon (2005: 49-55), some measures of accuracy relative to a perfect forecast have been developed, such as:

- $\text{Percent Error} = \frac{\text{Forecast}_t - \text{Sales}_t}{\text{Sales}_t} \times 100$, with t = time period in which the sales occurred;
  - o The Percent Error determines the forecast error in percent; If the Percent Error is positive, the forecast was higher than actual sales, if the Percent Error is negative, the forecast was lower than actual sales. The Percent Error Plot graphically displayed over a number of periods is highly valuable as it tells the forecaster in which periods the forecast was under- or over-forecasted; and
- $\text{Mean Absolute Percentage Error} = \Sigma \frac{|PE|}{N}$, with PE = Absolute value of the percent error and N = Number of periods for which the percent error have been tracked;
  - o The Mean Absolute Percentage Error usually is the standard percentage where literature refers to forecast error in percentage. It determines how good the forecast is over time in terms of percent error (Bamiatzi, Bozos and Nikolopoulos, 2010: 279-283).

Accuracy measures relative to a perfect forecasting method are based upon Theil's U statistic that calculates the ratio of the accuracy of the used method compared to the naive forecast's accuracy (a naive forecast is the sum of sales from last period) (Makridakis et al., 1998: 48 - 50; Mentzer and Moon, 2005: 45 -59).

2.8. SALES PERFORMANCE

In general, performance measurement in business is *the assessment of the relationship between business activities and business performance* (Clark et al., 2006: 191-208). The challenge of performance measurement, especially in sales is that sales activities influence intermediate outcomes (customer thoughts behaviour to buy the product), but immediately influence the financial performance of the company (e.g. costs for the sales force) (Rust, Ambler, Carpenter, Kumar and Srivastava, 2004a: 76-89). This fact is reflected in increased demand for greater accountability in scientific research; most notably, performance measurement topics have been consistently listed among the Marketing Science Institute's top priorities in 1998, 2000, 2002, 2004, 2006 (Clark, 2000: 3-25; Rust et al., 2004a: 76-89; Clark et al., 2005: 241-259).

Early in the history of measuring marketing and sales performance, it was common to use one or some financial or volume measures to track the output of marketing and sales (Clark, 1999: 711-732). In the beginning of the 1970's this view changed with the introduction of the multidimensional audit (Kotler, 1977: 25-43) aiming at long-term shareholder value (Srivastava, Shervani and Fahey, 1998: 2-18). According to John Philip Jones (1990: 145-152), marketers and sales managers did not expect advertising campaigns to generate short-term sales, they use advertising campaigns to support long-term, hard to measure goals, such as increase of customer relations and they rely on promotions for short-term returns. This indicates that most marketing and sales managers did not have an effective tool to measure the immediate results of the relationship between the advertising campaign and the consumer in the 1990s and 2000s (Maruca, 1995: 11-12; Rust et al., 2004a: 76-89). Rust (2004a: 76-89) described that there are three challenges to the measurement of marketing and sales performance. The first challenge is related to activities to long-term effects, the second is the separation of individual activities from other actions and the third challenge is the use of purely financial methods, which proved inadequate for justifying marketing and sales investments. The 2006 Marketing-Performance-Measurement conference "Metrics and Marketing Performance Management" in Greensboro, NC, USA, stated that performance measurement has a high priority, but many companies still not invest heavily in the people, technology and processes necessary to handle the increasing amounts of data and analysis for performance measurement (Maddox, 2006: 1-69). Referring to Clark (1999: 711 - 713), measurement have moved in three consistent directions over the years: first, from financial to non-financial output measures, second, from output to input measures and third, from non-dimensional to multidimensional measures. The multidimensional measure approach, which is the most common one, is divided into three research streams: measurement of productivity, identification of metrics in use and, measurement of brand equity (Rust et al., 2004b: 109-127).

For the broad field of sales performance measurement, scientific literature offers a large number of performance measures. Such sales performance measures are *customer engagement*, the rational and emotional attachment a customer has to the company, *sales team skills*, process and technical skills of the sales team to satisfy customer needs, *effective sales communication*, *grade of facilitation of communication between business and IT systems*, *customer loyalty*, *frequency of new product introduction, proliferation of sales channels* or the *job-hopping quote of sales personnel*, thus the satisfaction of the sales team (Smith and Rutigliano, 2003: 68; Ariyachandra and Frolick, 2008: 113-120). However, taken the primary responsibility of a sales manager into consideration, sales turnover should be included in the measures of choice (Yu Ha and Florea, 2009: 139-156). As a result, the performance measure for sales for this research project is in accordance to Murphy, Trailer and Hill's (1996: 15-23) factors of success and Carton's (2004: 229-240) well known study about performance by the dimensions productivity, growth of productivity (and market position), all based on the consolidated sales turnover of the companies. This approach is also in line with the already cited and common approach *measurement of productivity* by Rust, Lemon and Zeithaml (2004b: 109-127). Furthermore, it can be mentioned that the sales performance measure sales productivity in Euro or Dollar (sales turnover divided by number of sales employees) is a commonly defined operating performance ratio by investopedia.com and used by a large number of companies, such as Cisco, Siemens and Coca-Cola (http://www.investopedia.com/university/ratios/operating-performance/ratio2.asp#axzz1p6uOPOmo).

The measurable figures of sales performance for this research project are as follows:

- Consolidated sales turnover per sales employee (sales force) in 2010, measured at the end of the year 2010 in absolute figures in T€ (productivity);
- Consolidated sales turnover per sales employee (sales force) development from 2008 to 2010, measured at the end of the year 2010 in percent (growth of productivity); and
- Market position, measured at the end of the year 2010.

An important advantage of these three measures was the high external availability and accessibility (external source of evidence) by several sources, such as the

German Machine Tool Builders Association (2010), *Automotive Association* (Verband der Automobilindustrie, 2010), *Hoppenstedt* (Hoppenstedt, 2011a) and *wer-liefert-was?* (WLW, 2011).

According to the actual performance measures, the investigated companies were afterwards clustered into three categories, such as low, medium and high performant. This classification into clusters was done by pure statistics (see attachments). The market position of the company was clustered into the categories market leader, top 5, top 10 and good market performance according to the company's current position in the market position, ranked by the *German Institute for Economic Analysis*, the *German Automotive Association* and the *German Machine Tool Builders Association* (Institut für Wirtschaftsanalyse und Kommunikation, 2004; VDMA, 2010; Verband der Automobilindustrie, 2010).

The connection between planning and forecasting methods and response models to improve planning is expected to be (especially in the industrial context) not very well researched. This expectation is discussed in chapter three.

CHAPTER 3: MARKET RESPONSE RESEARCH

This chapter gives a broad literature review about the evolution of model building, especially market response research as part of model building. Furthermore, five eras of history in model building are introduced and common classifications discussed. Afterwards methods to model market responses are introduced to discuss model based planning and forecasting in industrial sales.

3.1. MARKET RESPONSE MODELS AS PART OF MODEL-BASED PLANNING AND FORECASTING

For 50 years now, market response research has produced generalisations about the effects of marketing mix variables on sales (Hanssens et al., 2001: 3). Before this time, sales and marketing decisions were mainly based on judgement and experience. Since 2008, market response models support the most important Marketing Science Institute research priorities, such as the accountability of marketing and sales expenditures, the understanding of consumer behaviour and the development of new approaches to generate customer insights (Leeflang and Hunneman, 2010: 71). Thus, continuous research on this topic can add significant value to a company's performance, such as:

- To measure the return on investment of marketing and sales expenditures, e.g. sales force efforts or exhibition actions, to make these investments accountable;
- To better understand customer behaviour by building models for given stimuli and the answer of the customers; and
- To develop new approaches and model customer-supplier interactions in B2B and generate customer insights.

Taking all this into account, market response models can infuse planning and forecasting with discipline and logic (Hanssens et al., 2001: 11). They are intended to help scholars and managers understand how consumers individually and collectively respond to marketing and sales activities, and how competitors interact (Hanssens, Leeflang and Witting, 2005: 423-234). Therefore, they are built and used to aid in planning and forecasting sales and are part of the sales system (Kotler, Armstrong, Saunders and Wong, 2000: 118; Andrews, 2002: 387-388; Abramson, Currim and Sarin, 2005: 195-207).

3.2. MODEL BUILDING IN MARKETING AND SALES

The early beginning of model building in marketing can be attributed to the Russian scientist Ivan Pavlov in the early 1910s, documented by Skinner (1999: 463). Pavlov recognised that a given stimulus would produce a given response, called stimulus-response view. A direct application to selling suggests that each sales representative (from the supplier) would have a variety of stimuli in the form of words to say or products to show, that produce a response from the customer.

That view of selling was first used during the 1950s and assumes that a positive response (the purchase) is the typical outcome of the exchange between buyer (customer) and seller (supplier) after time (Cash and Crissy, 1958: 30-31).

The original idea to support marketing and sales decisions by models (such models are known as decision models) was established during the 1960s. At this time, collecting information was emphasised more than analysing the collected information and a sales manager's decision was mainly based on judgment and experience (Alderson, 1962: xi-xvii). Why the topic of building marketing models came up during the 1960s was regularly discussed. Several possible explanations can be mentioned. First, computers entered organisations in the early sixties (King, 1970: 8). Second, the field of management was going through a transition towards a more science-based field with increased attention to behavioural sciences, social sciences and statistics, driven by the Carnegie Foundation and the Ford Foundation. Third, the sixties were the heydays of Operations Research (OR) which started as a field of developing mathematical models to support military operations and later became a modelling and optimisation field with applications in all areas of society (Wierenga, 2008: 3-4). Taking all these into consideration, model building was a highly discussed topic by researchers and practitioners in the past (Leeflang and Hunneman, 2010: 72).

The dimension of time is part of model building in marketing and sales; therefore the evolution of model building will be discussed next with some explanatory notes and limitations. According to the exponential growth of publications at the end of the 1970s, the third, fourth and fifth era of model building only discuss response models as a part of marketing and sales modelling and major research directions in general.

3.2.1. Five eras of model building in marketing and sales

Five eras of model building in marketing and sales are defined and afterwards described recently by Wierenga (2008: 5) and Leeflang and Hunneman (2010: 72) both displayed in the following charts. These classifications both seem to be useful and will be introduced shortly; however, literature does not indicate the exact beginnings and endings of the eras of model building.

In 2010, Leeflang and Hunneman (2010: 71-80) discussed model building on the basis of a paper by Leeflang and Wittink (2000: 237-253) by adding various developments and trends in market response modelling. They specified the necessary evolutions that may overhaul existing models and methods to provide the required customer or market insights and defined five eras of model building.

Figure 12: Classification of model building according to Leeflang and Hunneman

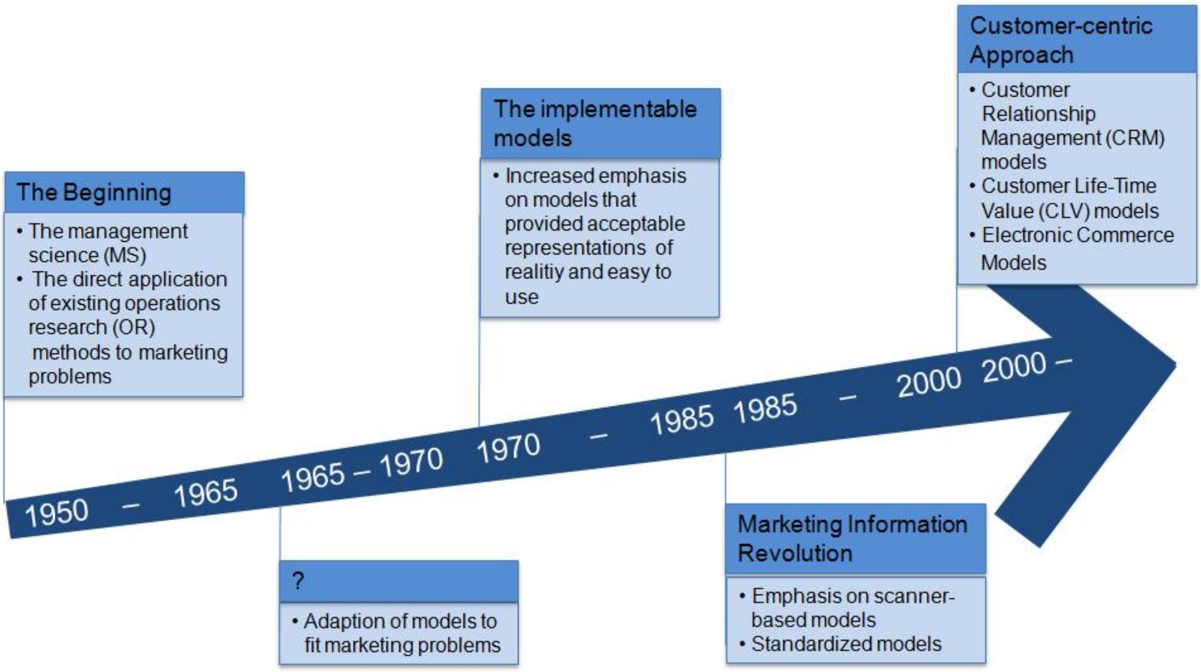


Figure: Information adapted from Leeflang and Hunneman (2010: 71-80), figure developed by the researcher

The above model indicates the eras as follows:

- From 1950 to 1965, known as the *Beginning,* defined by direct applications of existing OR methods to marketing problems;
- From 1965 to 1970, nameless but distinguished as the adaption of models to fit marketing problems as they are larger and more complex to capture marketplace reality better, however there was a lack in simplicity of these models;
- From 1970 to 1985, called the *implementable models*, indicated by increased emphasis on models that provided acceptable representations of reality and their easy usability;
- From 1985 to 2000, called the *Marketing Information Revolution*, distinguished by an enormous interest in market decision support systems and more routines model applications that result in meta-analyses and studies of the generalisation of results; and
- From 2000 to 2010, called the *Customer-centric Approach*, defined by the focus on customers with new approaches like Customer Relationship Management (CRM), Customer Lifetime Value (CLV) models and Electronic Commerce (EC) models.

In 2008, Wierenga (2008: 3-20) gave a sketch of the developments in decision models by formulating the most important and most prominent approaches. He defined five decades as follows:

Figure 13: Classification of model building according to Wierenga

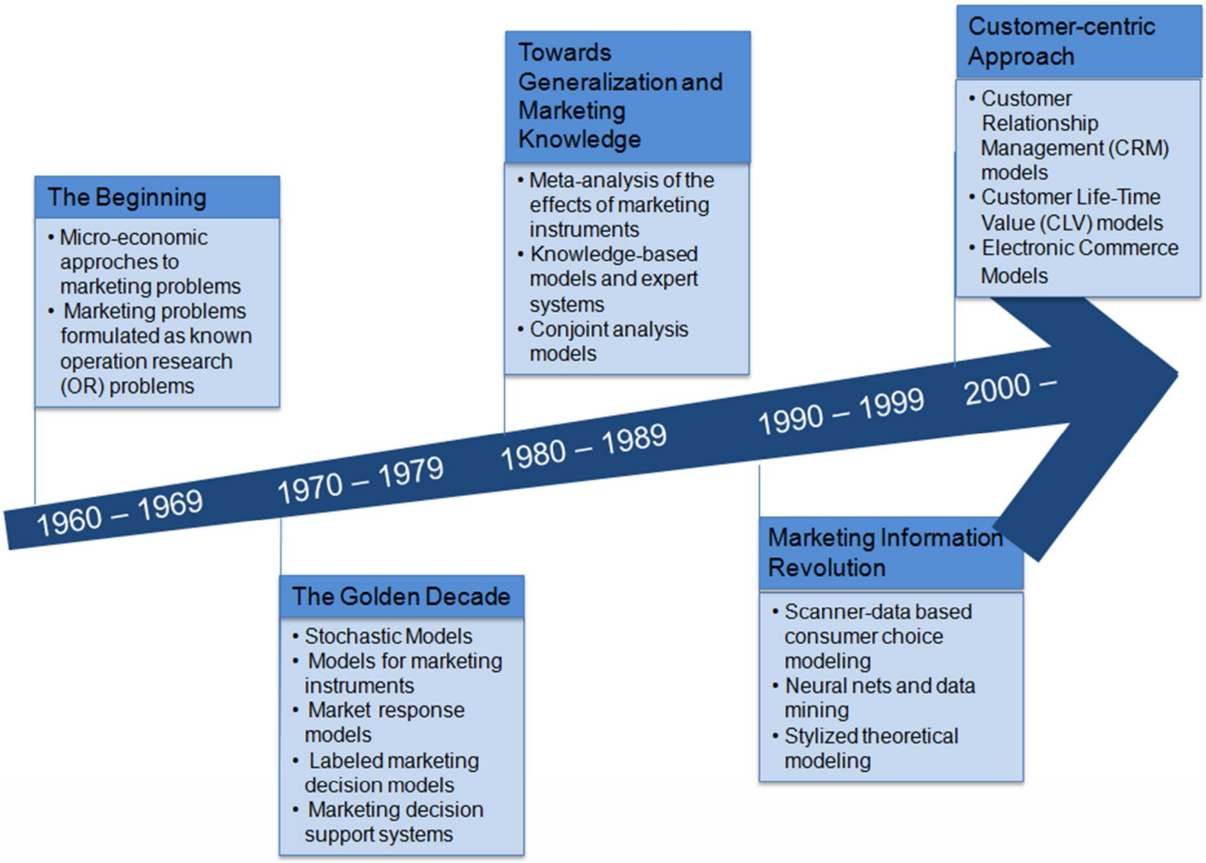


Figure: Information adapted from Wierenga (2008), figure developed by the researcher

- From 1960 to 1969, called the *Beginning*, defined by the first mathematical and micro-economic approaches to marketing problems and their definitions as know OR problems;
- From 1970 to 1979, known as the *Golden Decade*, as in this decade the field of marketing models grew exponentially and developed an identity of its own, first market response models by Clarke (1976: 345-357) and Little (1979a: 629);
- From 1980 to 1989, called the era *Towards Generalisation and Marketing Knowledge*, distinguished by the sufficiently large number of empirical studies in order to make generalisations;

- From 1990 to 1999, called the *Marketing Information Revolution*, which is the decade in which point-of-purchase data by scanners became available on a large scale which enhanced consumer choice modelling; and
- From 2000 to 2008, called *Customer-centric Approach*, defined by the most important development of the recent years that the individual customer now becomes the unit of analysis by CRM, CLV and EC. This was only possible by increased capacity of information technology to handle the huge databases with records of the individual customer.

3.2.2. History of model building in marketing and sales

3.2.2.1. The beginning of model building

The first era of model building in marketing and sales from 1953 to 1967 was a direct application of existing OR and management science methods. Optimisation models (e.g. linear programming and goal programming), Markov Models, simulation techniques, and game theory were applied and became standard applications (Wierenga, 2008: 4).

This kind of mathematical approaches to marketing and sales problems obviously started in the 1950s, which represents the beginning or, expressed by Leeflang (2010: 72), *the transposition of operations research and management science methods* to marketing and sales. In contrast, Hanssens, Parsons and Schultz (2001: 3) indicate the year 1960 as the early beginning of model building in marketing by the fact that market share models became then core ideas of marketing science. This project set the early beginning of model building to the year 1953. In 1953 and 1954, Dorfman and Steiner published the first paper using a mathematical approach to pattern micro-economic factors influencing marketing by optimising the marketing mix, called *Dorfman-Steiner-theorem* (Lee, 2002: 7-9). Only a few papers on the subject of OR or modelling in the field of marketing (in these times marketing is known as advertising) could be identified before the breaking through of the Dorfman-Steiner-theorem: These are research papers by Levinson (1953: 220-237), Koopman (1953:52-74) and Magee (1953: 64-74). Levinson (1953: 220-237) made the first experiences with OR in a commercial environment (the field of advertising) in

1953 by giving a broad statement about the necessity and contribution of an OR department in a company. The research paper by Koopman (1953: 52-74) discussed the optimum distribution for a given and limited amount of advertising effort to provide the best overall result by giving a simple mathematical solution. Finally, the research paper by Magee (1953: 64-74) on behalf of Arthur D. Little, Inc., is about the effect of promotional efforts on sales volume to answer the question of how much advertising, selling, or promotional effort is economically justified. Further micro-economic approaches were designed by Weinberg (1956: 152-186) (multiple factor break-even analysis), Nerlove and Arrow (Sethi, 1979: 839) as well as Vidale and Wolfe (1957: 370). Vidale and Wolfe (1957: 370) for example stated that once the relation between sales response and advertising has been established, the optimum budget allocation can be determined. Correlation studies of the impact of marketing decision variables on sales were modelled and completed in the 1960s titled *Some correlates of coffee and cleanser brand shares* by Seymour Banks and only discussed by Parsons and Schultz (1994: 181-189).

Engel and Warshaw (1964: 42-48) formulated marketing problems as known OR problems in 1964. This legitimates the expression by Leeflang (2010: 72), that the application of OR techniques to marketing problems highlights this period. In the same year, Massy and Webster's (1964: 9-13) article about *Model-building in Marketing Research* defined characteristics of some behavioural and optimisation models. They discussed the implications of the behavioural-optimisation model dichotomy for the marketing research department and suggested an organisational arrangement for using research data more effectively in management decision making. This highlights the statement from Alderson (1962: xi-xvii) at the beginning of this section that collecting information was emphasised in the early stages more than analysing the collected information to support a marketing or sales managers' decision.

Wierenga (2008: 5) adds by referring to Pratt that interestingly in these days, the OR approach to marketing or advertising problems was often combined with concepts from the mathematical driven theory of decision making, so called Bayesian concepts, possibly stimulated by the enormously increased capacity of computers (Kuehn and Rohloff, 1967: 43-47).

3.2.2.2. The increased complexity and exponential growth of the models

Leeflang and Hunneman (2010: 71-80) are linking the beginning of the second era to the point of adaption of models to fit marketing problems in 1965 but in parallel do not link researchers or papers to the year 1965 to prove their statement. In fact, the first analytical approach to decision making was given in 1961 by Bass, Buzzel and Greene (1961) by introducing the concept of marketing models and discussing their advantages and disadvantages. In this context, Leeflang (2010: 72) indicated the increasing complexity (possibly referring to Massy and Webster (1964: 9-13) who suggested an organisational arrangement for using research data more effectively in management decision making) where models captured marketplace reality better, but with a huge lack of simplicity. Wierenga (2008: 6) defines the seventies as the golden decade of marketing models based upon the fact that during this time marketing models grew exponentially, and developed an identity of its own.

The author is determining, taking all this into account, the beginning of the second era of marketing model building (1967-1979) to be the year 1967. This is in agreement with the different opinions discussed afore and based on the reason of the increasing complexity of models (Kuehn and Rohloff, 1967: 72; Leeflang and Hunneman, 2010: 72) and the exponentially growth of new models indicated by Little (Little, 1979a: 629) in the late 1960s (Wierenga, 2008: 6). Concluding it can be stated that the first era was defined by technique seeking for a special task and whereas now, the marketing problems as such became the point of interest (Wierenga, 2008: 6).

For this research project, Kuehn and Rohloff (Kuehn and Rohloff, 1967: 43-47) heralded the second era of model building in marketing in 1967. The authors developed the first models to aggregate data in marketing model building and identified that sales and market share are functions of many variables in addition to advertising. In 1969, Montgomery and Urban (1969) formulated simple marketing problems as OR problems in their book *Management Science in Marketing.* They gave indications that these problems could be solved by mathematical equations and continued the theses of Engel and Warshaw from 1964 (1964: 42-48) that nearly all marketing and sales problems can be formulated as known OR problems. This statement is supported by King (1970: 8) who agreed to the question if computer simulation techniques can be applied to the analyst's problem of selecting the best techniques for analysing marketing and sales decisions. Another example for computer simulations of marketing and sales challenges is the book by Massy, Montgomery and Morrison (1970), which discusses stochastic models for the buying behaviour of customers.

In 1971, Lodish (1971: 25-40) developed CALLPLAN, which is an interactive computer system designed to support salesmen in allocating sales call time more efficiently. In the same year, Schultz (1971: 153-164) developed a marketing planning model in his doctoral dissertation, including future sales and market share response functions to utilise a normative model of decision making. Moriarty (1975: 142-150) combined this model with a variance of cross-sectional time-series data resulting in a model that includes industry characteristics. His findings affected the outcome of the paper from Aaker (1975: 37-45). Aaker (1975: 37-45) developed ADMOD, an advertising decision model for consumer markets to address simultaneously the budget decision, the copy decision, and the media allocation decision to focus specific consumer decisions that advertising is attempting to precipitate. In 1973, Nakanishi (1973: 242-249) developed a stochastic model which is one of the first models to generate conditional forecasts of product sales to evaluate alternative marketing programs for new product information. Not only advertising and sales was measured at this time. Brown (1973: 380-389) published a paper about a simple and inexpensive system to measure changes in channel inventories and consumer demand by channel by geographical area according to different market strategies, such as promotions.

One year later, Wildt (1974: 50-62) displayed on the example of several case studies in the B2B and B2R context, that the consideration of the market environment is essential for developing a equation-model. In 1975, Rao and Miller (1975: 7-15) discussed a procedure for empirically estimating advertising/sales relationships from historical data.

More time relevant research in model building and sales is given by Clarke (1976: 345-357) in 1976. The author determined the duration of cumulative advertising effects on sales, based on a survey of the econometric literature. According to Wierenga (2008: 5), this is the first paper which can be assigned to the field of market response research.

In 1978, Silk and Urban (1978: 171-191) developed ASSESSOR because the substantial failure rate of new packaged goods in the markets stimulated firms to seek improved methods of pre-test-market evaluation. ASSESSOR is a set of measurement procedures and models to produce this desired estimation of the sales potential of a new packaged good before test marketing is presented (Silk and Urban, 1978: 171-191).

Another approach to design decision models for marketing and sales was done by Little (1979b). The author defined a decision support system as a coordinated collection of data, models and analytic tools, and computing power by which an organisation gathers information from the environment and turns it into a basis for action to increase productivity of the organisation (Little, 1979b: 9-26).

In 1979, *Operations Research* published a paper from Little (Little, 1979a: 629-666) about model building in marketing and sales. Little (1979a: 629-666) aggregated advertising models that related product sales to advertising expenditures. He concluded that although many models have been built, they frequently contradict each other and considerable doubt exists as to which models best represent the advertising processes. This paper marked the end of the second era of model building in marketing, called *The increased complexity and exponentially growth of marketing models (1967-1979).* Concluding, much attention in this era was devoted to models for marketing mix instruments with the issue of how to model the relationship between a particular marketing and sales instrument and sales, specified and called *market response models*. The development of Marketing Decision Support Systems (MDSS) (Little, 1979b) bridged the distance between the abstract marketing and sales model and the reality of marketing and sales decision making in practice.

3.2.2.3. The increasing importance of market response models

The third era of marketing decision models from 1980 to 1989 is marked by market response models with the intention to generalise and summarise available marketing and sales knowledge. Benefit and cost relations entered the discussion due to the fact that time and duration in relation to expenditures (especially advertising expenditures) became the focus of discussion. The third era is furthermore defined by a sufficiently large number of marketing techniques and marketing models as well as knowledge-based systems and expert systems, mostly developed for advertising and sales promotions (Wierenga, 2008: 7).

In the increasingly confusing research landscape (due to more and more publications), Hanssens (1980: 329-339) heralded this era by focusing on empirical model building of the sales-advertising relationship on basis of a combined Box-Jenkins (2008) econometric approach from 1976 to model this relationship. In the same year, Robertson (1980: 16) addressed the question of how market response could be used in planning and forecasting in the industrial context. According to Schultz (2004: 8-9), mainly personal selling interactions need to be considered in these market response models. One year later, in 1981, Blattberg and Jeuland (1981: 988-1005) derived a micromodel of advertising effects on the firm's sales across individuals and over time to produce a macromodel of the aggregated sales-advertising relationship for a single product. In the micromodel two factors are incorporated: The reach of the advertisements and the rate of decay of their effectiveness over time (Blattberg and Jeuland, 1981: 994).

In 1983, Leone (1983: 291-295) discussed the distinctions between the econometric and time-series approaches. Its realisation has been weakened by researchers' perceptions based on the early univariate Box-Jenkins-Type models (Box et al., 2008) which provided little information that could be useful for decision making (Leone, 1983: 291-295). In 1984, Assmus et al. (1984: 65-74) assessed the lessons-learned from 128 econometric models about the short- and long-term effects of advertising on sales, known as advertising response. Further effects of marketing instruments (here the price) were discussed by Tellis (1988: 331-342). The author described a meta-analysis of econometric studies that estimated the elasticity of sales or market share. He concluded that elasticity’s differ significantly over the life cycle, product categories, estimation methods, and countries (Tellis, 1988: 331-342). Further marketing and sales knowledge-based models and expert systems were designed by Abraham and Lodish (1987: 101-122) and Burke, Rangaswamy, Wind and Eliashberg (Abraham and Lodish, 1987: 100-102; Burke, Rangaswamy, Wind and Eliashberg, 1990: 212).

In 1987, Abraham and Lodish (1987: 101-122) designed a system for evaluating manufacturers' trade promotions by incorporating expert systems in order to evaluate promotions on a mass scale, known as PROMOTER System (Abraham and Lodish, 1987: 111). In 1988 Rao, Wind and DeSarbo (1988: 128) developed a methodology for building models of marketing mix responses to incorporate realistic restrictions and managerial prior information on the parameters. The authors featured an aggregate promotion response model and described the customised market response.

3.2.2.4. The advent of marketing decision support systems

The fourth era from 1990 to 1997 is defined by the advent of the point-of-purchase data. Scanner data became available on a large scale which was a major stimulating factor in modelling consumer choices in B2C (Wierenga, 2008: 8). The quickly growing amount of data made the development of new techniques, e.g. artificial intelligence and computer science, possible. Artificial neural nets, for example, are capable to find regularities in huge data bases, often called *data mining* (Wierenga, 2008: 8). In the second part of the 1990s, theoretical modelling, also called *stylised theoretical modelling* became popular, especially by Choi (1991: 271-296) and Moorthy (1993: 92-107). In this approach a marketing phenomenon is described by mathematical equations which have rapidly become an important style of research in marketing.

In 1990, Burke, Rangaswamy, Wind and Eliashberg (1990: 212-228) described the application of expert system techniques to the development of a system to assist advertisers of consumer products with the formulation of advertising objectives, copy strategy, and the selection of communication approaches, known as ADCAD. Burke et al. (1990: 212) concluded that knowledge-based systems have significant potential for the consolidation and integration of marketing and sales knowledge as interactive input for decision makers.

In the early 1990s, a large amount of literature was published in the field of scanner-data-based consumer choice modelling (Neslin, 1990; Chintagunta, Jain and Vilcassim, 1991; Abraham and Lodish, 1993) which is of less interest for the research question. The important thing is, that from the early 1990s, time-series had been incorporated into the standard methodology of market response research as an updated methodology for econometric model building (Ryans and Weinberg, 1987, Hanssens, 1990: 409-464). Data information became one of the most important factors for the success of response models (Wittink, 1991: 246-248; Gedenk, 1993; Parsons and Schultz, 1994: 181-189). Therefore, some authors expect that, by enhancement of data gathering methods, response models will be more precise hence more usable (Gedenk, 1993: 638).

In 1993, Hruschka (1993: 27-35) discussed basic concepts of artificial networks. Moorthy's (1993: 92-106) article stated the advent in attempting to explain theoretical modelling and he is arguing that even though theoretical modelling is quantitative, it is closer to behavioural marketing in purpose and methodology than to quantitative decision support modelling. Whereas behavioural marketing involves empirical experiments, theoretical modelling involves logical experiments.

In 1994, Parsons and Schultz (1994: 181-189) described the pivotal role of market response to sales forecasting and designed new response models by involving variables, relations among variables, functional forms and data for B2B markets. According to the authors a large number of sales data bases contain a combination of cross-section and time-series data. Methodological issues such as appropriate aggregation level and estimation methods in forecasting with response models are addressed (Parsons and Schultz, 1994: 181-189). Bowman and Gatignon (1995: 42-53) investigated the determinants of competitor response time to a new product introduction to support the ability to forecast the time a competitor takes to respond to help the introducing firm narrow down its entry strategy options. The author concluded that the frequency of product changes in the industry, and the market share of the threatening company appear to be significant determinants of reaction time (Bowman and Gatignon, 1995: 42-53).

3.2.2.5. The customer-centric approach and increasing level of technology

The most important development in this fifth era from 2000 to 2011 is that the individual customer became the unit of analysis (Wierenga, 2008: 8). Customer Relationship Management (CRM) models (Reinartz and Kumar, 2000: 17:35; Hardie, Lee and Fader, 2005: 275-284), Customer Life-Time Value (CLV) models (Gupta, Lehmann and Stuart, 2004: 71-80) and Electronic Commerce (EC) models, e.g. by Ansari et al. (2003: 131-145) became the standard application.

The development of market models changed because several trends have fundamentally changed the marketing and sales manager's job and therefore have influenced model building (Lilien and Rangaswamy, 1998). Firstly, Andrews (2002: 387-388) argued that marketing and sales managers now have impressive computing power and software availability. Instead of relying on staff members, sales managers are increasingly using computers and software packages to perform sales analyses themselves (Lilien and Rangaswamy, 1998: 261; Lilien, Rangaswamy, van Bruggen and Wierenga, 2002: 111-121). Secondly, the volume of available data exploded, but the human brain has not grown at a comparable rate. Therefore managers need computers and models to make better decisions in the complex environment.

In 1998, Huff and Alden (1998: 47-56) developed models that examine consumer response to sales promotions, especially for developing or newly industrialised countries with collectivist cultures. He suggested that managers should consider cultural and economic differences when planning sales strategies. One year later time is mentioned in market response models in the context of the company's scarce marketing resources to where they have the greatest long-term benefit, discussed by Dekimpe and Hanssens (1999: 397-412). This principle, however, is easier to accept than it is to execute, because long-run effects of marketing and sales spendings are difficult to estimate and highly discussed until today (refer also to the discussion of sales performance measurement in section 2.8, page 62-65).

A first deep perspective about market response models in the industrial context is given by Leeflang and Wittink (2000: 237-253). The authors propose that market response models support the decision of sales managers in industrial forecasting. Marketing scholars and practitioners frequently infer market responses from cross-sectional or pooled cross-section by time data. Such cases occur especially when historical data is either absent or not representative of the current market situation. Bronnenberg and Mahajan (2001: 284) argued that inferring market responses using cross-sections of multimarket data may in some cases be misleading because this data also reflects unobserved actions. Moreover, some research has focused on how consumers and industrial competitors respond to short-term changes in advertising and promotion (Ailawadi, Lehmann and Neslin, 2001: 44-61).

In 2002, Leeflang and Wittink (2002: 19-22) examined the effectiveness of marketing decisions based on econometric models. The authors stated that the application of econometric models to marketing and sales problems is actually a phenomenon. They estimated market response analysis to be a $125 million sector of the marketing research industry, and therefore prove its economic value to marketing and sales management (Rust et al., 2004a: 76-89).

Van Heerde, Leeflang and Wittnik (2004: 317-334) investigated sales actions and their return on investment after time in the retail market. The authors proved that sales promotions generate substantial short-term sales increases. Rust et al. (2004a: 76-89) discussed in the same year the accountability of marketers and salesmen for their expenditures to add shareholder value.

However, there have been a large number of tools developed in marketing science, but their use and impact have often been disappointing (Steenkamp, Nijs, Hanssens and Dekimpe, 2005). Therefore, more and more papers, e.g. from Roberts, Morrison and Nelson (2004: 186-191), described the challenges of applying marketing science models in practice and the benefits from doing so. One major reason for this is the difficulty of adapting these models to the managerial context at which they are targeted (including ensuring completeness, providing timeliness, and calibrating total effects). While the two major problems of managers are growth and defence, the use of marketing science models for the latter is less prevalent than for growth (Leeflang, 2000: 105-126). On the other hand, models have been seen as highly valuable: Models based on time-series econometrics, provide valuable tools and open exciting research opportunities to researchers as Pauwels et al. (2004a: 167-183) explained in 2004.

Nevertheless, long-term marketing and sales effectiveness is a high-priority research topic for managers, and emerges from the complex interplay among dynamic reactions of several market players (Pauwels, 2004: 596-610). Therefore, managers are urged to evaluate company decision rules for inertia and support when assessing long-term effectiveness. Another study from Pauwels (2004b: 142-156) in 2004 investigates the short- and long-term impact of marketing actions on financial metrics. The authors concluded that new product introductions increase long-term financial performance and firm value, but promotions do not (Pauwels et al., 2004b: 142-156).

Referring to Abramson (2005: 195) managers often employ market response models as decision aids for historical information of competitors' market outcomes to aid their competitive decisions in oligopolistic markets. However, little is known about how access to a decision aid or the availability of competitors' market outcomes impact a firm's competitive decisions (e.g., time) or market outcomes resulting from those decisions (e.g., profits), or how managers make these decisions across such informational conditions (Abramson et al., 2005: 195-207). It was further expected, that for this reason, factors of market response models, e.g. time, were not important for solving these questions.

Steenkamp, Nijs, Hanssens and Dekimpe (2005: 35-54) discussed the question of how competitors react to each other's price-promotion and advertising attacks and what are the reasons for the observed reaction behaviour by performing a large-scale empirical study on the short-run and long-run reactions to promotion and advertising. They concluded that the most predominant form of competitive response is passive in nature. When a reaction does occur, it is usually retaliatory in the same instrument, e.g., promotion attacks are countered with promotions, and advertising attacks are countered with advertising. In 2006, Tellis and Franses (2006: 217-229) discussed the abundance of highly disaggregate data and raised the question of the optimal data interval to estimate advertising carryover. The study from Moon, Kamakura and Ledolter (2007: 503-515) in 2007 addresses a problem commonly encountered by marketers who attempt to assess the impact of their sales promotions. In most industries, competing firms may have competitive sales data from syndicated services or trade organisations, but they seldom have access to data on competitive promotions at the customer level. Promotion response models in the literature either have ignored competitive promotions, focusing instead on the local firm's promotions and sales response, or have considered the ideal situation in which the analyst has access to full information about each firm's sales and promotion activity.

Computer and web-based interviewing tools have made response times ubiquitous in marketing research. Practitioners use this data as an indicator of data quality, and academics use it as an indicator of latent processes related to memory, attributes, and decision making (Otter, Allenby and van Zandt, 2008: 593-607). Otter et al. (2008: 593-607) investigated a Poisson race model with choice and response times as dependent variables. The model facilitates inference about respondents' preferences for choice alternatives, their diligence in providing responses, and the accessibility of attitudes and the speed of thinking. Thus, the model distinguishes between respondents who are quick to think and those who are quick to react but do so without much thought. Empirically, Otter et al. found support for the endogenous nature of response times and demonstrate that models that treat response times as exogenous variables may result in misleading inferences. In 2010, Srinivasan, Vanhuele and Pauwels (2010: 672-684) merged the direct sales effects of the marketing mix and customer mind-set metrics (e.g. awareness) in a sales response model for short- and long-term effects of advertising, price, distribution, and promotion (Srinivasan et al., 2010: 672-684). Wear-in times reveal that mind-set metrics can be used as advance warning signals that allow enough time for managerial action before market performance itself is affected.

3.2.3. Trends of market response models

Several trends in the application of market response models and future developments of the models are identified by Leeflang and Hunneman (2010: 71-80) and are classified in three trend channels, such as

- New paradigm from B2C to C2B by CRM and CLV models;

- Growing areas in modelling marketing services, retailing, electronic marketing but only some single growth in B2B; and
- Shifts to internationalisation and comparison (horizontal and vertical competition), to multiple brands, to store-level models and some limited shifts to strategic decision models in the field of marketing-finance interface (Leeflang and Hunneman, 2010: 74).

Important is the statement of the authors that it seemed to be remarkable that there have been less papers in the industrial context (Leeflang and Hunneman, 2010: 75). One possible reason for this is the necessity of data availability and methodology for successfully implementation market response models in the industrial context (Leeflang and Hunneman, 2010: 76-77).

3.3. DESIGN OF MARKET RESPONSE MODELS

The basic idea of market response models and its methodology known as econometric and time-series analysis (ETS), is to describe how one variable depends on one or more other variables (Hanssens et al., 2005: 423-434). It is therefore also called descriptive, which is the interaction between these variables, the dependent and the independent one. The dependent variable is the one to investigate, e.g. company sales or any other variable or variables of interest to managers, the dependent (explanatory) variable is the one which can be influenced by the company, e.g. advertising or activity of the sales force, to produce changes in the dependent variable. This can be displayed best in an example in which it is assumed that a firm only had one marketing decision variable, e.g. advertising (A = advertising expenditures at time t), to influence future sales (M = sales at time t) and other environmental factors (E = environmental factors at time t) which cannot be influenced. A response model of this market behaviour might be the sales response function as follows:

$$M_t = f(A_t, E_t)$$

The customer in the market is responding to a supplier's action (e.g. advertising) in some manner, if he/she becomes aware of it. He/she then develops preferences for the supplier's action, thus purchase it or react negatively to it. It is the interaction of the customer and supplier, thus the sales process itself, transferred on a theoretical level, which can be modelled.

Figure 14: Market response model in the industrial context

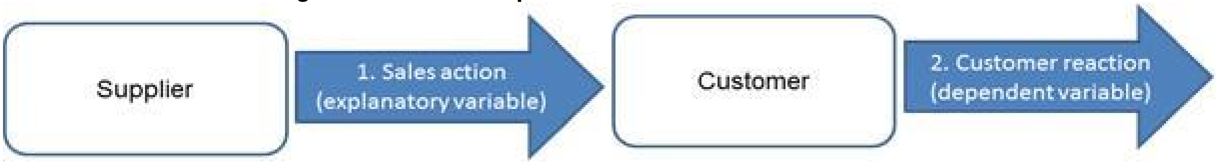


Figure: Developed by the researcher

The supplier obtains the customer's reaction in the field of, e.g. sales, directly or in the field of, e.g. brand awareness, through market research. On this basis of its sales in the period t, the company makes sales plans for the period (t + 1) which can be displayed in the formula:

$$M_t / Q_t = f\,(A_{t-1}, E_{t-1})$$

This descriptive model contains nearly the same factors as afore explained, thus regarding the question of sales (M at time t) and advertising expenditures (A) as well as environmental factors (E) at time t – 1. Therefore the company plans its sales (M) or sales in units (Q) as a percentage of the prior time or period t.

Time-series can handle a single variable, e.g. sales, but can also concern a vector of variables, e.g. sales, prices and advertising in parallel (Dekimpe, Franses, Hanssens and Naik, 2006: 2). To forecast exogenous variables univariate or when the number of variables to be analysed is too large, multivariate models for a time-series can be built (Dekimpe et al., 2006: 2). At a glance, time-series data can all be summarised in time-series models. This is exactly what kind of models are formulated, estimated and tested in ETS research. Most marketing systems or market(ing) (response) models are not as simple as the illustrated ones due to many exogenous effects (e.g. competition, multiple products, distribution channels) what makes the task of modelling complex marketing systems a difficult one (Hanssens et al., 2001: 8).

3.4. EMPIRICAL RESPONSE MODELS

3.4.1. Overview

Empirical response models work similar to market response models, but are only based on time-series or cross-section data (Parsons and Schultz, 1994: 181-189; Hanssens et al., 2001: 8). Empirical response models include competitive reactions and are known as *models of market mechanisms* (Parsons, 1994: 181). The largest category of empirical response models are those dealing with sales and market share as dependent variables because the question the company always have, is "what are the sales drivers?", or in other words "what influences sales?" and therefore "how to forecast sales?" which requires knowledge of the process *generating sales*, the *sales response function* (Hanssens et al., 2001: 8). *Structural models* are built to describe the entire market mechanism, e.g. reaction functions or cost functions. Furthermore, *simultaneous-equation models* attempt to explain all competitors decision rules endogenously (Hanssens et al., 2001: 9). Taking all this into account, the objects of interest in this research thesis are such *empirical response models* as they are all based on historical data, e.g. length of the product life cycle or market information.

All these empirical response models are based upon historical data, thus time-series data. The time-series techniques can be grouped into two broad categories: fixed-model time-series methods and open-model time-series methods (Donate, Sanchez and De Miguel, 2012: 1-26). Open-model time-series (OMTS) methods analyse the time-series to determine which patterns exist and then build a unique model of that time-series to project the patterns into the future and thus, to forecast the time-series. This is in contrast to fixed-model time-series (FMTS) methods, which have fixed equations that are based upon previous assumptions that certain patterns do or do not exist in data (Mentzer and Moon, 2005: 76).

To gather market or sales response information, two principle kinds of data are used in ETS: Time-series data and cross-section data. A definition for both kinds of data is given best by Hanssens et al. *A time-series is a set of observations on a variable representing one entity over t periods of time and a cross-section is a set of* *observations on n entities at one point in time* (Hanssens et al., 2001: 14; Weber, Bartels and Lebo, 2009: 1-34). As an example for time-series the sales of a product for 10 weeks can be made, for cross-section the price for 100 products during these 10 weeks is an example.

3.4.2. Fixed-model time-series methods

All fixed-model time-series methods (FMTS) methods are essentially a form of average. The advantage of average as a forecast, no matter if it is the simple average, the moving average, exponentially weighted moving average, adaptive smoothing, exponential smoothing with trend, exponential smoothing with trend and seasonality or even adaptive exponential smoothing with trend and seasonality, is that the average is designed to smooth any fluctuations. Thus, the average takes the fluctuations (which time-series assume cannot be forecasted anyway) out of the forecast. However, as a disadvantage, the average also smooths out any fluctuations, including such important fluctuations as trends and seasonality's (Mentzer and Moon, 2005: 74-107). The most important FMTS are such, as:

- Trend fitting is a technique where historical actual data is plotted and the trend projected;
- Moving annual totals or moving annual averages are practical techniques that smooth data in a time-series, showing a trend that is not distorted by serious seasonal, cyclical or random fluctuations. A big disadvantage is that they do not respond quickly to unexpected or significant changes in the patterns of sales; and
- Exponential smoothing is applied where extra weight is given either to earlier or to more recent data (depending on which data is seen as more likely to be representative of the future sales pattern), in an attempt to take account of more significant changes in the pattern of sales (Noonan, 1998: 199).

For most companies, time-series analysis finds practical application mainly in making long-range forecasts. Predictions on a year-to-year basis, such as are necessary for an operating sales forecast, generally are little more than approximations. Only where sales patterns are clearly defined and relatively stable from year to year is time-series appropriately used for short-term operating sales forecasts (Still et al., 1998: 45).

In general, FMTS methods should be used when a limited amount of data is available on anything other than an actual history of sales. This lack of outside (exogenous) data precludes the use of regression analysis. Further, FMTS methods are useful when the time-series components change fairly regularly. That is, the trend rate changes, the seasonal pattern changes, or the overall level of demand changes. FMTS is much more effective at adjusting to these changes in time-series components than are the OMTS methods, which require more data with stable time-series components over a long period of time.

3.4.3. Open-model time-series methods

Open-model time-series (OMTS) methods assume that the same components exists in any time-series, such as level, trend seasonality and noise, but take a different approach to forecast these components. Where FMTS techniques assume that certain components exist in the time-series and use one set of formulae to forecast this series (that is, the formulae are “fixed”), OMTS methods first analyse the components in the Time-series to see which exist and what their nature is. From this information, a set of forecasting formulae unique to that time-series is built (Mentzer and Moon, 2005: 107-108).

3.5. PLANNING AND FORECASTING BY MARKET RESPONSE MODELS

Despite the large number of approaches to sales forecasting which were described earlier in chapter three, there are relatively few studies about model-based planning and forecasting which address company-specific and even industry-specific structured models (Hong Long, 2010: 310). The main description about *model-based forecasting and planning* is given by Hanssens (2001: 16).

Figure 15: Model-based planning and forecasting

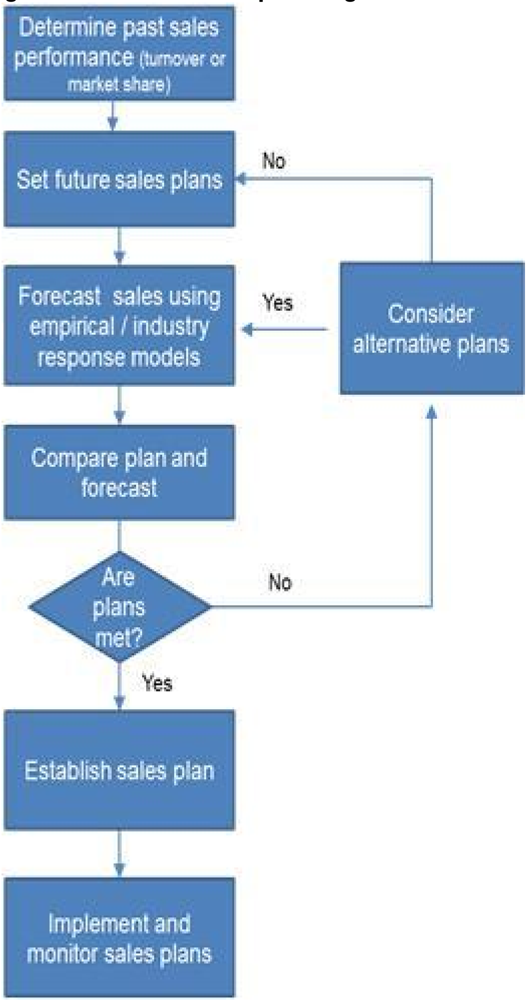


Figure: Adapted from Hanssens (2001: 17)

The first step in the model-based planning and forecasting process is to determine the past sales performance. Naturally, to the sales performance other performance measures and factors, different planning levels and different organisational structures for planning and forecasting can be accommodated, which makes this standard process quite robust. The most commonly used performance measures are sales turnover, market share, or contribution cost, but usually increasing sales turnover as the main goal of the sales manager (Yu Ha and Florea, 2009: 139-156).

Based on past sales figures, future sales goals need to be set. In addition to past performance, current market situations and market opportunities will have a leading role in determining this sales target. Three possible approaches are common to set future sales goals: it is top-down planning, bottom-up planning or mixed-planning (see section 2.4, page 34-36).

The next step after setting sales goals is to forecast industry sales by using empirical and / or industry response models. Nevertheless, industry response models capture factors which are usually beyond the control of the company, e.g. total market sales. Since there is finally a model on which to base the forecasts, sales managers can see how the forecast depends on the company's own assumptions about the factors determining industry sales.

After finalising the sales forecast, the next step is to compare the sales plan and sales forecast. As a result, the company must have specific planned levels for influencable (by the company) sales drivers. If the plans met the forecast and the outcome is satisfactory, the plans can be established, if not, alternative plans have to be made. The last step in the process is to implement and steadily monitor the execution of the plans. Summarised, the model-based planning approach is similar to the planning and forecasting process (see figure 7, page 30); except the usage of any response model.

3.6. FACTORS THAT INFLUENCE (EMPIRICAL) SALES RESPONSES

Literature provides several investigations about factors that influence sales, thus also influence sales response models. Such factors are interesting for the field of market response in general. For this reason, they are shortly discussed (Narayanan, Desiraju and Chintagunta, 2004: 90-105; Ledingham, Kovac and Simon, 2006: 124-133; Zoltners, Sinha and Lorimer, 2008: 115-131).

According to the authors, sales is influenced by a large number factors that can be classified into influencable and non-influencable factors. Influencable factors are the effort of the salesperson and the effort of the company. These factors can be controlled and measured by the sales manager. Non-influencable factors, such as the carryover effect, the characteristic of the response unit (potential customer) and the competition, cannot be influenced and controlled, even not very well anticipated (forecasted). They are outside of control of the company.

Figure 16: Factors influencing empirical sales response models

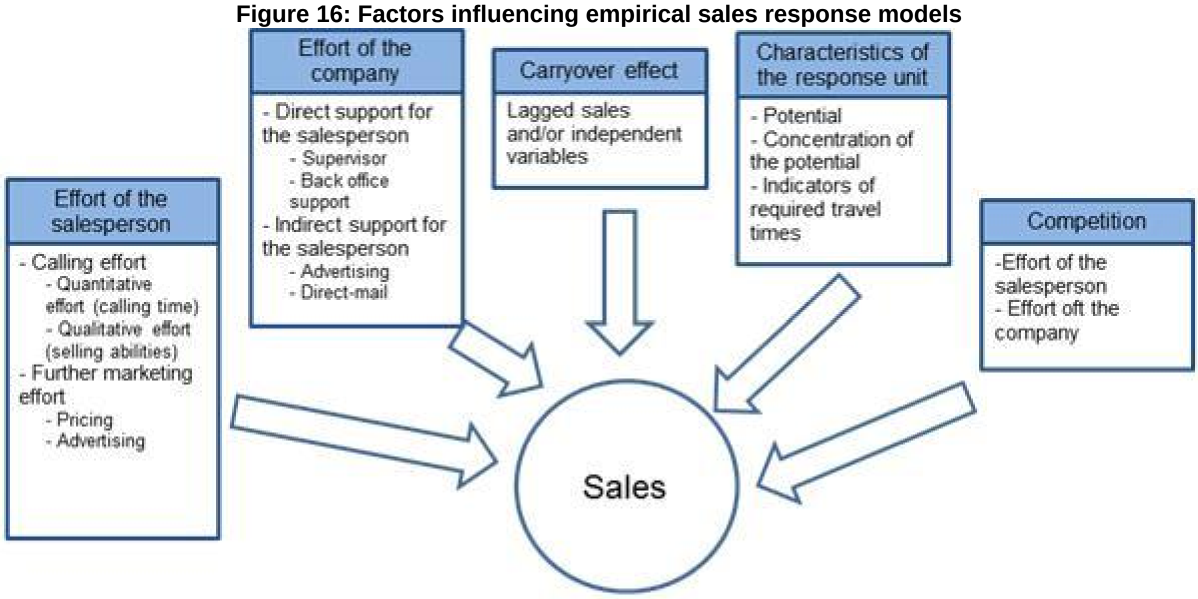


Figure: Adapted from (Narayanan et al., 2004: 90-105; Ledingham et al., 2006: 124-133; Zoltners et al., 2008: 115-131)

As a result it might be expected that MRT is also infused by factors that can be classified into influencable and non-influencable.

3.7. CONCLUSION

Model-based planning and forecasting enhance the standard planning and forecasting process, because the key to reliably plan and forecast sales is market knowledge which can be best determined by market response models (Ingram, 2006: 114). Such market response models are usually part of the sales system (Kotler et al., 2000: 118). Especially, when forecasting is based on time-series analysis, explanatory models and market response models can be used to simulate sales outcomes of different resource allocations. A large number of investigations are done in the field of market response research. The connection between planning and forecasting methods and such response models is, especially in the industrial context, not very well researched. The question still remains in literature, if model-based planning and forecasting is applied in the industrial real life context.

CHAPTER 4: RESEARCH METHODOLOGY

There are many scientific research methodologies to consider when conducting an empirical study. Every method has its own advantages and disadvantages and all methodologies are based on accepted scientific research. The intention of this chapter is to first discuss the two main research paradigms, the quantitative and the qualitative research paradigm to clarify available research methodologies and to identify and describe the suitable methods. After this introduction to research methodologies, the most suitable methodology for this project, which is the case study method, is discussed. Afterwards, the research project is described.

4.1. SCIENTIFIC RESEARCH: THE QUANTITATIVE AND QUALITATIVE RESEARCH PARADIGM

Research is commonly known as generating new knowledge (Lategan, Le Roux and Holzbaur, 2009: 1). This is the process of thoroughly studying and analysing the situational factors surrounding a problem in order to seek out its new solutions in a systematic, controlled, empirical, and critical way (Cavana, Delahaye and Sekaran, 2001: 4). However, the process of generating new knowledge or new solutions does not imply a search for certainty or absolute truth, but a search for the most valid or best approximation to the investigated problem (Babbie, 2004: 16).

There are two main research paradigms discussed over the last 100 years, namely the quantitative and the qualitative research paradigm (Schwarz and Teichler, 2000: 15; Conrad, Haworth and Lattuca, 2001: xi; Thomas and Magilvy, 2011: 151-155). The discussion, which method is better than the other or which method to apply for which research question, seems to be a never ending discussion for scientific researchers (Conrad et al., 2001: 27-29). Traditionally, the distinction between each methods is focused mostly on the contexts in which they were applied (Payne and Wansink, 2011: 377-390). Further distinctions are, that the quantitative approach is based on pure facts and statistical data, the qualitative approach on judgment and experience (Blaxter, Hughes and Tight, 2001: 85). The differences of quantitative and qualitative research are further reflected in the respective languages of each and in the different logical character in which key information is processed and displayed (Pring, 2000: 43). The discussion in the last ten years is however not about the differences between the two approaches but is more about the question whether they can be used within the same investigation (Cherry, 2000: 88-90; Pring, 2000: 43; Östlund, Kidd, Wengström and Rowa-Dewar, 2011: 369-383). For this research project it is necessary to differentiate the two approaches for a clear understanding of which approach suits best.

If time and resources are limited, quantitative research may be appropriate by applying one or more of the following methods during the research approach (Hancock and Algozzine, 2006: 7): The researcher can apply a survey, an experiment, official statistics, structured observations or a content analysis (Silverman, 2006: 37). They all have advantages relating to the reliability of measures, thus the simple quantification of constructs (Babbie and Mouton, 2001: 49). Sometimes quantitative research based literature assumes that scientific research can only be valid if based on operational definitions of variables, experimental data, official statistics or the random sampling of populations (Silverman, 2006: 33-39). Such research is indirect and abstract in order to be able to treat phenomenon (e.g. human behaviour, processes or any other construct of interest) as similar, adding, or multipliable facts (Cherry, 2000: 77). These methods may not be appropriate for some of the tasks of social and environmental science. For instance, they cannot describe human behaviour, because it is much more complex than figures (Silvermann, 2006: 43). Most advanced survey procedures only manipulate data that had to be gained at some point by asking people. Quantitative research is statistical logic in testing hypotheses and to gather quantity; it is especially efficient to get structural features of social life, while qualitative research is usually strong on process aspects. An in-depth view of real lifetime and first-hand holistic understanding of phenomena cannot be given by quantitative research (Holme, 1997: 94-97; Blaxter et al., 2001: 85).

Qualitative research is difficult to define because it is an interdisciplinary field (Denzin and Lincoln, 2000: 6-8). Yin (2009: 8-9) describes major research strategies (see table 2, page 95) in this field and all of them have different ways to collect and analyse data, thus providing different outcomes in terms of validity, generalisability and representativeness. Qualitative research methods should be used when it is necessary for the researcher to create a deeper rather than broader understanding, for example, if cases, circumstances or organisational goals with high complexities and processes are investigated; if relevant variables have not be identified yet and if “how” and “why” questions mainly need to be asked during the interview (Marshall and Rossman, 1999: 46; Babbie and Mouton, 2001: 53). As more knowledge is gained, the research question may shift and the data collection methods with the least possible interference by the investigator may be adjusted accordingly and not that strictly formalised (Holme, 1997: 97-102; Fortune, 1999: 94; Silvermann, 2006: 56). Qualitative research is less concerned about control and more concerned with the interpretation of the investigated phenomena (Payne and Wansink, 2011: 377-390).

Summarised, quantitative research is based on figures and expressed in numbers and statistics with the objective of a wide-spread understanding of everything structured and processed (Blaxter et al., 2001: 85). Quantitative research is less concerned about details but concentrates more on generalisations. Therefore, it usually includes a greater number of research samples than qualitative studies do, while the amount of information required on each sample is less. Qualitative research leads to a deep understanding of the observable facts, processes and observation of organisational goals and embed the findings into the real world (Denzin and Lincoln, 2000: 10; Nuttall, Shankar and Beverland, 2011: 153-163).

However, there is a trend and growing acceptance of the use of pluralism in research methodology, called a multi-methodology approach (Ledington and Watson, 1998: 156-171; Laws and McLeod, 2005: 2). This multi-method approach is a combination of both quantitative and qualitative research and based on some similarities of both methodologies (Östlund et al., 2011: 369-383). Such similarities are that both approaches require explicit descriptions of data collection and analysis procedures, both approaches can be combined to qualitatively generate theories or hypotheses and quantitatively test these theories and both approaches can include quantitative and qualitative statements. This means that in qualitative research interview questions can include quantitative statements such as “more/ less” or specific numbers with a low number of participants; and in quantitative research open-ended interview questions can be posed, answered by a large research sample for generalisation (Blaxter et al., 2001: 65; McMillan and Schumacher, 2001: 11).

4.2. THE QUALITATIVE CASE STUDY APPROACH AS RESEARCH APPROACH FOR THIS PROJECT

As indicated in the previous section 4.1, quantitative research is based on figures and expressed in numbers and statistics. The primary aim of this research project is, however, to investigate the sales planning and forecasting behaviour by sales managers. Firstly, behaviour can neither be only explained by statistics, nor only investigated by figures. Secondly, no figures are yet available to generate questionnaires as this is the first study about time frames in the sales process for the three investigated industry sectors. For this case, a qualitative study (with quantitative statements for the time frames) needed to be undertaken to investigate circumstances and behaviours that embed the findings into the real world (the three industry sectors) and to understand complex phenomena (Vissak, 2010: 370-388).

In qualitative studies, five major research methods can be undertaken, such as to do an experiment, a survey, a history, an archival analysis, or setup a case study. Each method, simply described by its name, is different in the way of collecting and analysing empirical evidence. The decision of which method to use, can be answered by three questions and the decision table displayed below (Yin, 2009: 8):

- What is the form of the research questions?
- Does the research require control of behavioural events? and
- Does the research focus on contemporary events?

As this project investigates “how” and “why” questions, such as *how do you plan your future sales, how do you forecast your future sales*, or *how accurate is your sales forecast*, experiments, histories and case studies are likely to be the favourable methods to use.

Table 2: Decision table for the five major qualitative research methods

Method	Form of research question	Requires control of behavioural events?	Focuses on contemporary events?
Experiment	- how? - why?	- yes	- yes
Survey	- who? - what? - where? - how many? - how much?	- no	- yes
History	- how? - why?	- no	- no
Archival Analysis	- who? - what? - where? - how many? - how much?	- no	- yes / no
Case Study	- how? - why?	- no	- yes

Table: Adapted from Yin (2009: 8)

A further distinction is the extent of the researcher's control over and access to actual behavioural events (Yin, 2009: 11). As this research project investigates real life situations, no control or interaction of the behaviour of the investigated planning and forecasting process is needed and even not possible to manipulate: The interview participants answers are embedded in an organisation with standardised and common processes which are not easily changeable or adaptable. A possible interaction would even falsify the research results. The last distinction between the methods is the question if contemporary events are investigated. The case study may be preferred in examining contemporary events, if the investigated behaviours cannot be manipulated (Yin, 2009: 11). Finally, the case study distinguishes between a history by the direct observation of the event, and the possibility to interview the person involved in the event (which both cannot be done in an historical study). As a result, the case study methodology is the method of choice for this research project.

4.3. REASONING TO DEVELOP THEORIES

In order to understand the process of how to form practice generalisations, it is essential to devote attention to the modes of deductive, inductive, diagnostic and abductive reasoning (Vos, 2005: 47).

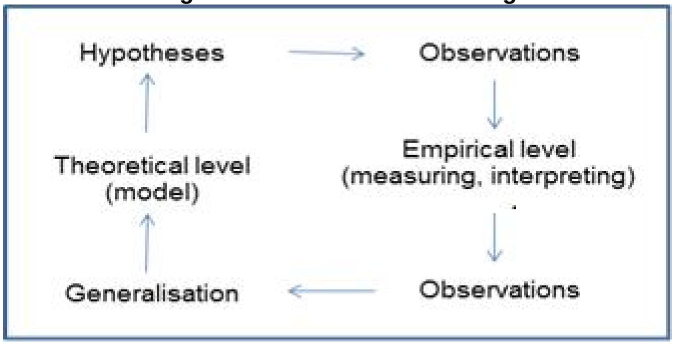
Deductive reasoning, or deduction, moves from the general to the specific (Babbie, 2004: 35). It moves from a pattern that might be logically or theoretically expected, e.g. by literature review, to hypotheses, then to observations in an empirical study and finally to the empirical level that tests whether the expected pattern actually occurs or not (Babbie, 2004: 35; Vos, 2005: 47). Deductive reasoning is a form of reasoning where two premises are relevant. The first premise states the case and the second premise states the generalisation of which the case is an example (Vos, 2005: 47).

Inductive reasoning, or induction, moves from the particular to the general. It moves from a set of specific observations to the discovery of a pattern that represents some degree of order among all the given events (Babbie, 2004: 34). In the case of induction there are two premises under review: the case and the characteristic of the case. Therefore, the conclusion is a tentative generalisation. One of the differences between deduction and induction is that in the case of induction, a new thought is added which is not necessarily contained in the premise. In inductive reasoning, the conclusion is not, as it is in the case of deduction, completely certain, but without obligations possible (Vos, 2005: 48).

The “third form of mediating reasoning” developed in the 1950s by Lehrman (1954: 192-199) is called diagnostic reasoning or diagnosis. It derives in a creative way from a characteristic and a generalisation, leading, by way of conclusion, to a tentative placement of the case (Lehrman, 1954: 192-199). The conclusion is not formally contained in the premises but, based on these premises as evidence. It is possible to reach beyond a designation of the class of objects to which the particular case may possibly belong to. This is by testing the case against various (known) characteristics of that particular class of objects (Vos, 2005: 49). The conclusion is never certain, similar to inductive reasoning, although its probability may be strengthened by testing the case against additional characteristics or even undertaking more cases.

Abductive reasoning is a combination of induction and deduction and implies alternating between the empirical and theoretical levels. This method is commonly used when the purpose of the research is to further develop or challenge a theory through empirical studies and is applied in this project.

Figure 17: Abductive reasoning



Adapted from Babbie (2004: 34)

This reasoning procedure starts on a theoretical level based on a broad literature review as to create a conceptual level that will guide the collection and analysis of data. Once the hypotheses are established, the observations (collection) can be done. Afterwards, the interpretation of the data will be conducted using a deductive approach to bring the research to the empirical level. Subsequently, based on the empirical level, further observations can be made in order to determine if an analytical generalisation can be made or not. This final step of the study will consequently entail inductive reasoning to finally come back to the theoretical level describing the best solution (Babbie, 2004: 34).

4.4. PILOT STUDY

To prevent considerable trial and error in the empirical study as well as to rethink the methodology, it is recommended to field-test the interview situation, as well as the wording, ordering of questions and the interview design by a pilot study (Seidman, 1998: 32; Van der Merwe, 2011: 32). Primary data should be collected to gain a first overview and understanding about the topic to develop relevant lines of questions, to provide some conceptual clarification for the research designs and to help to refine the data collection plans with respect to both the content of the data and the procedures to be followed in data collection.

Based on the theoretical knowledge, an interview questionnaire with open-ended questions was established for six in-depth interviews with a chosen sample of three interview participants of the Machinery & Equipment and Automotive Supplier

Industry sector, each with a duration of about 180 minutes in length. Nevertheless, the scope of the inquiry for the pilot study was (and can be) much broader and less focused than for the empirical study. The sample of the pilot study was selected with the same purpose in mind as the sample for the main study. Afterwards the collected data was summarised and intensely discussed with the supervisors of this research project. Furthermore, all six interview participants were again interviewed (face to face or by phone due to sometimes huge local distances, e.g. interview participants in Switzerland) about improvements in the interview guide. The review of the results of the pilot study is highly recommended to add support to its trustworthiness (Thompson, 2004: 4).

4.5. CASE STUDY METHODOLOGY AND SCIENTIFIC STEPS IN THE RESEARCH PROJECT

The case study methodology is part of qualitative research and appropriate when answering “how” and “why” questions (Laws and McLeod, 2005: 3; Yin, 2009: 9) as already indicated in section 4.3. It is an approach using a variety of data sources with a high grade of flexibility (Baxter and Jack, 2008: 544). It studies what people or companies are doing in their natural context, it is well placed to study processes as well as outcomes, and studies, meanings and causes (Silvermann, 2006: 349).

This methodology is a research approach situated between concrete data taking techniques and methodological paradigms (Flyvberg, 2006: 219-246). It is an empirical inquiry that investigates a contemporary phenomenon in depth and within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident and need to be defined (Yin, 2009: 18). The case study approach is furthermore recommended for “International Business Research” (Vissak, 2010: 370-388). The scientific steps in undertaking this project are to:

- Determine the case and research questions;
- Establish the boundaries for the case and set aims;
- Establish a conceptual framework;
- Determine the type / design of the case study;
- Determine the data collection and sampling techniques;

- Determine the data analysis techniques;
- Collect the data in the field; and
- Process the data / to analyse the data and conclude (Soy, 1997: 1-9; Halinen and Törnross, 2005; Baxter and Jack, 2008: 544-559; Yin, 2009: 25-185; Piekkari, Plakoyiannaki and Welch, 2010: 110).

4.5.1. Case and research questions

A case study can be regarded as an exploration or in-depth analysis of a *bounded system*. A bounded system is a clearly defined object of investigation. Actually, the case is the unit of analysis and defined as a phenomenon that occurs in a bounded context (Babbie, 2004: 285). The case being studied may be a process, activity, event, program or individual or multiple individuals with the opportunity to learn something new (Vos, 2005: 272). In order to determine what the case is, it is recommended to ask several detailed questions in terms of what exactly the researcher wants to know (Baxter and Jack, 2008: 546).

In this research project, the case can be derived by its aims of the empirical study as mentioned in section 1.7.2 (page 19). According to this aims, the cases can be clearly defined as to “analyse the sales system (of different companies in different industry sectors)”.

Figure 18: Case of the research project

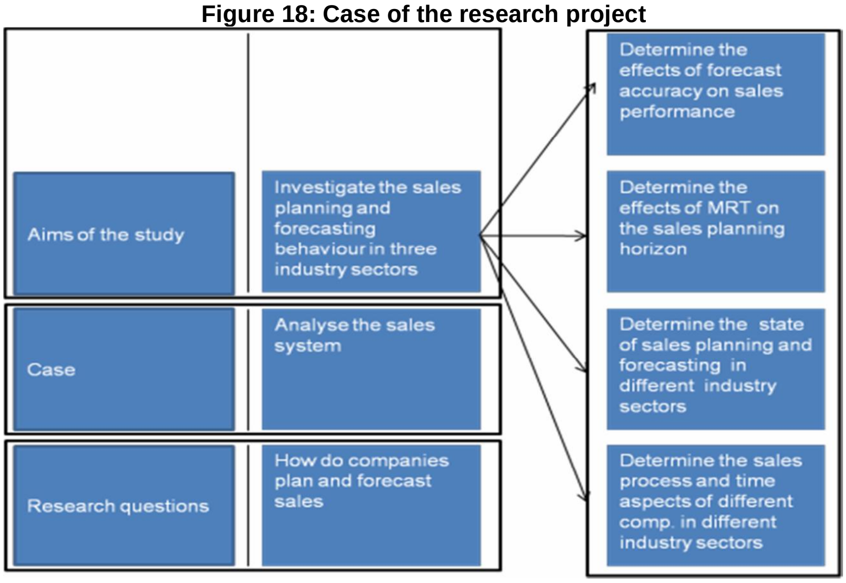


Figure: Developed by the researcher

Based on this, the main research question can be defined as “how do companies plan and forecast sales”. The research question confirms again the case study methodology as the most adequate research methodology as there are mainly “how” questions to be investigated.

4.5.2. Boundaries and aims for the case

There is a tendency for researchers using case study methodology to attempt to answer questions that have too many objectives for one study (Baxter and Jack, 2008: 546-547). Baxter and Jack (2008: 546-547) referred to older sources (there seems to be a gap of new scientific investigations) and stated in order to avoid too many objectives that it is necessary to place boundaries on a case (or to set aims). Such boundaries can be defined either by time and place (Creswell, 1998: 61), by time and activity (Stake, 1995: 23), or by definition and context (Miles and Huberman, 1994: 102) or by a limited number of people involved (Laws and McLeod, 2005: 8). The definition of boundaries indicates what will and will not be investigated in the research project, thus they can increase the likelihood that the researcher will be able to place limits on the scope of the study (Koro-Ljungberg and Hayes, 2010: 114-124). Such aims are necessary elements in case study research as they form the foundation for a conceptual framework that guides the research process (Miles and Huberman, 1994; Stake, 1995: 17). Based on Miles and Huberman (1994: 102), the boundaries of this research project are defined by definition and context as displayed in figure 19 on page 101.

The boundary “definition” is defined as “planning and forecasting future sales turnover in Euro”. The boundary “context” is defined by the industry sectors to investigate, thus Machinery & Equipment Industry and Automotive Tier 1 and Tier 2 Supplier Industry sector.

Figure 19: Boundaries of the case

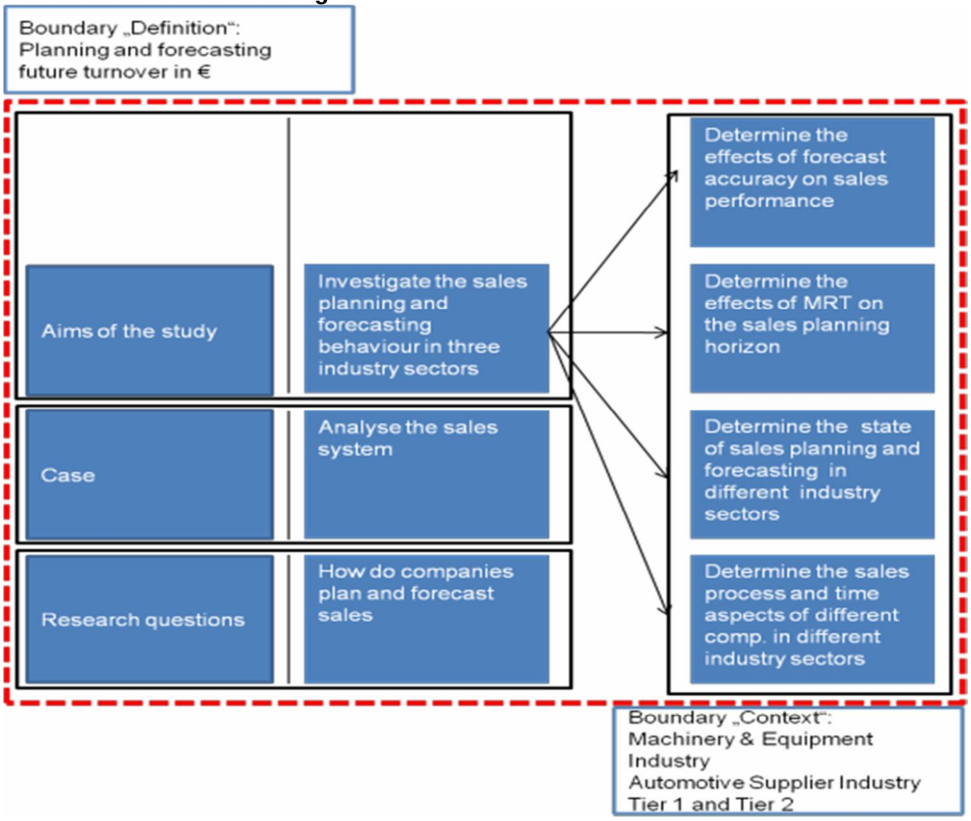
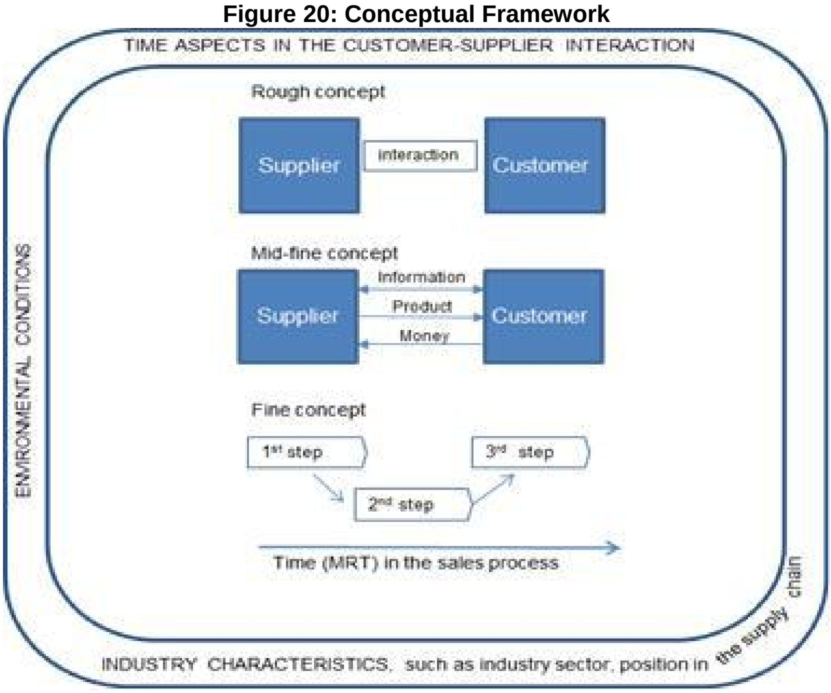


Figure: Developed by the researcher

4.5.3. Conceptual framework

The intentions to establish a conceptual framework are to identify who or what will be included in the project, to describe what relationships may be present in the project based on theory and / or experience (before the empirical study) and to provide the researcher with the opportunity to gather general constructs into intellectual constructs (Baxter and Jack, 2008: 553; Yin, 2009: 85). Such a framework should continue to develop and be completed with the progress of the research project. The relationships between the proposed constructs will emerge as soon as data is analysed. Further, the final models (for each investigated industry sector) will include the very fine concept that emerged from the analysis of the results of the empirical study (see section 6.1, page 146 and following).

Figure 20: Conceptual Framework



Framework: Developed by the researcher

The framework displays from outside to inside the environmental conditions (such as the grade of competition, technology, trends, legislation and economy), the industry characteristics (such as the industry sector and the position of the company in the supply chain) as well as the time aspects in the customer-supplier interaction, where the industrial sales process is undertaken. The sales process, which is in fact an interaction between supplier and customer (rough concept), can be displayed finer as the transaction of information, products and money between the customer and supplier (mid-fine concept) (Goerne, 2009: 1-3). The fine concept displays the interaction between the customer and supplier by process steps which are influenced by time aspects (MRT) (research findings).

4.5.4. Type / design of the case study

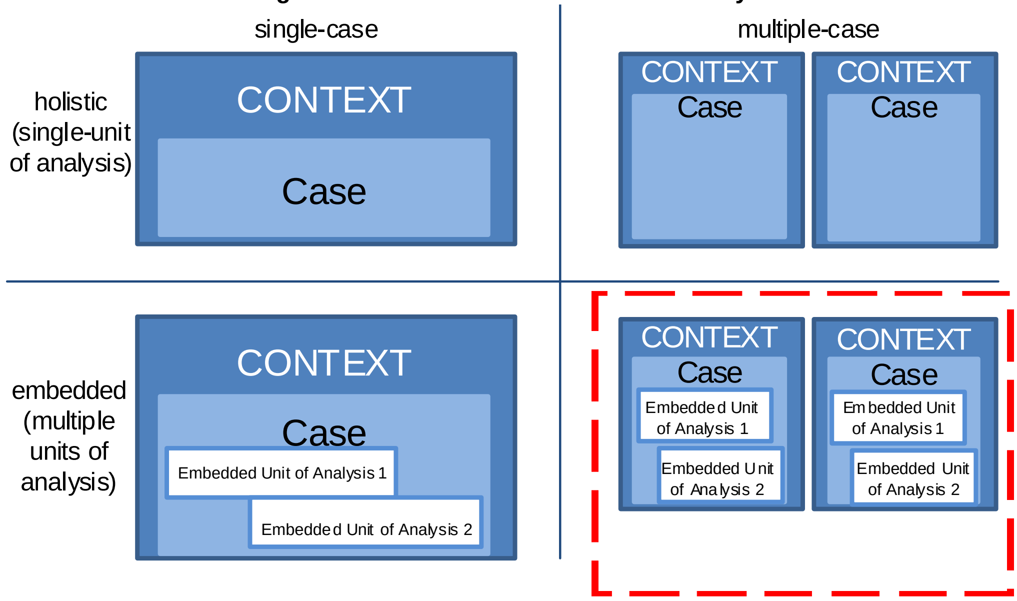
The decision for a special type or design for a case study is guided by the overall study purpose and the research question. It results in a number of contexts that need to be included in the research and how well it allows the full investigation of the particular research question (Hancock and Algozzine, 2006: 31). This can be either to describe a case, explore a case or comparison between cases (Baxter and Jack, 2008: 547).

There are several designs within case study research. Yin (2003: 46-65) categorise them into explanatory, exploratory and descriptive case studies. Explanatory case studies are appropriate to establish cause-and-effect relationships with the primary aim to determine how events occur and which ones may influence particular outcomes. These kinds of questions are too complex for surveys or experiments (Joia, 2002: 305-317; Baxter and Jack, 2008: 547). Exploratory case studies are appropriate to explore situations in which the intervention being evaluated has no clear and single set of outcomes (Lotzkar and Bottorff, 2001: 275-294). Descriptive case studies are appropriate to describe a complete phenomenon and the real-life context in which it occurred (Hancock and Algozzine, 2006: 33).

Case study research designs may also be classified as intrinsic, instrumental, or collective (Stake, 1995: 11-19; Hancock and Algozzine, 2006: 31). Intrinsic designs are engaged when more information about a particular individual is needed and instrumental designs are applied to better understand a theoretical question or problem. Finally, the collective research design is applied to better conceptualise a theory by adding issues to the literature base (Hancock and Algozzine, 2006: 33).

Yin (2009: 46) furthermore differentiates case studies into four classifications: It is the holistic single-case classification, the embedded single-case classification, the holistic multiple-case classification and the embedded multiple-case classification.

Figure 21: Classifications of the case study



Adapted from Yin (2009: 46), optimised for this research project

A holistic (or intrinsic, as already explained afore) case study design is appropriate to learn more about a particular individual, a group, an event, or an organisation but is not appropriate to create general theories. It is not appropriate to generate theories, because only one single case is investigated. Therefore, the purpose is not to understand a broad issue, but to describe the case being investigated. The focus is to gain a better understanding of the case by examining the case as one unit in one context (Rowley, 2002: 22).

On the other hand, the embedded (or instrumental, as already explained afore) case design is used to elaborate on a theory or to gain a better understanding of an issue. It merely serves the purpose of facilitating the researcher's gaining of knowledge about the issue. This design is appropriate to better understand a specific (theoretical) question or problem which is embedded into the case (Gruenbaum, 2007: 78-97). This is e.g. the question of sales planning and forecasting in companies that act in the Machinery & Equipment Industry sector.

Finally, multiple-case designs (or collective case) designs widen the understanding of the researcher about an issue or population to be studied (Baxter and Jack, 2008: 549). The interest in the individual case is secondary to the researcher's interest in a group of cases. Cases are chosen so that comparisons can be made between cases and concepts that theories can be extended and validated (or even indicated). This design attempts to address an issue in question while adding to the literature base that supports conceptualising a theory (Hancock and Algozzine, 2006: 31-38). They identify an amount of sub-units, called embedded units of analysis (Gruenbaum, 2007: 78-97).

Each design has its own strengths and weaknesses. However, multiple-case designs may be preferred over single-case designs. Single-case studies are vulnerable to criticism because the analytic benefit from having two (or more) cases may be substantial and strengthen the findings (Eilbert and Lafronza, 2005: 185-199). Finally, it is important to choose a case study design that matches the disciplinary perspective of the investigation best. The exploration and description of the cases takes place through detailed, in-depth data collection methods, involving multiple sources of information. The researcher situates the case within its larger context, but the focus remains on either the case or the issue illustrated by the case and by the boundaries set before (see figure 19, page 101). This implies that the case study researcher seeks to enter the field of knowledge of the relevant literature before conducting the field research (Vos, 2005: 272). This approach can be used to either predict similar results (literal replication) or predict contrasting results but for predictable reasons (theoretical replication) (Yin, 2009: 47).

The most appropriate design for this research project is the embedded multiple-case design, also called an embedded collective case design. The reason for this design is that this project investigates more than one context, such as three industry sectors, and embedded units of analyses, such as mentioned afore. Furthermore, it is the aim of this research project to attain a deep, comprehensive and comparable understanding of the internal and external factors affecting a company's sales planning and forecasting at a glance. Individual planning and forecasting processes are of less interest for this research study.

4.5.5. Data collection and sampling techniques

Case study evidence can come from many sources and it is most important to use multiple sources, at least external and internal data sources (McGloin, 2008: 45-54). The opportunity to gather data from a large number of sources is highly valuable for research, but there are also some dangers, such as to collect too much data (Baxter and Jack, 2008: 554). Sources can be documentation, archival records, interviews, direct observations, participant-observation, and physical artefacts (Yin, 2009: 99).

Interviewing is the dominant mode of data collection in qualitative research (Vos, 2005: 287-292). Especially in case study research, interviews are a very common method for data collection as it allows the researcher to gather rich and personalised information (Mason, 2002: 99). Sewell (2001: 1) defines qualitative interviews as attempts to understand the world from the participant's point of view, to unfold the meaning of people's experiences, and to uncover their living environment prior to scientific explanations. After identifying the focus groups for the study, interviews should be undertaken whether individually or in groups. Individual interviews are of more value than group interviews, however they are time consuming and expensive

(Hancock and Algozzine, 2006: 39). An interview schedule with appropriate questions should be developed. This can be an unstructured, semi-structured or structured interview schedule (Priest, 2006: 91-92; Whiting, 2008: 35-40).

Unstructured interviews are used to determine individuals' perceptions, opinions, facts, and their reactions to initial findings and potential solutions (Roulston, 2011: 348-366). The interviewer explore many facets and perceptions of the participant, however, subjects will be discussed when it presents itself in the conversation. This can lead the conversation in a number of directions rather than search for replicable answers.

Semi-structured interviews, also called focused interviews, are defined as those organised around areas of particular interest, while still allowing considerable flexibility in scope and depth (Whiting, 2008: 35-40). That means that the interviewer uses predetermined but open questions and if necessary ask follow-up questions designed to investigate issues of interest more deeply (Hancock and Algozzine, 2006: 40). If the researcher has learned the schedule in advance, then he will be able to concentrate on what the participant is saying during the interview, and also occasionally monitor the coverage of the scheduled topic (Smit, 1995: 9-26).

Structured interviews are ideal for obtaining comprehensive and comparable data, because all respondents have been asked the same questions. This kind of interview often produces quantitative data and therefore not often applied in case study research (Dicicco-Bloom and Crabtree, 2006: 314-321). Responses can be coded and tabulated, and descriptive statistics used to examine the data for relationships and evaluation. However, a high degree of structuring capitalises on the richness of qualitative responses. The questions are focused on a specific issue (or set of issues) which guide the course of the interview (Laws and McLeod, 2005: 13). The dichotomy between structured and unstructured interviews is misleading, as unstructured interviews are structured in a number of ways. It is, e.g. a conversation with a purpose by understanding the experience of other people and the meaning they make of that experience (Vos, 2005: 292-293). This kind of interview schedule is applied in this study.

During the literature review for case study research in this project, it became obvious that most of the plans on the conduction of interviews are based on the recommendations of Mason, Hancock and Algozinne (Mason, 2002; Hancock and Algozzine, 2006). For this reason, this research project is also based on the procedure recommended by these authors as follows:

- List the research questions what the research project will explore;
- Classify the research questions into researchable sub-questions;
- Develop possible topics for each sub-question;
- Ensure that nothing is overlooked by cross-referencing of the topics;
- Develop the interview structure;
- Determine the minimum information to be gathered from each participant;
- Confirm the appropriateness and adequacy of the interview schedule with the supervisors; and
- Conduct the interviews (Hancock and Algozzine, 2006: 42-43).

In cases where it is difficult to interview the entire target population, it is necessary to select a representative sample to gather statistical generalisation. In statistical generalisation, an inference is made about a population on the basis of collected empirical data about a sample from that population. This process allows determining the confidence with which generalisations can be made, dependent mostly upon the size and internal variation within the population and the sample. This is the most common way of generalising in quantitative research. The question about generalisation of qualitative research, especially case study findings, is extensively discussed since the 1980s (Brymann, 1988: 88). For a few authors who see qualitative research as purely descriptive, generalisability is not an issue. Referring to the intrinsic case study, there seems to be no attempt made to generalise beyond the single case or even to build theories (Stake, 1994: 236). Many other researchers resist and point out that qualitative research produce explanations which are generalisable in some way (Flyvberg, 2006; Silverman, 2006; Yin, 2009). Flyvberg (2006: 219-246) and McGloin (2008: 45-54) furthermore point out, that:

- For researchers, the closeness of the case study to real-life situations is important for the development of a nuanced view of reality and the case study is not limited to the initial framework but can be used to test a hypothesis;

- The case study contains no greater bias toward verification of the researcher`s preconceived notions than other methods of inquiry. On the contrary, experience indicates that the case study contains a greater bias toward falsification of preconceived notions than toward verification; and
- Case studies are often reported by a complex narrative; however a hard-to-summarise narrative is not a problem. Rather, it is often a sign that the study has uncovered a particularly rich problem.

Sampling is in qualitative research less structured and less strictly applied than in quantitative research (Sarantakos, 2000: 154; De Vaus, 2002: 240; Vos, 2005: 327). The overall purpose of sampling in qualitative research is to collect the richest data (Rubin, 2001: 403). Several sampling methods are available in scientific research; the recent ones are (Safman and Sobal, 2004: 9-21; Onwuegbuzie and Collins, 2007: 281-316):

- Random sampling, sometimes called probability sampling: This is a sample method where all the individuals in the population have an equal chance of being selected (Semon, 2004: 7);
- Non-probability sampling: In qualitative studies, non-probability sampling methods are mostly used and, in particular, theoretical or purposive sampling techniques are used rather than random sampling (Vos, 2005: 328). Non-probability sampling is used in research, where the specific processes being studied are most likely to occur which is based on the judgment of the researcher, who selects the participants;
- Purposive sampling: This kind of sampling is described as a random selection of sampling units within the segment of the population with the most information on the characteristic of interest (Guarte and Barrios, 2006: 277-284). It is therefore of big importance that clear identification and formulation of criteria for the selection of participants is done. The purposeful selection of participants represents a key decision point in a qualitative study. Researchers designing qualitative studies need clear criteria in mind and need to provide rationales for their decisions (Silverman, 2006: 104);
- Theoretical sampling: If voids are noticed during the process of refining various categories of the research, theoretical sampling can be used, in which only specific matters are studied in order to obtain more precise information

that would cast further light on the developing theory, thus making it definitive and useful (Vos, 2005: 329);

- Deviant case sampling: The goal of deviant case sampling is to locate a collection of special, unusual, different or peculiar cases that are not representative of the whole (Neumann, 2000: 200), but to learn more about this kind of exotic, unusual phenomenon by studying cases that fall outside the general pattern (Hignett and Wilson, 2004: 473-493);
- Sequential sampling: The principle of sequential sampling is to gather cases and data until the amount of new information or the diversity of cases is completed, hence to gather saturation (Neumann, 2000: 200; Vos, 2005: 330); and
- Snowball sampling: In snowball sampling qualitative research receives less attention, since it is directed at the identification of hard-to-reach individuals. Therefore this type of sampling commences with one respondent, because these are usually situations where very little knowledge and only a few respondents are available (Sarantakos, 2000: 153). In snowball sampling the researcher collects data on a few members of the target population that he/she is able to locate, then seeks information from those individuals that enables him/her to locate other members of that population if they are available, hence the term snowball sampling (Babbie, 2004: 180).

4.5.6. Data analysis techniques

The type of case study determines the data analysis technique recommended by case study researchers (Baxter and Jack, 2008: 554). Throughout the data evaluation and analysis process, it is important to remain open to new opportunities and insights. Collected data can be categorised, tabulated, and recombined to address the initial aims of the study, and conduct cross-checks of facts and discrepancies in accounts (Soy, 1997: 4). Furthermore, both kinds of data, quantitative and qualitative data, can be used to strengthen the research outcome in a case study approach (Yin, 2009: 132-133). Both of them need to be analysed, hence both quantitative and qualitative data need special skills to analyse the gathered data.

The most common ways in which qualitative researchers can make use of quantitative measures are by multi-method studies in which a qualitative case study is combined with some kind of quantitative transcription, and by using simple tabulations in an otherwise purely qualitative study (applied in this study) (Silverman, 2006: 299). Furthermore, there are two ways in which simple counting techniques have been used as an aid to gain validity in qualitative research as an initial means of obtaining a sense of the variance in the data, and at a later stage, after having identified some phenomenon, confirming its prevalence (Silverman, 2006: 299).

A key strength of the case study methodology is to use multiple data analysis techniques. Some techniques are common for case study analysis and they will be introduced afterwards (Baxter and Jack, 2008: 554; Yin, 2009: 136-160).

- Pattern matching: A pattern matching logic compares an empirically based pattern with a predicted one. If the patterns coincide, the results can help a case study strengthen its internal validity (Yin, 2009: 136). Every proposition derived from an aim can be formulated as an expected pattern, which should be observed in a case study to determine if the proposition is true (Hak and Dul, 2009: 6);
- Analytic Induction: After having identified some phenomenon and generated some hypothesis, analytic induction means to go on to take a small body of data (a case) and examine it to see whether the hypothesis relates to it or not (Silverman, 2006: 295). If the hypothesis does not relate to the gathered data, the hypothesis needs to be reformulated (or the phenomenon redefined to exclude the case). The steps of examination of cases, redefinition of the phenomenon and reformulation of hypotheses need to be repeated until a universal relationship can be shown. Analytic induction is the equivalent to the statistical testing of quantitative associations to see if it is greater than might be expected at random (random error), however in qualitative research there is no random error variance (Silverman, 2006: 295). All exceptions are eliminated by revising hypotheses until the data fits. The result of this procedure is that statistical tests are actually unnecessary once the negative cases are removed;

- Explanation building: The goal of explanation building is to analyse the case by building an explanation about the case itself (Yin, 2009: 141). The explanation of the case has to answer the how and why questions asked in any precise manner, before the case study was executed;
- Time-series Analysis: The logic of the time-series analysis is the match between the empirical trend and the theoretical proposition traced over time (Yin, 2009: 144-149);
- Logic models: The logic model consciously stipulates a complex chain of cause-effect-cause-effect patterns over a period of time. This technique intends to match empirically observed patterns to theoretically predicted propositions (Yin, 2009: 149);
- Cross-case synthesis: This technique applies to multiple cases, because it treats each case as a separate study. One possibility is, according to Yin (2009: 159-160), the creation of word tables that display the data from the individual case according to some uniform framework. An overall pattern in the word tables can lead to cross-case conclusions;
- The constant comparative method: The constant comparative method means that the qualitative researcher should always attempt to find another case against which to test the provisional hypothesis (Silverman, 2006: 296-297). Additionally, the method involves simply inspecting and comparing all the data fragments that arise even in a single case (Glaser, 1998). However, there is a scientific discussion on how much data fragments are necessary, as there is a limit to how much data a single researcher or a research team can transcribe and analyse. A large database has advantages as it can, e.g. be kept as a resource that is used only when the analysis has progressed so far that the phenomena under the study have been specified (Peräkylä, 2004: 288);
- Deviant- case analysis: The comparative method implies actively seeking out and addressing deviant cases (Silverman, 2006: 297). This method begins with a small number of gathered data and is processed as follows: A provisional analytic scheme is generated and compared to other data to make modifications in the scheme as necessary; and
- Comprehensive data treatment: In comprehensive data treatment, research findings are based on a subjectively selected, and probably biased, sample of cases that happen to fit in the analytic argument (Ten Have, 1998: ch. 7, p. 8).

> This comprehensiveness arises because, in qualitative research, all cases of data are incorporated in the analysis (Silverman, 2006: 298). The outcome of this treatment is a generalisation of the gathered data, which is as valid as statistical correlation. The result is an integrated, precise model that describes a specific phenomenon, instead of a simple correlation statement about antecedent and consequent conditions of explanatory case study research. Such comprehensive data treatment can be aided by the use of appropriate tabulations, where the categories are derived from theoretically defined concepts (Silverman, 2006: 299).

This case study method is a multi-method study, thus gathering quantitative and qualitative data. However, it is not the intention to gather statistical generalisation, even statistics were used to display the quantitative outcome of the empirical study. All applied statistics and its results, especially for the performance measures productivity and growth of productivity, were done to display indications for further quantitative research implications. The intention of this project was to display and discuss in depth several topics within industrial sales planning and forecasting, it was not to statistically prove its findings.

On the other side, pattern matching and cross-case synthesis were applied for qualitative data, supported by three logical models about the customer-supplier interaction in the investigated industry sectors. It is important to know that these methods already need to be applied during data collection to ensure the good construction of the project to meet the construct internal validity, external validity and reliability (Hancock and Algozzine, 2006: 66-67).

4.5.7. Collection of field data

It was already discussed that multiple sources increase case study evidence. Literature therefore introduces three principles to establish the construct validity and reliability of the case study evidence (Baxter and Jack, 2008: 553-554; Yin, 2009: 114). The principles are 1) use multiple sources of evidence, 2) create a case study database, and 3) maintain a chain of evidence (Yin, 2009: 114-124). All three principles are taken into account in this research project by a) the use of external and internal information, b) save all gathered data in a Microsoft Excel data base, and c) establish a case study research process as introduced later on.

There are some tests to judge the quality of the collected data by the case study research design in terms of external validity, construct validity, reliability and internal validity; most of them have to be executed during the process of data collection.

External validity can be tested by the number of case studies executed during the research project. Construct validity can be tested by the number of sources of evidence, the chain of evidence and continuously reviewing the case study report during the data collection phase. Reliability can be tested by the case study protocol and database during the data collection phase. Internal validity can be tested by pattern matching, logic models etc. during the data analysis phase.

Table 3: Case study tactics for case study quality

Tests	**Case Study Tactic**	**Phase of research in which the tactic occurs**
External validity	replication in multiple-case studies	research design
Construct validity	multiple sources of evidence	data collection
	chain of evidence	data collection
	review continuously the case study reports	composition
Reliability	case study protocol	data collection
	case study database	data collection
Internal validity	do pattern machting	data analysis
	explanation building	data analysis
	rival explanations	data analysis
	logic models	data analysis

Adapted from Yin (2009: 41) and Soy (1997: 2-5)

Two criteria for data collection need to be taken into account: The first criteria is sufficiency and the second is saturation of information (Vos, 2005: 294). Sufficiency answers the following question: Are there sufficient numbers to reflect the range of participants and sites that make up the population so that others outside the sample might have a chance to connect to the experience of those in it? The second criterion is saturation. Saturation is the point in the study where the researcher experiences the same information repeatedly being reported and he/she no longer learns anything new (Morse, 1991: 58; Seidman, 1998: 47-48) and where instances were found that do not fit into the expectations of the study, the researcher needs to conduct additional interviews (De Vaus, 2002: 240).

Based on the approach to gather multiple sources of evidence, the data in this research project will be collected externally and internally. External sources for this research project were such as:

- Databases that provide objective information about the investigated companies like VDMA Annual Reports, Hoppenstedt and Firmendatenbank (VDMA, 2010; Hoppenstedt, 2011b; WLW, 2011); and
- Information about the investigated companies provided by the public relations or management department of these companies on homepages, information sheets and company brochures (information not provided by the sales departments).

Internal sources for this research project were:

- Internal company data, gathered by in-depth interviews of the Sales Executive Officer and other related people (company specific).

The gathered internal data from this empirical study can be divided into two parts according to a semi-structured interview schedule. One part is the interview with fixed responses which means that questions are asked with one or multiple answers for participants to choose from (to clearly distinguish the answers). The advantage is that the answers can be simplified, compared and combined between each other. On the other hand, the meaning or richness of experiences may be limited by such response options (Patton, 2002). The main reason for executing one part of the interview schedule as a fixed responses interview is the following: One of the objectives is to identify the MRT in the investigated industry sectors. However, the pilot study did not give a clear and concise picture about the times in the sales process. For this reason, it was decided to indicate and limit multiple answers in questions of market performance, knowledge of the market, sales forecast accuracy and MRT.

The other part of the interview schedule is the interview with open-ended responses, which means that all participants are asked basic questions in the same order and all questions require open-ended responses by the participants. This kind of interview is ideal for obtaining comprehensive and comparable data, because all respondents were asked the same questions, responses were coded and tabulated to examine the data for relationships and to ensure the quality of the gathered data (Field, 1994: 67; Elliott and Jordan, 2010; Walls, Parahoo and Fleming, 2010). These questions were divided in the categories of planning and forecasting to elicit deep knowledge from the participant.

Consequently, two different ways of representation of the data were necessary. It is on the one hand the pure ratio of the chosen answers, given by the interview participant, and on the other hand the coded description of the answers to the open-ended questions. The sample size therefore is determined by this process to verify sufficiency and saturation (Vos, 2005: 294). This is exactly the point in the empirical study where the researcher experiences that the same information repeatedly being reported and he no longer learns anything new (Morse, 1991: 58; Seidman, 1998: 47-48).

Multiple cases, as undertaken in this research project, are similar to multiple experiments. For this reason, the mode of generalisation is analytic generalisation. This method is not the statistical generalisation to some defined population that has been sampled, but to a theory of the phenomenon being studied (Maxwell, 2005: 32-40).

The purposeful selection of participants is a key decision in a qualitative study to investigate comparable cases (Guarte and Barrios, 2006: 277-284). Clear identification and formulation of criteria for the selection of respondents are necessary and followed (Silverman, 2006: 104). For these reasons, purposive sampling was chosen as the underlying sampling method for this research project. Criteria for the purposive sampling are as follows:

- Companies acting in the Machinery & Equipment Industry sector (more than 80% of the sales turnover of the company is done in the Machinery & Equipment Industry sector);
- Sales turnover per sales employee of the companies acting in the Machinery & Equipment Industry sector is equal or more than 100 T€;

- Companies acting in the Automotive Supplier Industry sector (more than 80% of the sales turnover of the company is done in the Automotive Supplier Industry sector);
- Sales turnover per sales employee of the companies acting in the Automotive Supplier Industry sector is equal or more than 70 T€; and
- All companies are located in South-West Germany.

4.5.8. Data processing

The purpose of every qualitative study is to transform the mass of collected data into findings. This process is known as data processing (Patton, 2002: 432; Vos, 2005: 333). However, the challenge to gather valuable data in qualitative research is a big one, indicated by the many analytic methods described in literature and already discussed (Page and Meyer, 2000; Cavana et al., 2001; Estabrooks, 2001; Olson, 2001; Yin, 2009: 136-163).

All data collected is conceptually ordered and described in chapter five, afterwards concluded and theorised in chapter six. *Conceptually ordering* is classifying the gathered data into discrete clusters, according to their properties and dimensions structured in the interview schedule including external information. *Describing* is purely presenting the clustered data without conclusions to distinguish those clusters without necessarily relating to each other to form an overarching explanatory scheme (Strauss and Corbin, 1998: 19). *Concluding and theorising* is the act of constructing explanatory scheme from data, thus a conclusion, that systematically integrates various concepts through statements of relationships (Strauss and Corbin, 1998: 25). At a glance, the research findings move beyond conceptual ordering to theory. A theory is well-developed if its concepts are well defined according to their specific characteristics and can be defined as a set of well-developed clusters (e.g. themes, concepts) that are systematically interrelated through statements of relationships to form a model that explains the relevant objectives (Strauss and Corbin, 1998: 18-25).

4.6. THE EMPIRICAL STUDY AT A GLANCE

At a glance, several authors described the underlying research process of this research project in a similar way (Royse, 1995; Tutty, 1996; De Vos, 1998; Denzin and Lincoln, 2000; Babbie, 2004; Laws and McLeod, 2005; Yin, 2009). The chosen form of reasoning is abductive reasoning, commonly used when the purpose of the research is to, through empirical studies, further develop or challenge a theory.

Figure 22: Process of the empirical study

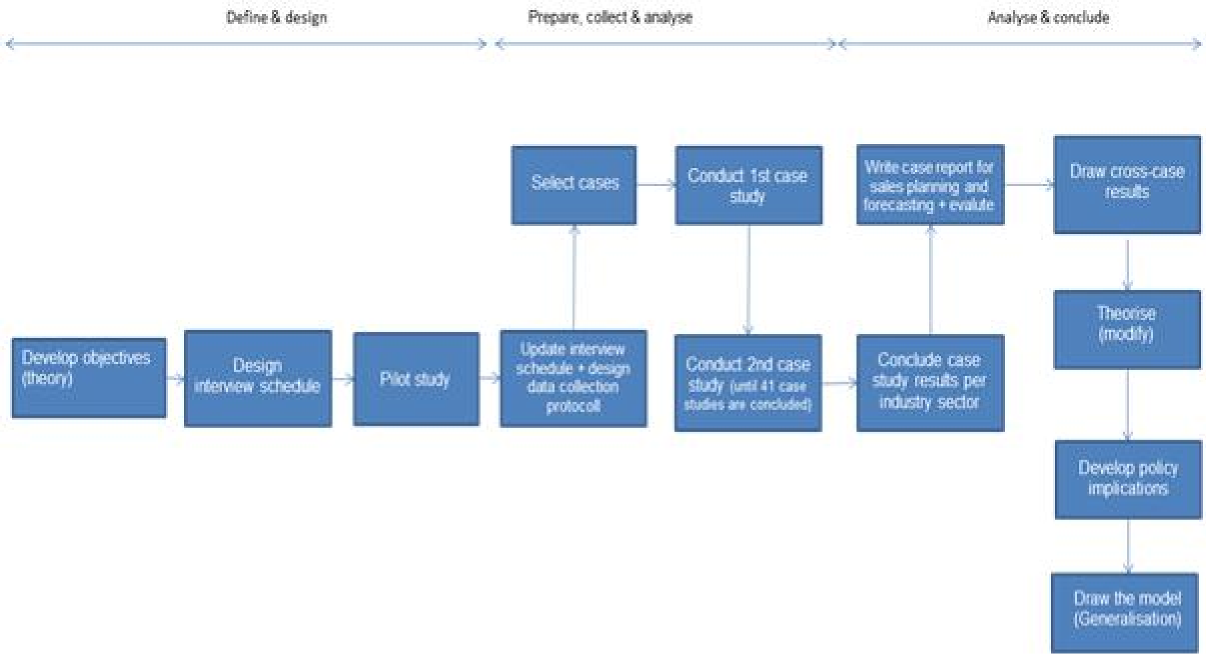


Figure: Adapted from Yin (2009: 57) and Hancock and Algozzine (2006: 7-68), optimised for this project by the researcher

Actually, the process of the empirical study already started with an in-depth literature review about sales planning and forecasting (chapter two) as well as market response research (chapter three) to develop the research objectives. As soon as the research objectives could be determined, an interview schedule was designed to undertake a pilot study. The results of the pilot study leads to updates of the semi-structured interview schedule and the design of the data collection protocol.

Afterwards, the cases (embedded multiple-case design) were selected by purposive sampling and conducted. One part of the case study was to gather internal data, such as the structured interview (with open-ended questions and questions with fixed answers). Based on the results of the case studies, case study results per industry sector were concluded by pattern matching and cross-case results. This resulted in a case report for sales planning and forecasting for each industry sector as well as an overall evaluation of the interview results, displayed in charts and tables (see chapter five).

The overall conclusion as described in chapter six is based on cross-case conclusions, thus on conclusions that take all results of the different industry sectors into account. These conclusions were theorised, the theory modified and implications indicated. As a result, three models were drawn to display the investigated situation as well as the results of the empirical study.

CHAPTER 5: EMPIRICAL RESULTS OF THE RESEARCH PROJECT

This chapter shortly introduces the background information of the empirical study of this research project. Afterwards the empirical results are displayed and explained.

5.1. RESULTS OF THE PILOT STUDY

The pilot study consisted of six semi-structured in-depth interviews; three interview participants in the Machinery & Equipment Industry sector and three interview participants in the Automotive Supplier Industry sector. The interview schedule was based on theoretical knowledge gained by the literature review (see chapter two and three) and each interview lasted about 180 minutes. After the collected data was summarised and intensely discussed with the supervisors of this project, all six participants were again interviewed to determine improvements in the interview and case study design.

It was concluded that not only open ended questions are suitable for this research project, but also questions with predefined answers to select. This conclusion is because especially in the field of time in the customer-supplier interaction, a large number of the interview participants could not clearly determine time frames in the pilot study. Sometimes, the time frames are not known, sometimes even unrealistic. Based on all this input, time frames were predefined for the main study to clearly distinguish different time frames for different steps in the sales process. Furthermore, semi-structured interviews could not be used, because they allowed the participants too much perceptions and imaginations of less related topics and the stringency of the interview schedule was too much affected. Therefore, the interview schedule was structured in the empirical study.

Taking all the findings of the literature review and of the pilot study into consideration, a conceptual framework was conducted (see figure 20, page 102). This framework was discussed with sales researchers during the Global Sales Science Institute Conference on 16th – 18th June 2010 in Poznan, Poland. This idea of discussing the conceptual framework with other researchers during the study is based on the recommendations for doctoral students using case study methodology by Baxter and Jack (2008: 553) and Yin (2009: 85).

5.2. BACKGROUND TO THE EMPIRICAL STUDY

This paragraph discusses some background information to the empirical study of this research project. Such background information includes the response rate, the interview participants, and the process of contacting, executing and evaluating the gathered information.

The response rate for this empirical study is 49.0%. This seems to be quite good, compared to other studies in the German Automotive Industry sector which gathered response rates between 21.0% and 34.0% (Brinkhoff, 2008: 67; Seidler, 2008: 178). The reason for this good response rate can be attributed to the qualitative approach where participants were directly contacted. Overall 102 companies were selected by purposive sampling and contacted, of which 52 disagreed to participate on the study and 50 agreed to participate. Several reasons for non-participation were mentioned, such as a lack of capacity (n = 30), no appropriate sales processes (in terms of fewer people, no structures and SEO and CEO in one person) for this study (n = 15), principally no participation on studies (n = 3) and no given reason (n = 4).

The process of contacting the companies, executing the interviews and evaluating the responses lasted altogether 13 months. All possible participants of the companies were first contacted by phone to explain details of the study. In a second step, written information about the supervisors and universities as well as further research project information were sent by e-mail to the participants.

Personal appointments were made with all 50 participants that agreed to participate to execute the personal interviews. The revised interview schedule (based on the findings of the pilot study) was used to investigate the research objectives. Out of 50 companies, however, only 41 case studies could be used for this research project. The reason for eliminating nine case study results was because of the following two circumstances:

- Some excluded participants (n = 6) acting in the Automotive Supplier Industry could not be clearly assigned to Tier 1 or Tier 2 suppliers, as these companies belong to both OEMs and Tier 1 companies. As the intention of this project was to investigate and find out the possible differences of sales planning and forecasting in the industry sectors, a mixture of industries could not be tolerated. The criterion for a company to be chosen as machinery or automotive case was that a company must generate more than 80% sales turnover in the Machinery or more than 80% sales turnover in the Automotive Industry. This criterion was necessary as it cannot be expected from the companies to generate sales turnover (do business) in one single industry only; and
- Three participants were eliminated because of a lack of information (n = 3) that was required to gather one of the three principles of data collection to establish the construct validity and reliability for case study evidence. For these case study participants, multiple sources of evidence were not available, hence these companies were not described and ranked in more than one external source, such as the German Machine Tool Builders Association (2010) and the Automotive Association (Verband der Automobilindustrie, 2010) and Hoppenstedt (Hoppenstedt, 2011a).

Figure 23: Sample size of the empirical study

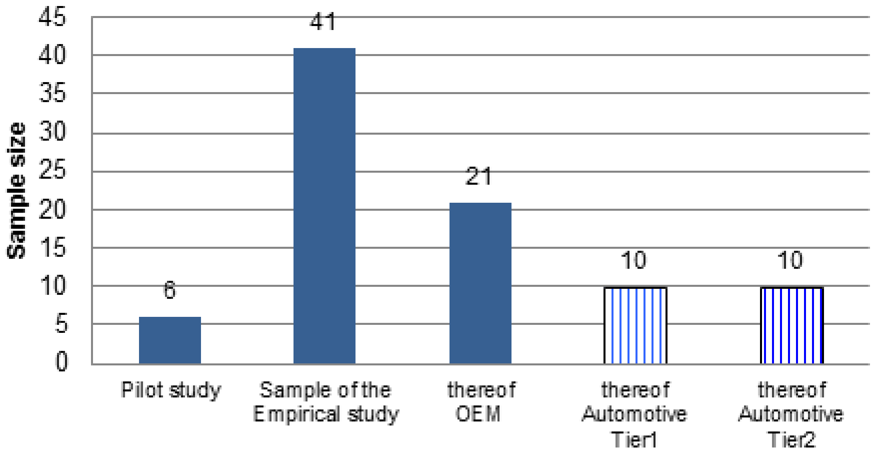


Figure: Developed by the researcher

Summarised, the sample size of 41 usable case studies fulfilled the discussed criteria. The fulfilment of these criteria was indicated on the basis of the open-ended questions about the sales planning and forecasting process discussed in chapter six.

Altogether, 101 persons participated in the empirical study, thus more than one person per case study was interviewed in accordance with the findings of the pilot cases and recommendation of the case study methodology.

Figure 24: Position of interview participants in the company

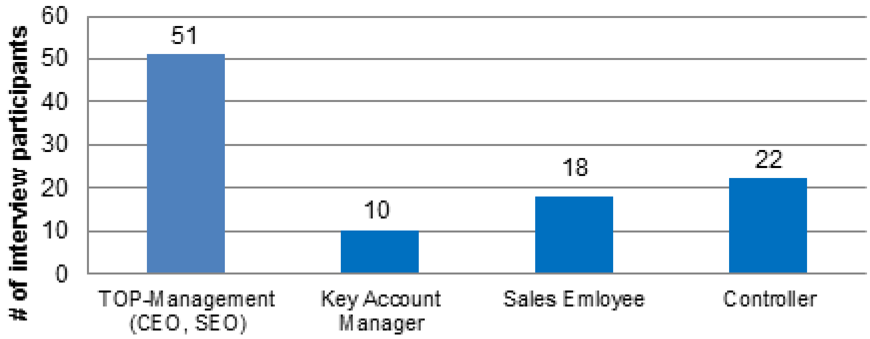


Figure: Developed by the researcher in order of company hierarchy

Fifty one out of 101 participants are appointed in Top-management positions, either as CEO or SEO, ten appointed in key account manager positions, 18 were sales employees and 22 were controllers. At least one interview participant per case is appointed in a Top-management position. These numbers and positions indicate that only knowledgeable people were selected to participate on this study.

5.3. CLASSIFICATION OF THE CASES IN TERMS OF SALES PERFORMANCE

5.3.1. Machinery & Equipment Industry

The sales performance of the Machinery & Equipment Industry cases (n = 21) was measured by actual figures, which are the sales turnover per sales employee in 2010, in 2009 and 2008. Based on these figures, the sales turnover per sales employee in 2010 (productivity) and the sales turnover development per sales employee (sales turnover development 2008 to 2010), thus the growth of productivity, was calculated as discussed in section 2.8 (pages 62-65).

Figure 25: Productivity and growth of productivity of the Machinery & Equipment cases

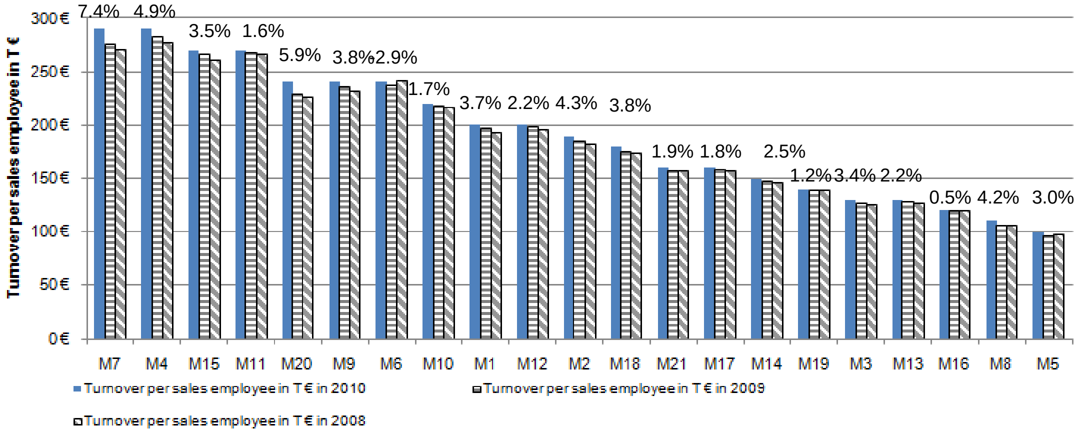


Figure: Developed by the researcher, (Mx = case numbers)

The cases M1 to M21 were arranged by falling sales turnover per sales employee in 2010. It is interesting to see that companies which had a comparably high productivity did not necessarily had a similar high growth rate as indicated by the productivity growth rate in percent at the top of the bars in figure 25 (compare e.g. M1, M2, or M8).

The ranking of the Machinery & Equipment responses in terms of productivity of the sales employees was the highest in company M7 with M4 in a close second place, followed by the company M15 and M11, higher than 250 T€. The highest number of companies were located in the interval between 100 T€ and 150 T€, which are M14, M19, M3, M13, M16, M8 and M5. A relation lower than 100 T€ between sales turnover and sales employee did not occur in this sample. Regarding the productivity growth rates of the cases, M7 was in the first position with the highest growth rate, namely 7.4%, followed by M20 (5.9%), M4 (4.9%), M2 (4.3%) and M8 (4.2%) with growth rates more than four percent. A large number of companies were located between the growth rates of 3.9% and 3.0% (M18, M9, M1, M15, M3, and M5). Growth rates less than 2.9% and more than 0.0% were achieved by the companies M14 (2.5%), M13 and M 12 (both 2.2%), M21 (1.9%), M17 (1.8%), M10 (1.7%), M11 (1.6%), M19 (1.2%) and M16 (0.5%). M6 was the only company with negative growth of -2.9%.

As a result it can be stated that the highest number of companies fall between 100T€ and 150T€. Therefore it can be said that sales people of bigger companies are more productive than their smaller counterparts.

Based on the Machinery & Equipment cases, the classification for both productivity and growth of productivity into high, medium and low performance was done by calculation of the mean, standard deviation and confidence interval of all cases for both measures. All statistical calculations were done by using *IBM SPSS Statistics 20* (for further information please refer to the attachments on the pages 208-211).

5.3.2. Clustered Machinery & Equipment Industry

The mean and standard deviation for the complete Machinery & Equipment sample in terms of productivity was 191.9 T€ and 60.8 T€. A deeper view into the company structures of the investigated Machinery & Equipment cases indicated that several clusters can be formed within the industry sector. Such clusters are defined according to what the companies manufactured. The investigated clusters for this project were Machine Tool Manufacturers (n = 13), Measurement Equipment Manufacturer (n = 1), Automation System Manufacturers (n = 5), and Paint Shop Manufacturers (n = 2).

Figure 26: Productivity of the clustered Machinery & Equipment cases

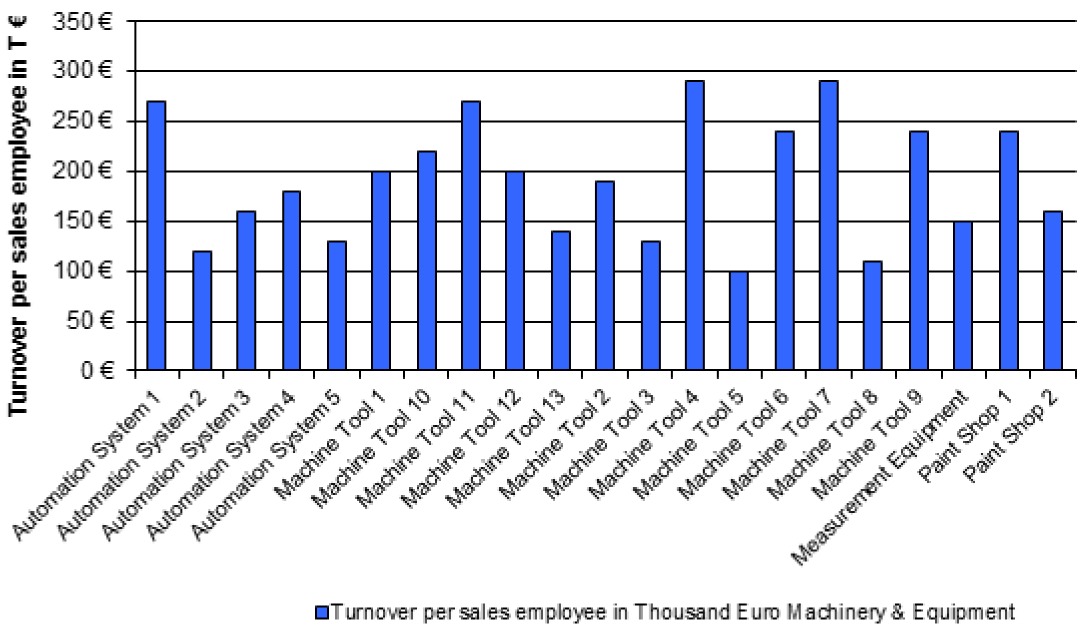


Figure: Developed by the researcher

For the cluster Machine Tool Manufacturer it can be stated that the productivity of the sales employees spans from 100 T€ to nearly 300 T€. Only one Measurement Equipment Manufacturer was investigated, with a productivity rate of 150 T€. The productivity of the Automation System Manufacturer spans from less than 150 T€ to more than 250 T€. The situation is similar for the Paint Shop Manufacturers with about 100 T€ difference between the two companies.

These results indicate that even a classification in several clusters make (for quantitative research) the statistical data in terms of mean, standard deviation or failure of the mean, not better. It would however be interesting to investigate the sales planning and forecasting process within these clusters on a bigger sample.

5.3.3. Automotive Supplier Industry

The sales performance of the Automotive Tier 1 and Tier 2 cases was similarly measured as in the Machinery & Equipment cases. Actual figures, which are the sales turnover per sales employee in 2010 for the Automotive Tier 1 and Tier 2, in 2009 and 2008 were collected. Based on these figures, the sales turnover per sales employee in 2010 (productivity) and the sales turnover development per sales employee (sales turnover development 2008 to 2010), thus the growth rate of productivity rate for every case in percent, was calculated.

Figure 27: Productivity and growth of productivity of the Automotive Tier 1 and Tier 2 supplier cases

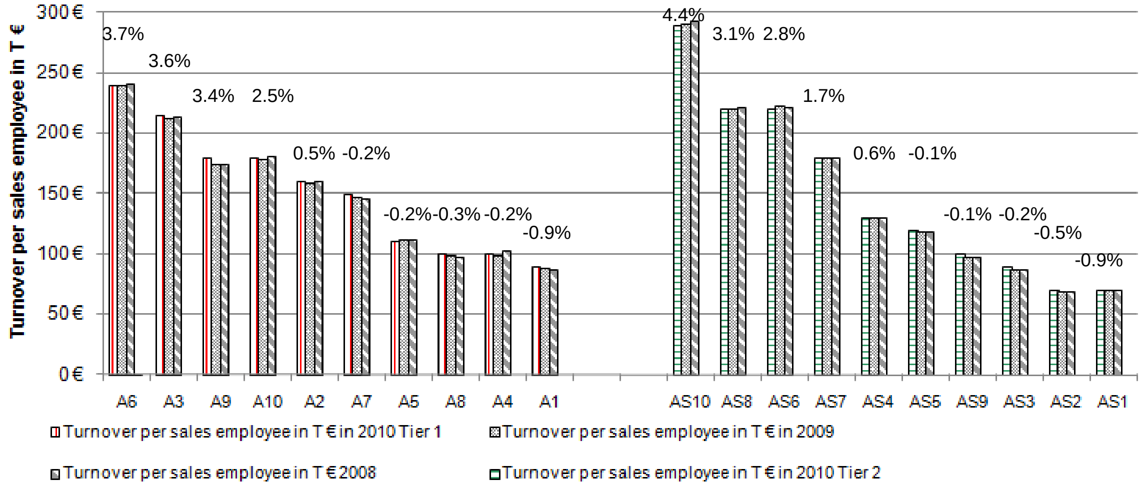


Figure: Developed by the researcher, (Ax = Automotive Tier 1 case numbers, ASx = Automotive Tier 2 case numbers)

In the ranking of the Automotive Tier 1 Supplier Industry sector, called A1 to A10, according to the productivity, the highest position is achieved by company A6 with nearly 250 T€. A3, A9 and A10 are next with considerably lower figures. The lowest productivity are companies A8, A4 and A1 with about 100 T€ sales turnover per sales employee. Regarding the growth rates, company A6 was in the first position with the highest growth rate, namely 3.7%, followed by A3 (3.6%) in a close second position and A9 (3.4%) with growth rates more than three percent. The companies A10 (2.5%) and A2 (0.5%) had still positive growth. All other companies had negative growth rates with less than zero percent (A7, A5, A8, A4 and A1).

In the ranking of the Automotive Tier 2 Supplier Industry sector, company AS10 with nearly 300 T€ was in the highest position, followed by AS8 and AS6 with more than 50 T€ less. The companies AS3, AS2 and AS1 had the lowest relation between sales turnover and sales employee with less than 100 T€ but more than 50 T€. Regarding the growth of the Automotive Tier 2 supplies, company AS10 had the best growth rate with 4.4%, followed by AS8 (3.1%), AS6 (2.8%), AS7 (1.7%) and AS4 (0.6%). The other cases had negative growth; in last was AS1 with -0.9%.

As a result it can be stated that there is a wide span of the companies in terms of the measured productivity and growth of productivity for both the Tier 1 and Tier 2 cases. Therefore it can be said that the companies in this industry sector does highly differ from each other and should, if possible, be further classified.

Based on the Automotive Tier 1 cases and Tier 2 cases, the classification for both productivity and productivity growth, into high, medium and low performance was done by calculation of the mean, standard deviation and confidence interval of all cases for both dimension measures. All statistical calculations were done using *IBM SPSS Statistics 20* (for further information please refer to the attachments on the pages 208-211).

5.3.4. Clustered Automotive Supplier Industry

The mean for the whole Tier 1 supplier cases regarding productivity was 152.5 T€ with a standard deviation of 52.0 T€ and the mean for the Tier 2 cases for the similar measure was 149.0 T€ with a standard deviation of 74.9 T€.

A deeper view into the company structures of the investigated cases indicated that several clusters can be formed according to what they manufactured. The investigated clusters for the Tier 1 were Steering Component Manufacturers (n = 2), Stamping Parts Manufacturers (n = 1) and Motor Component Manufacturers (n = 7). For Tier 2 suppliers the cases consisted of Motor Component Manufacturers (n = 2), Stamping Parts Manufacturers (n = 6), Steering Component Manufacturers (n = 1) and Electronic Component Manufacturer (n = 1).

Figure 28: Productivity of the clustered Automotive Tier 1 and Tier 2 supplier cases

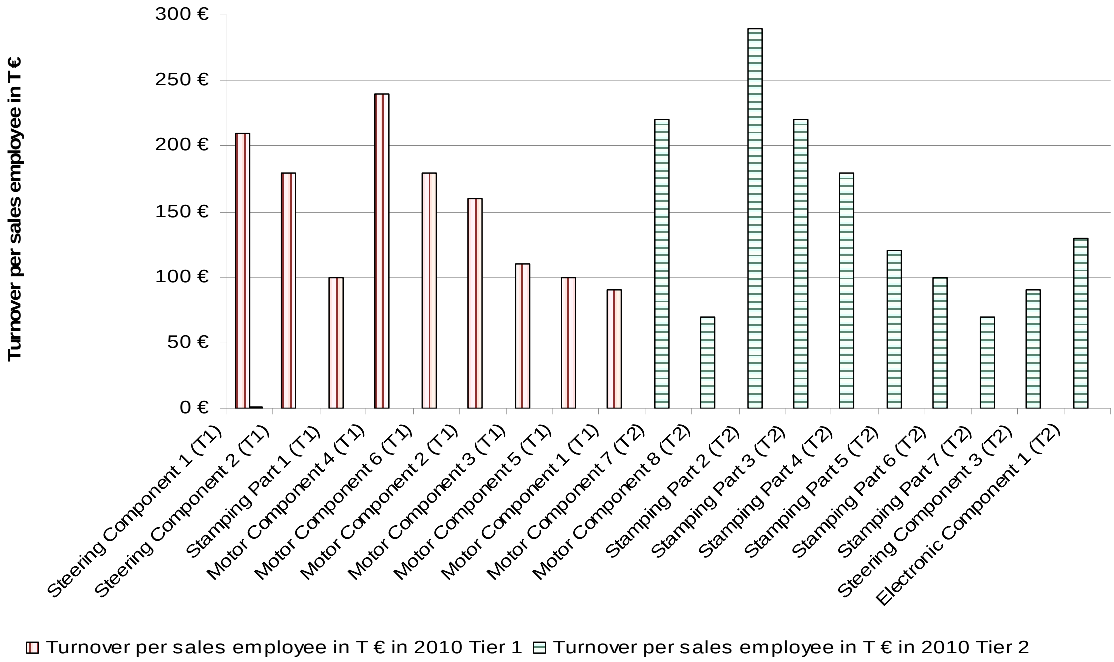


Figure: Developed by the researcher

For the cluster Steering Component Manufacturers it can be stated that the productivity of the sales employees spans from about 180 - 210 T€ as Tier 1 supplier and 90 T€ as Tier 2. The Stamping Part Manufacturers, which are usually Tier 2 suppliers, are ranked from 100 T€ sales turnover per sales employee to 290 T€. For the Motor Component Manufacturers, the situation is similar, its productivity spans from 70 T€ to nearly 250 T€. The only Electronic Component Manufacturer which is included in the project has a productivity of about 140 T€. Even the classification into several clusters did not provide better statistical data than for the whole automotive sector calculated afore.

As a result, it can be stated that the position in the supply chain the company occupies (whether Tier 1 or Tier 2 supplier), seems to be independent from the cluster this company can be assigned to.

5.3.5. Market position of the investigated cases

As the third criterion regarding performance, the current market position of the companies was investigated. The results were based on several rankinglists in official statistics, such as the German Machine Tool Builders Association statistic (2010), Automotive Association statistic (Verband der Automobilindustrie, 2010) and Hoppenstedt statistic (Hoppenstedt, 2011a). Taken all three statistics into consideration, there were interestingly no differences in the rankings (the position the companies occupied in the market) of the investigated cases.

Figure 29: Market position rankings of the investigated cases

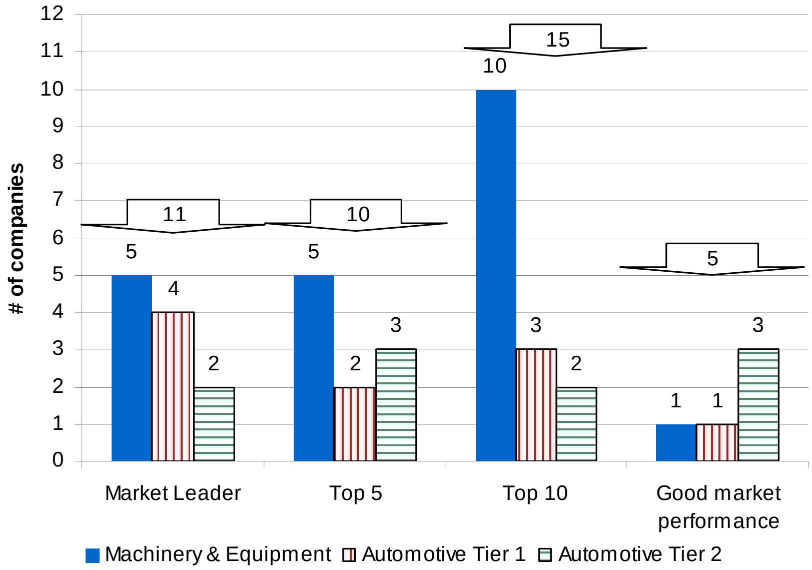


Figure: Developed by the researcher

As a result it can be stated that altogether eleven companies were in the market leader category in their respective field of specialisation, of which five in the

Machinery & Equipment, four in the Automotive Tier 1 and two in the Automotive Tier 2 Supplier Industry. Ten companies were ranked in the top five category, of which five companies of the Machinery & Equipment, two of the Tier 1 and three of the Tier 2 cases. Most of the investigated cases were ranked as Top 10 of the market, of which ten Machinery & Equipment, three Tier 1 and two Tier 2 companies. A small number of the cases (n = 5) were not placed in the rankings and therefore were called companies with good market performance (estimation).

Figure 29 show that most of the investigated companies did achieve either a market leader or a top market position (within the top 10). This indicates that the process of planning and forecasting of the cases should be at least similar (or better) than other companies positioned elsewhere in the market which were not investigated.

5.4. SALES PLANNING AND FORECASTING PROCESS

5.4.1. Information horizon about the market development

As indicated in the introduction (page 5), information about the future market development and the reliability of information is important for planning and forecasting. The empirical study therefore investigated the time frames of how far into the future the companies had information about the development of the markets, called information horizon.

Figure 30: Information horizon of the investigated cases

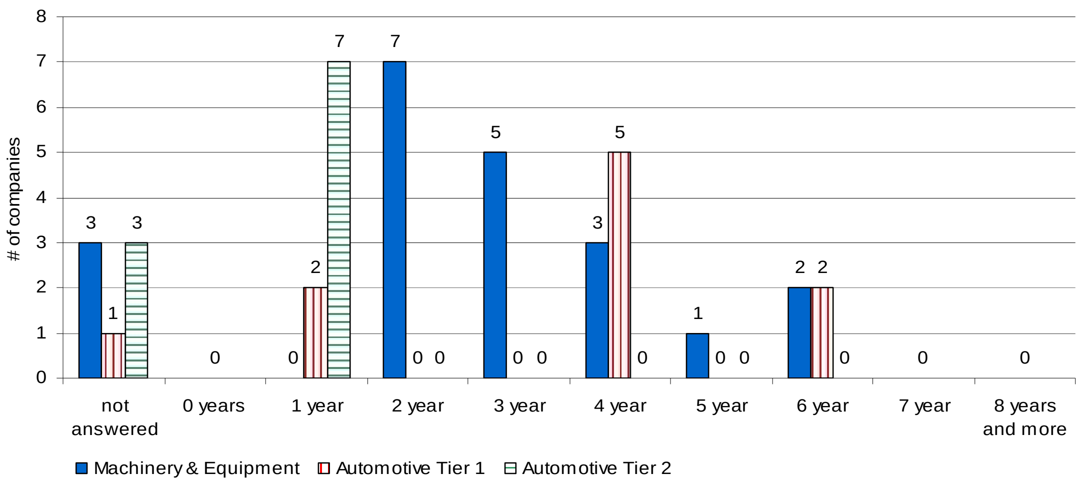


Figure: Developed by the researcher

For the Machinery & Equipment Industry it can be stated that most of the companies (n = 12) had information about future market development for the next two to three years. Most of the Automotive Tier 1 cases (n = 5) had an information horizon of about four years. The whole of Automotive Tier 2 cases (n = 7) that answered this questions in the interview had information about market development for only one year in advance. Three Machinery & Equipment, one Tier 1 supplier and three Tier 2 suppliers did not answer this question.

As a result it can be said that most of the cases (n = 30) had an information horizon of four years and less. This results in the question if further information (for five or six years) is not necessary or cannot be gathered by the investigated cases.

5.4.2. Sales planning horizon

As it is indicated that the long-term view in planning is very important, the question arises how far the investigated company plans go into the future. This is exactly the definition of the sales planning horizon, for which the results are indicated as follows.

Figure 31: Sales planning horizon of the investigated cases

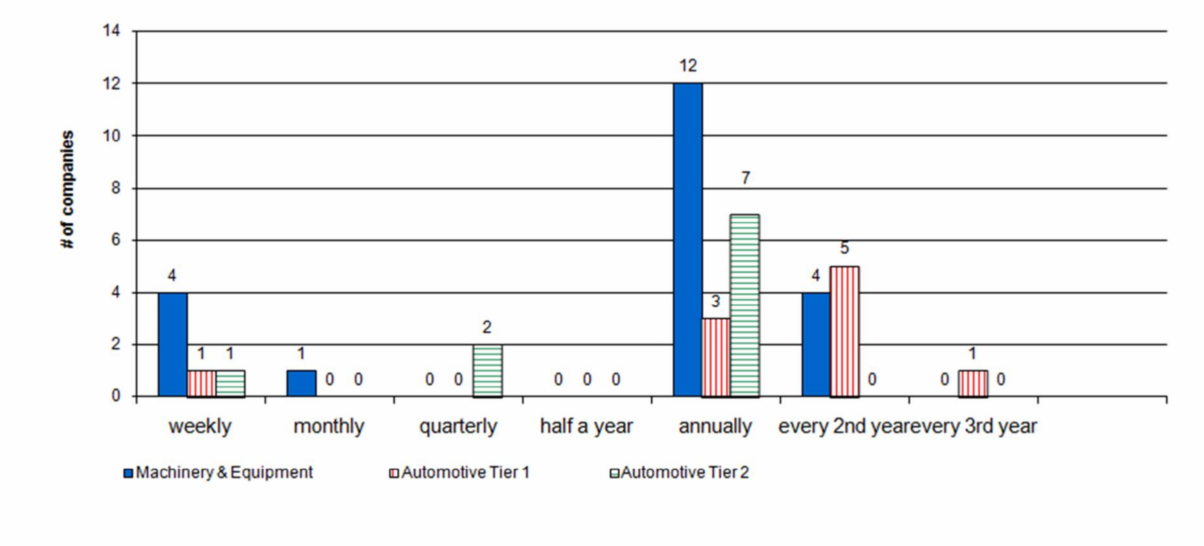


Figure: Developed by the researcher

Four of the machinery companies had an information horizon of about one week and one company had a monthly planning horizon. For a large number of the investigated companies of the Machinery & Equipment Industry sector (n = 12) the sales planning horizon is about one year. Four companies had a planning horizon of two years.

One of the Automotive Tier 1 Supplier companies had a planning horizon of one week. Three Tier 1 suppliers had a sales planning horizon of one year, five suppliers of two years and one Tier 1 supplier of about three years. One of the Automotive Tier 2 suppliers had a planning horizon of one week and two of one quarter. Most of the Automotive Tier 2 suppliers (n = 7) were found to have a sales planning horizon of one year.

As a result it can be said that most of the cases (n = 22) had a sales planning horizon of about one year. This indicates the further question (see figure 37, page 137) if this sales planning horizon is sufficient enough for the (required) forecast accuracy and reliability of the sales plan.

5.4.3. Early indicators for order income

As it is obvious that the early indicator for future sales turnover is *order income*, it seems interesting what kind of early indicators are used in the industry sectors to predict order income itself. The figure hereunder displays the early indicators for order income in the Machinery & Equipment Industry sector.

Figure 32: Early indicators for order income in the Machinery & Equipment cases

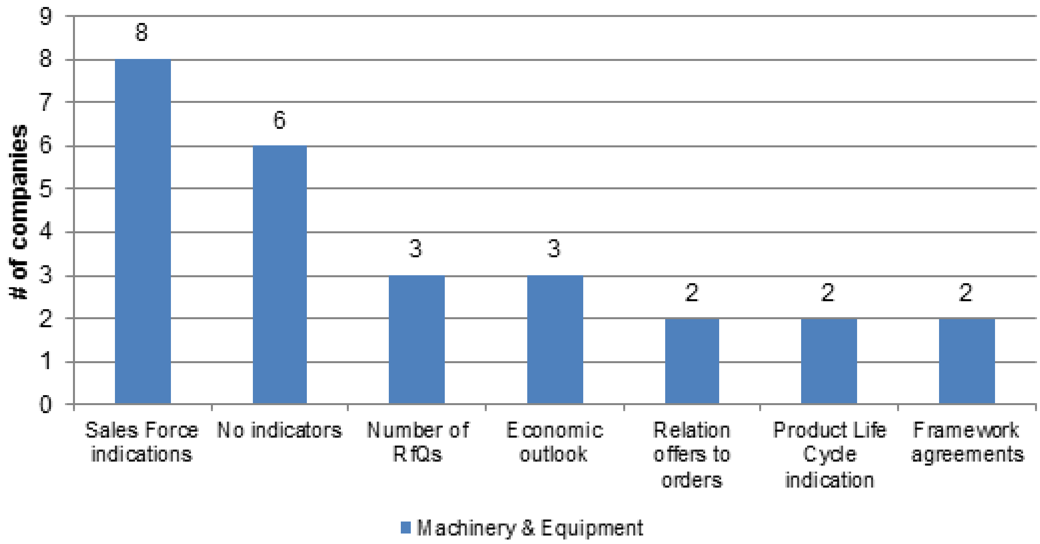


Figure: Developed by the researcher, participants were allowed to list more than one indicator

Eight companies use the indications of their sales force members as early indicators and six companies have no early indicators for their order income. Three participants used both the number of RfQs and the economical development as an indication for future orders as early indicators for their order income. Two participants used the relation from offers to orders, product life cycle indications, and the indication of framework agreements (available if they are in the automotive business).

The situation of early indicators for order income in the Automotive Tier 1 Supplier and Tier 2 Supplier Industry is displayed together in figure 33 (page 133). This is because such early indicators are industry specific (see the study of Goerne (2010: 5 - 11)) and no difference between Tier 1, Tier 2 and even Tier 3 and Tier 4 suppliers could be stated.

Figure 33: Early indicators for order income in the Automotive Tier 1 and Tier 2 supplier cases

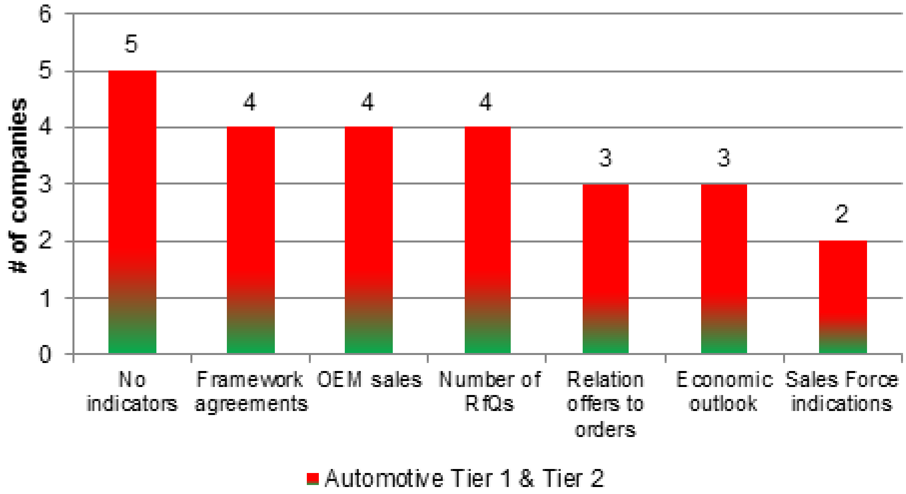


Figure: Developed by the researcher, participants were allowed to list more than one indicator

Twenty five percent of the companies (n = 5) did not have early indicators for order income at all. For four companies the framework agreements, OEM sales, and the number of RfQs are early indicators for order income. Three companies used the relationship between offer and order as well as the economical development as early indicators. Sales force indications as early indicators for order income were applied by two Automotive Supplier companies.

As a result for the Machinery & Equipment Industry it can be stated that there sales force indications (n = 8) are mostly used to predict future order incomes. In the Automotive Supplier Industry mostly no indicators are applied. Therefore it can be stated that the prediction of future development of the business by early indicators is disregarded by a large number of the investigated cases in all investigated industry sectors.

5.4.4. Company reactions to sustainable order income decrease

If the order income situation gets worse and even the early indicators for the order income, as discussed in the previous section, get worse, the question arises how (sales) managers react to this situation (it is expected that this situation is sustainable for a company's success in the upcoming years). Figure 34 (page 134) displays the investigated reactions.

Figure 34: Reaction of (sales) managers to a decline in order income

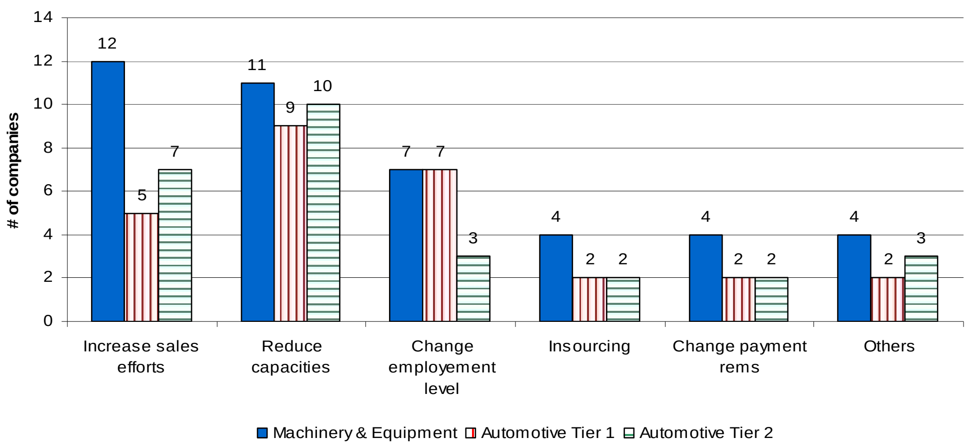


Figure: Developed by the researcher, participants were allowed to give more than one answer

Twelve of 21 investigated Machinery & Equipment cases increase their sales efforts if their order income situation gets sustainably worse. Eleven companies reduce their internal capacities, such as to reduce the number of shifts per week, reduce leased staff, or relocate permanent employees and seven companies reduce their permanent employement level. Four of the Machinery & Equipment managers did insource production processes and did change their payment terms (shorten), four companies did apply other actions, such as increased bank loans or look for co-operation.

In the Automotive Tier 1 Supplier Industry, most of the participants (n = 9) did reduce their internal capacities, followed by the reduction of their permanent employment level (n = 7) in a close second place. Five companies (which are 50% of the cases) did also increase their sales efforts and two companies did insource processes, change their payment terms or apply other activities (increase bank loans, n = 2). In the Tier 2 Supplier Industry ten companies indicated that it would also decrease their internal capacities and seven companies would increase their sales efforts. Two companies would insource processes and change their payment terms. Three Tier 2 suppliers would apply other actions, such as think about moving to another businesses (n = 2) or looking for co-operation (n = 1).

As a result it can be said that a large number of the interviewed managers (n = 24) increase sales efforts if the order income situation gets worse. This indicates that the managers are not aware of time aspects in sales planning and forecasting.

5.4.5. Sales forecasting methods

The following figure displays the forecasting methods of the investigated cases which were used to predict sales.

Figure 35: Sales forecasting methods

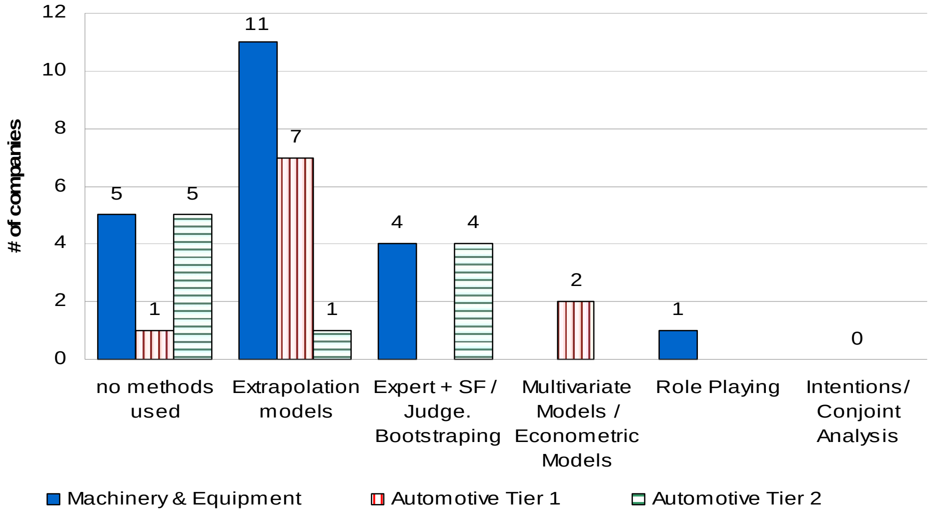


Figure: Developed by the researcher

Nearly 25% of the investigated companies (n = 11) did not forecast sales at all. Five companies are from the Machinery & Equipment manufacturer segment, one from Tier 1 suppliers and five from Tier 2 suppliers. Eleven of 21 Machinery & Equipment companies used extrapolation methods to forecast sales, seven investigated Tier 1 and one of the Tier 2 suppliers used the same method. Future sales was forecasted by experts or sales force opinions at four Machinery & Equipment and four Tier 2 companies. Only two Automotive Tier 1 suppliers did forecast their sales by multivariate or econometric models and one Machinery & Equipment company did use role playing for sales forecasting.

As a conclusion it can be stated that most of the researched cases (n = 19) did use extrapolation methods to forecast sales. Furthermore it can be said that more than 25% of the investigated cases (n = 11) did not forecast sales at all. This indicates that simple forecasting methods are preferred over complex methods and a substantial number of the investigated cases did disregard the importance of sales forecasting.

5.4.6. Sales forecast accuracy measurement method and forecast accuracy

As indicated in section 2.7 (pages 58-62), forecast accuracy can be measured in several ways. The investigated situation is displayed in figure 37.

Figure 36: Forecast accuracy measures

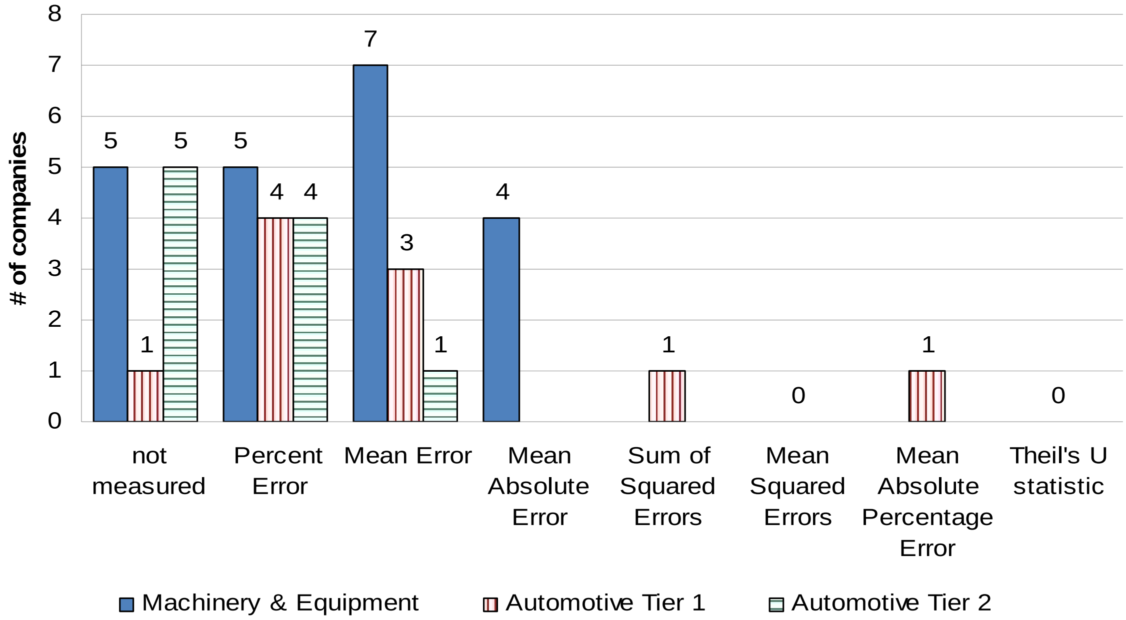


Figure: Developed by the researcher

As eleven of the investigated companies did not measure their forecast accuracy, they also did not have accuracy measurements. Most of the investigated companies (24 out of 41) did either use the percent error (n = 13) or the mean error calculation (n = 11). Of the previous mentioned companies five are from Machinery & Equipment companies, and four companies of both the Tier 1 and Tier 2 suppliers use the percent error calculation. Seven Machinery & Equipment companies, three Tier 1 and one Tier 2 supplier did use mean error calculation methods to determine the forecast accuracy. Other accuracy calculation methods were used only by a small number of the cases, such as the mean absolute error (Machinery & Equipment cases, n = 4), sum of squared errors (Tier 1 supplier, n = 1) and mean absolute percentage error (Tier 1 supplier, n = 1). As a result it can be said that most of the researched cases did either use simple accuracy measures, such as PE, ME or MAE (n = 28) or did not measure forecast accuracy (n = 11).

The success of a sales plan depends on its reliability, thus on its grade of accuracy. The measure of choice is therefore always the forecast accuracy of a sales plan. This empirical study therefore measured the sales forecast accuracy of the research sample on a scale that varies from less than 80% accuracy to more than 95% accuracy on a verifiably basis of empirical controlling data.

Figure 37: Sales forecast accuracy in percent

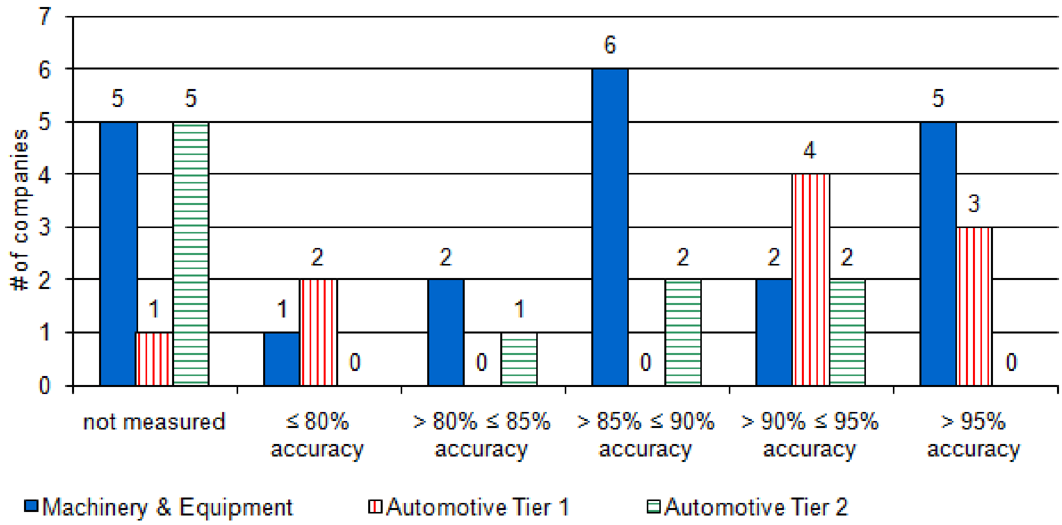


Figure: Developed by the researcher

A large number of the investigated companies (n = 11) did not measure their forecast accuracy, of which five are from the Machinery & Equipment manufacturer segment, one from the Tier 1 supplier and five from Tier 2 supplier segment. Only one of the Machinery & Equipment and two of the Tier 1 sample did achieve a forecast accuracy of less than 80%, and two Machinery & Equipment as well as one Tier 2 supplier did achieve a verifiably forecast accuracy of more than 80% but less than 85%. Six of the Machinery & Equipment and two Tier 2 cases did achieve an accuracy of more than 85% but less than 90%. A forecast accuracy between 90% and 95% was achieved by two Machinery & Equipment, four Automotive Tier 1 and two Tier 2 supplier companies. Five Machinery & Equipment and three Automotive Tier 1 companies achieved a forecast accuracy of more than 95%.

This investigation about accuracy showed that a large number of the researched cases (n = 16) did achieve an accuracy of better than 85% and less than 95% which is indicated to be in a suitable relation between cost and necessity (required accuracy).

5.5. TIME FRAMES IN THE CUSTOMER-SUPPLIER INTERACTION PER INDUSTRY SECTOR

5.5.1. Duration from (first) contact to RfQ income

In this paragraph the investigated time frames in the sales process step "time from the (first) contact between the potential supplier and the customer until the potential supplier received an RfQ by the interested customer" is discussed. The results are displayed per industry sector. This is because of the huge differences of the time frames in the three industry sectors. This situation in the Machinery & Equipment Industry sector is as follows.

Figure 38: Time from (first) contact to RfQ income (Machinery & Equipment Industry)

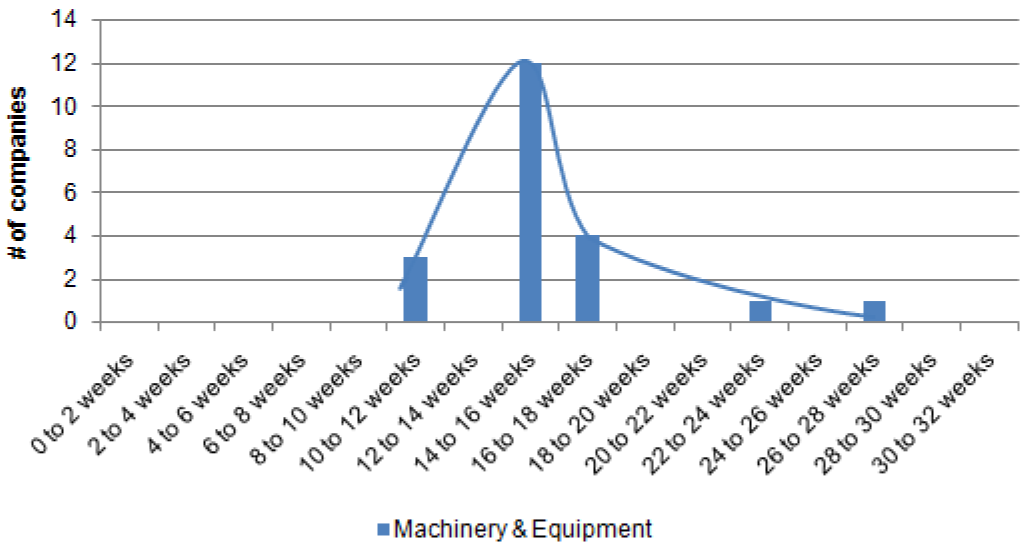


Figure: Developed by the researcher

Most of the investigated machinery cases (n = 12 out of 21) belong to the response time category from first contact to RfQ income by the potential customer of 14 to 16 weeks. For one company, the time frame was measured between 26 to 28 weeks, and for another company between 22 to 24 weeks. Four companies answered that this response time is 16 to 18 weeks long and three companies determined the time frame between ten to twelve weeks.

For the Automotive Tier 1 cases (figure 39), the response time was much longer and wider distributed than for the Machinery & Equipment cases.

Figure 39: Time from (first) contact to RfQ income (Automotive Tier 1 Supplier Industry)

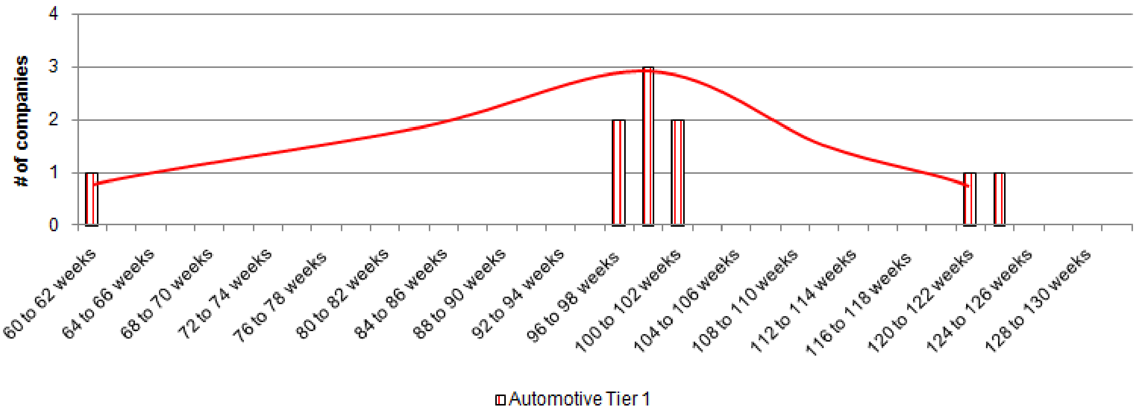


Figure: Developed by the researcher

Most of the Automotive Tier 1 sample (n = 7 out of 10) belong to the response time category (cumulated) of between 96 to 102 weeks (n = 2 for 100 to 102 weeks, n = 3 for 98 to 100 weeks, n = 2 for 96 to 98 weeks). Single companies answered that they experienced this time in the category of between 122 to 124 weeks (n = 1), 120 to 122 weeks (n = 1) and 60 to 62 weeks (n = 1).

In the Automotive Supplier Tier 2 Industry sector (figure 40), the investigated time frame for this process step was more similar to the Machinery & Equipment, rather than to the Automotive Tier 1 Supplier Industry sector.

Figure 40: Time from (first) contact to RfQ income (Automotive Tier 2 Supplier Industry)

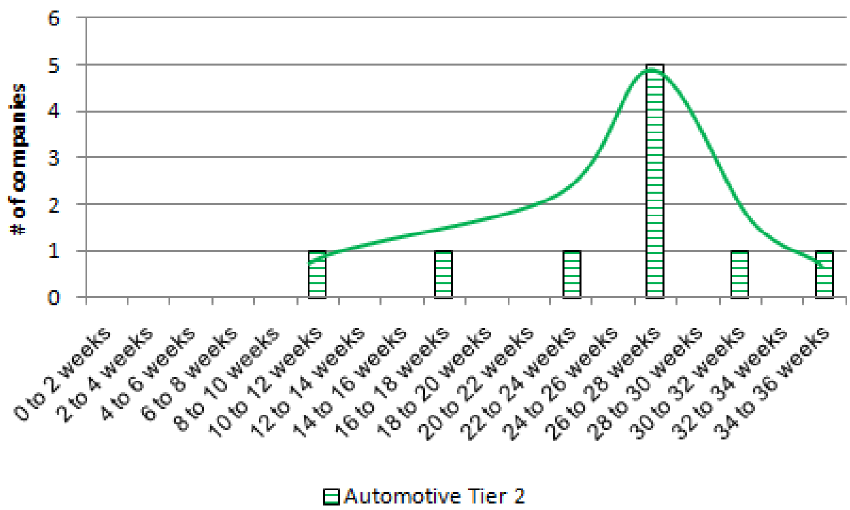


Figure: Developed by the researcher

Five out of ten companies experienced the time from first contact until response of the potential customer by RfQ income between 26 to 28 weeks. Two companies experienced the time frames to the categories of 34 to 36 weeks (n = 1) and 30 to 32 weeks (n = 1). Some companies experience this time shorter, with 22 to 24 weeks (n = 1), 16 to 18 weeks (n = 1) and 10 to 12 weeks (n = 1).

The conclusion about the several time frames discussed above and below is done in section 5.6 on page 143 and following.

5.5.2. Duration from RfQ income to final offer sent out

Figure 41 displays the time from RfQ income at the potential suppliers side until the final offer is sent out to the customer. The time frames in the three industry sectors are similar to each other; therefore one x-axis classification in two-week clusters could be chosen to present the time frames in one figure.

Figure 41: Time from RfQ income to final offer sent out

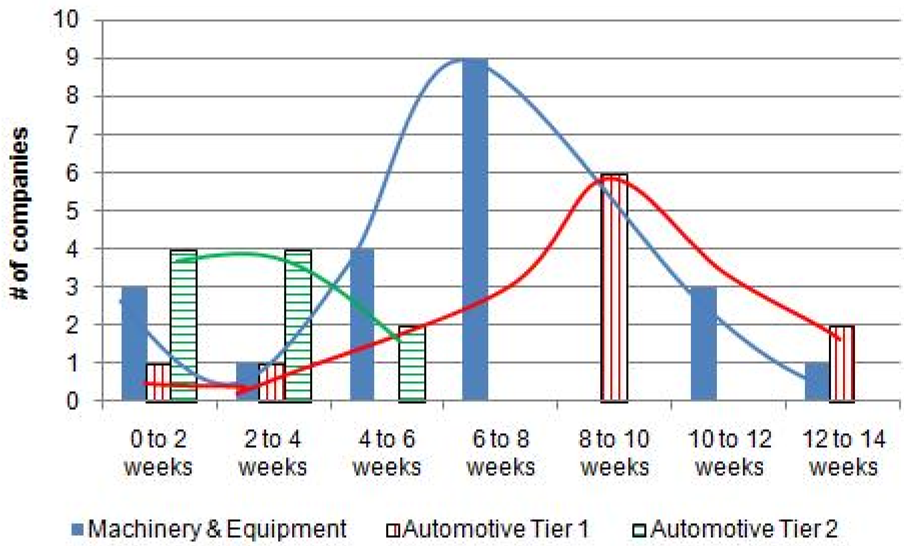


Figure: Developed by the researcher

The time frame from RfQ income to final offer sent out by the potential supplier is in the Machinery & Equipment Industry for a large number of the investigated cases between six to eight weeks (n = 9). One machinery company indicated that the time frame is between twelve to 14 weeks and three companies experienced it as between ten to twelve weeks. Four of the Machinery & Equipment companies did realise time frames of four to six weeks, one of two to four weeks and three cases of zero to two weeks.

The Automotive Tier 1 cases did mostly (n = 6) indicate the time to the category of eight to ten weeks. Two companies experienced the time between twelve to 14 weeks and two companies indicated the time between zero to two and between two to four weeks each. In the Automotive Tier 2 Industry, the time from RfQ income until the final offer is sent out to the potential customer was mostly classified to the category of zero to four weeks (n = 4 for 2 to 4 weeks, n = 4 for 0 to 2 weeks). Two companies did determine the time frame to four to six weeks.

5.5.3. Duration from final offer sent out to order income

The figure 42 hereunder displays the time from final offer sent out to the customer until order income at the supplier's side, also in two-week clusters on the x-axis.

Figure 42: Time from final offer sent out to order income

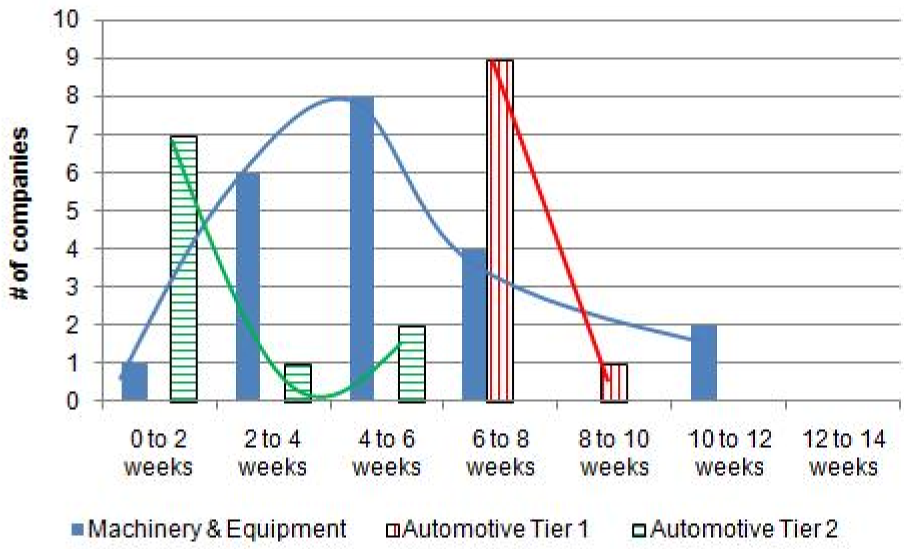


Figure: Developed by the researcher

For a large number of companies in the Machinery & Equipment Industry (n = 8) the time in this category is between four to six weeks. Two Machinery & Equipment companies perceived the time from the final offer until order income in the time frame of ten to twelve weeks and four companies indicated this time as six to eight weeks. Six Machinery & Equipment cases realised the time between two to four weeks and one company between zero to two weeks.

The Automotive Tier 1 suppliers mostly (n = 9) realised this time to be in the category of six to eight weeks. One Tier 1 supplier answered that the time is between eight to ten weeks. As for Tier 2 suppliers this time was shorter with zero to two weeks (n = 7), four to six weeks (n = 2) and two to four weeks (n = 1).

5.5.4. Duration from order income to sales turnover increase

The figure below displays the time from order income until sales turnover increase at the supplier's side.

Figure 43: Time from order income to sales turnover increase

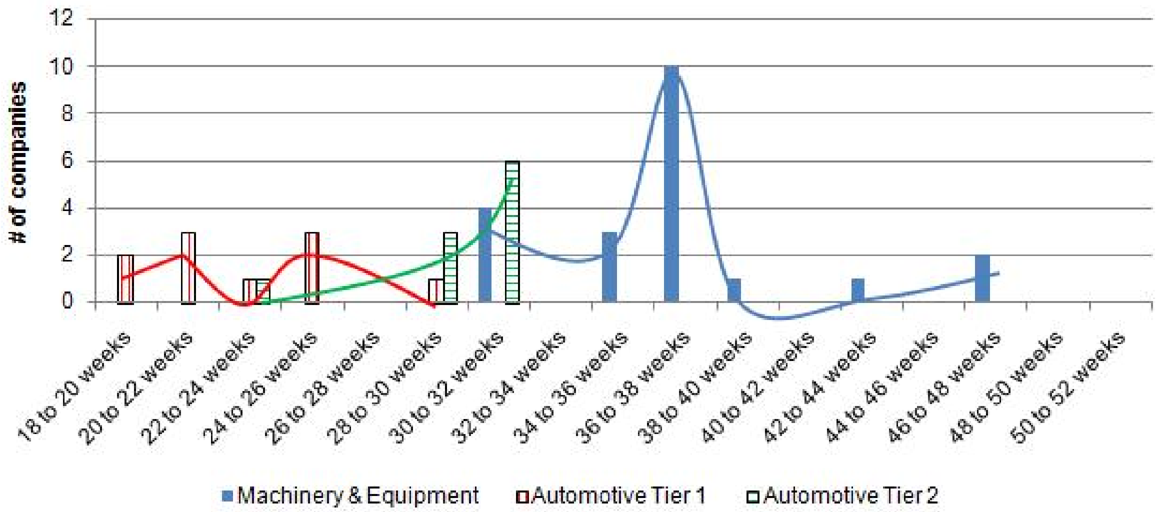


Figure: Developed by the researcher

Fourteen respondents of the Machinery & Equipment cases classified the time from order income until sales turnover increase to the categories of 34 to 40 weeks (n = 3 for 34 to 36 weeks, n = 10 for 36 to 38 weeks, n = 1 for 38 to 40 weeks). Two companies indicated the time to the category of 46 to 48 weeks and one company to the category of 42 to 44 weeks. Four companies realised this time as 30 to 32 weeks.

In the Automotive Tier 1 Supplier Industry, one company experienced the time frame as 28 to 30 weeks, three companies as 24 to 26 weeks and one company realised the investigated time frame to the category of 22 to 24 weeks. Three Tier 1 suppliers did categorise the time to 20 to 22 weeks and two categorised it to 18 to 20 weeks. Six Tier 2 suppliers (60%) did indicate the time between 30 to 32 weeks and three to the category of 28 to 30 weeks. One Tier 2 case answered that the time is between 22 to 24 weeks.

5.6. MARKET RESPONSE TIME AND KNOWLEDGE ABOUT TIME PER INDUSTRY SECTOR

As indicated in the section 5.5 (pages 138-142) the whole duration of the customer-supplier interaction can be detailed in four sales process steps. It is estimated that the whole duration, referred to as MRT, is important for sales planning and forecasting.

Figure 44: MRT in the investigated industry sectors

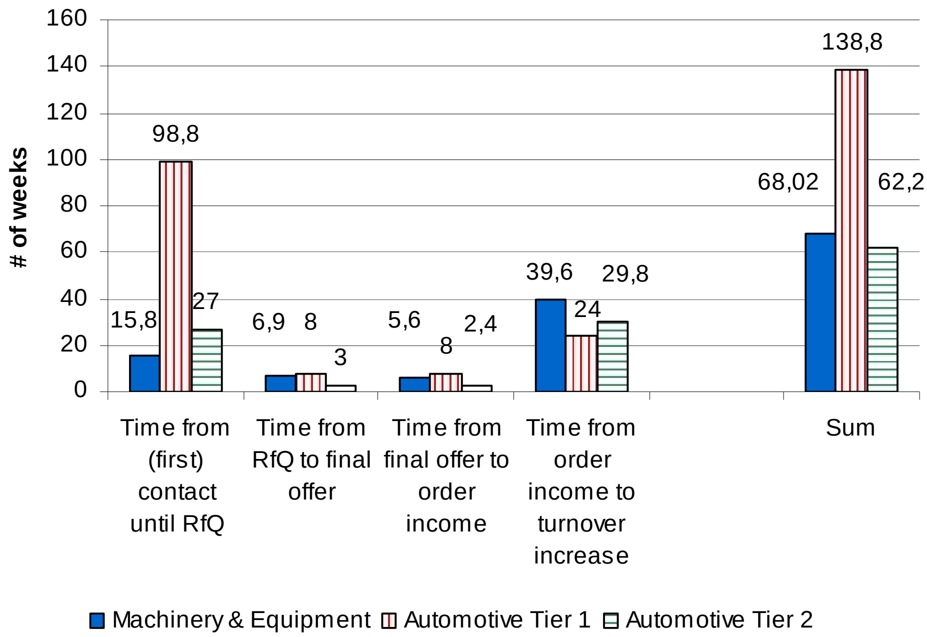


Figure: Developed by the researcher

The MRT for the single sales process steps was calculated as the simple average of each process step and the indicated duration by the participants. This indicates that the first measured process step, called *time from (first) contact until RfQ* income at the potential suppliers side, was for the Machinery & Equipment Industry about 16 weeks, for the Automotive Tier 1 supplier about 99 weeks and for the Tier 2 supplier about 27 weeks. The following process step, called *time from RfQ* income at the potential suppliers' side *to final offer* sent out to the potential customer, was measured in the Machinery & Equipment Industry about seven weeks, in the Automotive Tier 1 Supplier Industry eight weeks and in the Tier 2 Industry about three weeks. The process step, called *time from final offer* sent out to the potential customer *to order income* at the suppliers' side, was measured for the Machinery & Equipment Industry about six weeks, for the Automotive Tier 1 supplier about eight weeks and for the Tier 2 supplier about two weeks. The last process step, called *time from order income* at the supplier's side *until sales turnover increase* at the supplier's side, was measured for the Machinery & Equipment Industry as being about 40 weeks, for the Automotive Tier 1 Supplier Industry about 24 weeks and for the Tier 2 Supplier Industry about 30 weeks. Concluding it can be said that the sum of all sales process steps was defined as MRT, which is in total for the Machinery & Equipment Industry about 68 weeks, for the Automotive Tier 1 supplier about 139 weeks in total and for the Automotive Tier 2 supplier about 62 weeks in total. It is indicated that the longer the MRT is, the more difficult the sales planning and forecasting process is (compare figure 47 on page 150, figure 48 on page 154 and figure 49 on page 159).

Along with the time frames in the empirical study, two more questions regarding time in sales planning and forecasting were asked. This was firstly about general knowledge of MRT, and secondly if the companies already implement factors of time in sales planning and forecasting.

Figure 45: Knowledge of MRT by the investigated participants

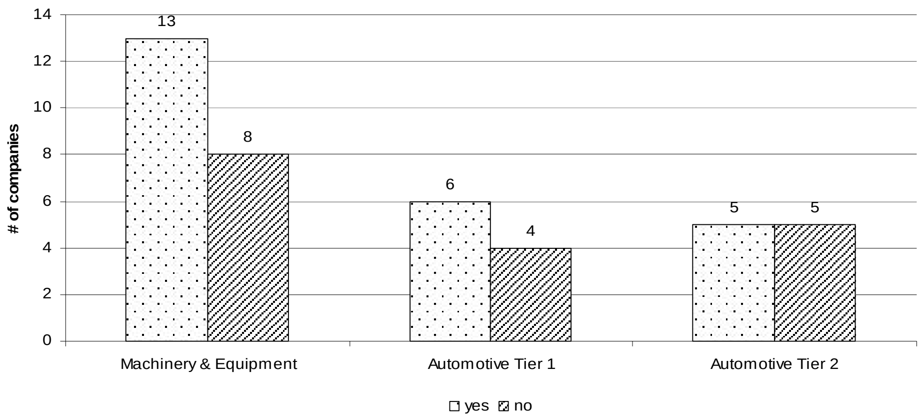


Figure: Developed by the researcher

As indicated in the figure above, 13 companies in the Machinery & Equipment Industry knew about MRT, eight did not. For the Automotive Tier 1 supplier it can be stated that six companies knew about MRT and four did not. Fifty percent of the Tier 2 suppliers knew about MRT before and 50% did not.

The question about implementation of time aspects in sales planning and forecasting, was answered as follows.

Figure 46: Implementation of time aspects in sales by the investigated companies

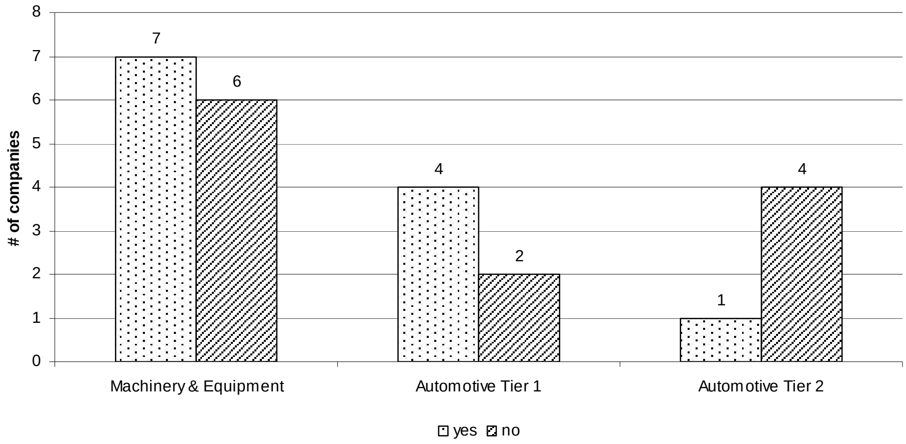


Figure: Developed by the researcher

Seven companies of the Machinery and Equipment Industry already implement time aspects into planning and forecasting and six do not. Four Automotive Tier 1 respondents already implement time aspects into planning and forecasting and two do not. A large number of Tier 2 supplier cases (n = 4) do not implement time factors in sales planning and forecasting; only one of the companies do.

As a result it can be said that more than 50% (n = 24) of the researched cases know about MRT, however only about 25% (n = 12) of the investigated companies implement time aspects into sales planning and forecasting. This indicates that companies are not aware about the effects of time if implemented in sales planning and forecasting.

The following chapter will contain further discussions, conclusions and recommendations for this research study.

CHAPTER 6: DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

This chapter discusses the research findings of chapter five, concludes them and gives recommendations for a better understanding of the sales process to increase sales planning and forecasting performance (measured by the performance measures productivity, growth of productivity and market position). This starts with the discussion of the sales planning and forecasting behaviour for every investigated industry sector (see primary aim of the research project, page 19). For each of the Machinery & Equipment, the Automotive Tier 1 and the Automotive Tier 2 Industry sector, a framework of the sales process (based on the conceptual framework, figure 20, page 102) was developed by the researcher (see figures 47 on page 150, figure 48 on page 154 and figure 49 on page 159). This is in order to show the different time frames of the process steps and the overall MRT to better understand the sales process to be planned and forecasted (see secondary aims of the research project, page 19). It is then recommended for every company in the investigated industry sector to take the developed framework with the MRT into consideration to avoid inefficient planning and forecasting (see research problem, page 15). Afterwards, cross-case conclusions of the industry sectors are summarised into overall discussions, conclusions and recommendations. The chapter concludes with the limitations of the findings as well as ideas for further research implications.

6.1. THE SALES PROCESS IN PLANNING AND FORECASTING AND THE SALES PROCESS MODELS

6.1.1. Machinery & Equipment Industry

In the Machinery & Equipment Industry sector, all orders are served according to their order date, known as an individual transaction. As indicated by the interview participants, one of the important measures for future sales is the early indicator *order income* expressed in months. That is, for this industry sector, more or less the sales turnover for the following year. As long as the order income is constant, the sales turnover for the upcoming year is safe. This time lag of one year (from order income to sales turnover increase) is most relevant for the cash flow in the company and the ability of the company to re-invest in machines and research and development activities. The order income is constant, if the current sales in Euro is equal to the sum of new acquisitions expressed in Euro. Small variations in the number of orders (small decrease or increase of order income) usually do not influence the future sales turnover if the order backlog is sufficient enough. If the order backlog shrinks (decrease in order income), the manufacturer has the following options to adapt the company (see figure 34, page 134):

- Internal:
    - Reduce capacities (reduce shift operations and leased employees);
    - Change permanent employment level;
    - In-sourcing of processes;
    - Shorten payment terms; and
- External:
    - Increase sales efforts.

If the relation between order backlog and order income remains unbalanced (in case the internal adaptations fail and none/ to little order income), the sales turnover of the company will decrease. The reason for this is because the only external option the company has to increase the amount of order income is to increase sales efforts. These activities, however, will only be successful after time, which is referred to as Market Response Time. This illustrates the importance of planning and forecasting sales with a long-term perspective.

This long-term view of forecasting in the Machinery & Equipment Industry depends highly on external factors, such as environmental conditions, industry characteristics and the time aspects (compare the conceptual framework). Environmental conditions and industry characteristics are important to understand as well as to predict future sales. This importance is shown by the question about the information horizon about the future market development (see figure 30, page 130). Machinery & Equipment companies have a long information horizon about the future market development which indicates that they know about the necessity to look out for environmental conditions a long time in advance before planning. The sales planning horizon of the investigated cases furthermore indicates this long-term perspective for this industry sector (see figure 31, page 131). The prediction of the future development of the order income situation based on early indicators, is however disregarded by a large number of the investigated cases (see figure 32, page 132, n = 6). An innovative system to indicate future order income (and in conclusion future sales turnover) could not be detected by the investigations. Instead, a large number (n = 8) of the Machinery & Equipment companies did rely on sales force indications about future order income.

The special interests of this project are the time aspects in sales planning and forecasting which heavily influence the continuing existence of the business. It could be stated that such time aspects are only implemented in sales planning and forecasting by a minority of companies (seven of 21 cases) in the Machinery & Equipment sector (see figure 46, page 145). The majority of investigated companies (n = 12) did react to shrinking order income and backlogs caused by the afore mentioned internal activities and by increased sales efforts (to externally gain new orders). This fact showed that at least half of the investigated cases are not aware of time aspects that influence future sales and their impact on sales performance. The sales turnover will decrease, even if enhancements of sales activities, such as increase sales efforts, internationalisation, or price increase to stabilise profits, are applied. The option to reduce price to sell more will only be successful in the short run, as margins in this industry sector are seriously low which will affect the profitability of the company. The short-term failure of sales efforts is because the generation of sales turnover can only be achieved by either acquiring new customers or new products sold to existing customers which both need time. It is therefore not possible to immediately compensate a loss of sales turnover within the planning period by increased sales efforts.

The investigated sales process in the Machinery & Equipment Industry, defined by the MRT, has a duration that is about 68 weeks in total. This indicates that the sales turnover raise will come at earliest in more than one year, thus in a later period and simply too late for the current planning period.

The mixed sales approach (see attachments *planning approach*, page 206), that is applied by a large number of cases (n = 13) to establish sales plans, is undertaken as follows: In some cases (n = 10), the sales force was highly involved by giving an indication about the evolution of each customer for each quarter or each year and their contribution cost as well as expenses (cost to establish offers). All indications are summarised in a mini business plan per product or product group or account or key account by applying the bottom-up approach. After completion of the mini business plan, it is adapted from a bottom-up approach to a top-down approach. As indicated by the cross-case conclusions (see table 5, page 165), most of the high and medium performance cases used this kind of planning approach. A small number of the participants (n = 4) established operational plans for three years and "zero+12" plans for the next year on a rolling basis. This means, that the plans are continuously updated, mostly every quarter. Another small number of participants (n = 3) controlled its sales figures by appropriate action plans at both sales increases or sales decreases. The possibility to control or measure sales by internal measurement systems (as indicated in the definition of sales planning and forecasting in chapter one and two) could not be detected in the investigated companies. Most of these participants (n = 16) review their sales plans and budgets every quarter. This process usually starts in the beginning of the financial year for about four months to gather information, summarise information, make indications for the next year, establish the sales plan and distribute it in the company.

Based on this information, the interview results seem obvious, that most of the participants in this industry sector forecast their sales plans according to their order income and sales history situation of the previous few years by extrapolation (see figure 35, page 135). The customer-supplier interaction in the Machinery & Equipment Industry was discussed in section 2.5.2 (pages 38-39). This interaction is now displayed as a model and interfered with the investigated time frames and its influencing factors in the specific process steps in figure 47 on page 150.

The researcher developed the following diagram of the sales process to better plan the several process steps for the Machinery & Equipment sector to enable those companies acting in this industry sector to plan better and more accurately for the future by incorporating the MRT and its influencing factors.

Figure 47: Customer-supplier interaction and the MRT in the Machinery & Equipment Industry

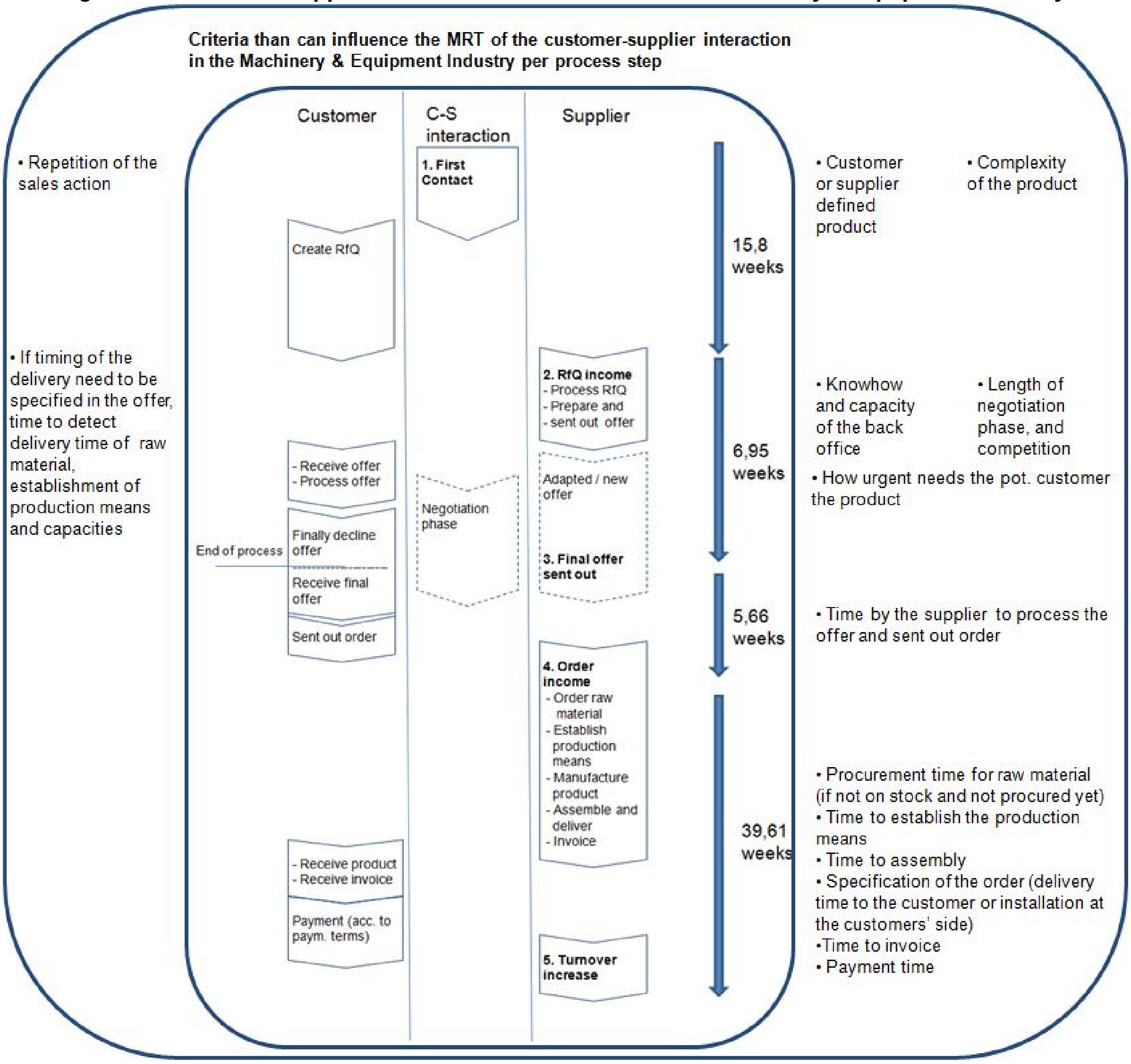


Figure: Developed by the researcher

(1) First contact: The response time from the first contact to RfQ income at the potential suppliers' side is about 16 weeks. This time frame depends on whether it is a customer defined or a supplier defined product and on its complexity the RfQ has to be established. The duration of this process step furthermore depends on the level of repetition of the sales action between the potential customer and supplier: It is either a new investment, a reinvestment or a reinvestment with several changes. If the interaction will be about a new customer defined product, time further depends on the complexity of the product. This indicates that the time to define such a RfQ until RfQ income at the suppliers side depends to a large extend on the potential customer.

(2) RfQ income: As soon as the RfQ is received by the potential supplier, the sales back office prepares an offer according to the customer specifications. The time to establish the final offer (that is afterwards accepted by the customer) is seven weeks as indicated in figure 47. This time frame depends on a large number of factors: In the case of a (new) customer defined product, the time frame depends on the question of available raw material and its delivery times, the establishment of production means and necessary production capacities, logistical knowhow and supplier-internal process times. If it is a supplier defined product, more information about delivery time for raw materials are available (or maybe already in stock), however capacities need to be established. This time of the process can be heavily influenced by the potential customer. In any case, no matter if customer or supplier defined, the time of the negotiation phase cannot be influenced by the supplier; it depends on the economic situation, on the number of competitors and on how fast the potential customer needs the product.
(3) Final offer sent out: As soon as the negotiation (process) is successful, a final offer is sent out by the potential supplier to the potential customer, who then accepts it and sends it back as an order to the supplier. This process step mostly depends on the supplier and lasts about six weeks.
(4) Order income: The time frame from order income until sales turnover increase at the suppliers' side lasts about 40 weeks in total. This time depends on a large number of factors, such as on the procurement time of the raw material (if it is not in stock and not procured yet), the time to establish the production means (tools, machines, devices; if not established yet), the production of the product(s) and assembly, the delivery time (or installation time at the customer's side), the time to invoice the customer and the payment terms according to the order. The time of invoicing furthermore depends on the specifications of the order, if for instance, the installation of the product (machine) at the customer's side is included or not, or if delivery is ex works or other delivery terms are agreed. The duration of the payment process depends on the individually agreed payment terms and therefore cannot be generalised. For the Machinery & Equipment Industry, usually, the payment does consist of a down payment as soon as the order is done and a final payment after delivery.

(5) Sales turnover increase.

The MRT of the investigated Machinery & Equipment cases for the whole sales process is about 68 weeks in total which is more than one year (see figure 44, page 143). This MRT seems to have a longer span into the future than the discussed and currently applied order income measure (as early indicator for future sales which is one year as indicated by the interview participants). Concluding it can be stated that the sales process is affected by a large number of customer and supplier driven factors that need to be taken into account. The length of the process furthermore can be anticipated by the Market Response Time. The MRT is a better indicator for future sales than the measure order income. It is therefore recommended to take notice of the investigated factors that influence the sales process and use the MRT as a pre-indicator for order income (and future sales turnover) and of the length of the sales process itself in order to support better planning and forecasting capabilities/ performance.

6.1.2. Automotive Tier 1 Supplier Industry

The Automotive Tier 1 Supplier Industry sector differs significantly from the Machinery & Equipment Industry sector. The business of the Automotive Tier 1 supplier with the Automotive OEM is characterised by high buying volumes (in terms of product quantity) and the market position of the supplier. There are only about 20 possible customers (Automotive OEMs) in the market worldwide and the environment is therefore characterised by high competition, price pressure, political buying decisions and especially long-term customer-supplier relations (see section 1.1, pages 1-6). If businesses are involved in such long-term interaction, it is a very important aspect for such a business.

The customer-supplier interaction in this industry starts with a formal agreement which predefines future conditions, such as price per product and delivery time, for the duration of this agreement. If an order is placed in the Machinery & Equipment Industry, it will be manufactured according to the capacities of the machinery supplier. If a framework agreement is closed in the Automotive Industry, the products have to be delivered according to the requirements (call) of the customer, which can be done in a broad predefined time frame (usually for the product lifetime of the automobile). This makes the sales process in this industry sector a complex one and to plan and forecast sales requires even longer-term planning compared to the machinery sector.

In the Automotive Supplier Industry sector, only the number of products requested by a call of the customer (based on a framework agreement that was established before) generates sales turnover for the supplier. Each call implies a number of products that can be manufactured in parallel to other (incoming) calls. If a series supplier acquires an additional order, its capacity utilisation will increase. In fact, the sales turnover of a series supplier only decreases if a framework agreement is fulfilled. It is usually fulfilled when the product lifetime of the product (this is in the investigated cases an automobile), which is manufactured by the OEM, ends. The product lifetime for an automobile is usually calculated as five to six years. Mathematically, however, and this is not recognised in a large number of the investigated automotive cases, the sales turnover situation gets worse every year if no new framework agreements can be closed by the supplier. This is because the sales loss can be displayed as the quotient of total sales and average lifetime of the products currently manufactured.

Based on this information, it seems obvious that most of the participants plan future sales according to their current sales turnover and contribution of products, thus based on historical data (n = 6, also see the forecasting methods in figure 35, page 135). Only a small number of the sample included economical factors into sales planning (n = 3). A small number of participants plan their sales by support of mathematical equations such as exponential smoothing (n = 3). The sales planning approach for five companies was a mixed approach, four companies plan their future sales bottom-up and only one company plan sales top-down by management objectives (see attachments *sales planning approach*, page 206). Most of the participants in the TOP performance category plan its most valuable products or product groups with indications by the key account manager for key customers. Furthermore, the complete market is analysed by the supplier according to automobile volumes and import quotas and used to estimate the market volume, hence the suppliers potential product volume. Sometimes a simple deviation in automobile volumes influences sales planning. Some of the participants (n = 4) have a fixed strategy (mostly five year strategy) and therefore sales plans need to be established and adapted to the strategy. A two and one year planning horizon is common and necessary because of the high volume of demand experienced by Automotive OEM (see figure 31, page 131).

The researcher developed the following diagram (figure 48) of the sales process to better plan the several process steps for the Automotive Tier 1 Supplier sector to enable those companies acting in this industry sector to plan better and more accurately for the future by incorporating the MRT and its influencing factors.

Figure 48: Customer-supplier interaction and the MRT in the Automotive Tier 1 Supplier Industry

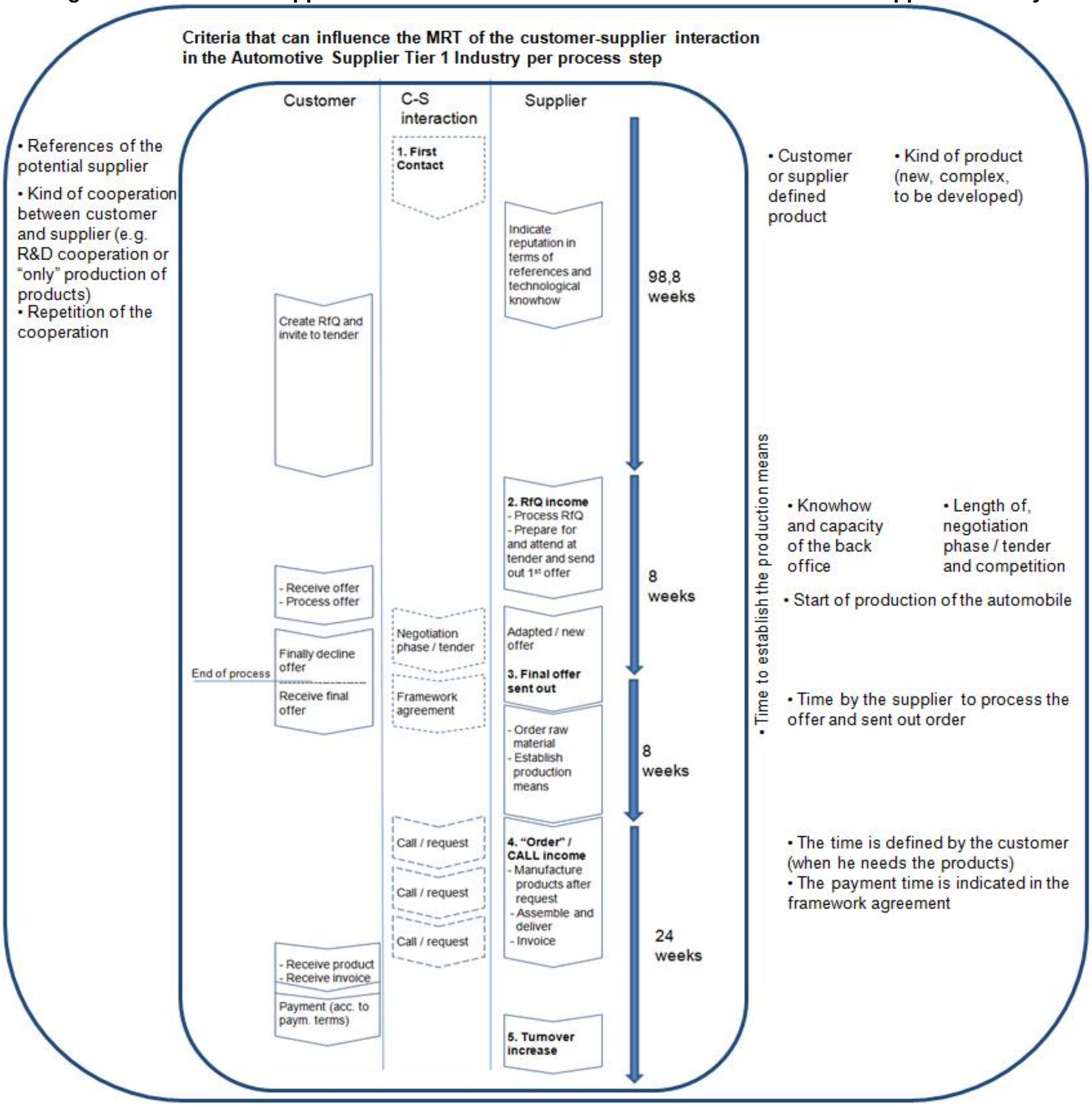


Figure: Developed by the researcher

(1) First contact: The first step in the sales process is the first contact between the potential supplier and the potential customer. In the Automotive Tier 1 Supplier Industry, the response to this first contact is the RfQ and invitation to a tender by the interested customer. However, before the RfQ is sent out to the potential supplier, the supplier had to indicate its reputation as a reliable supplier in the Tier 1 sector in terms of references and available technology (process knowhow). Usually, the potential supplier is chosen by the customer, because the supplier is already supplying products to this customer or the supplier already supplies another OEM. Such an RfQ that is then sent out to the potential supplier is either A) a customer defined product by a specification document, or B) a defined and explained problem to be solved by the potential supplier. The speciality of this process step is that mostly unofficial RfQs are sent out to a number of potential suppliers (up to five suppliers as indicated by the interview participants) to already interact with the potential customer before the “official phase”. Based on this interaction (communication, meetings, concepts) and the suppliers rough concepts, the supplier decides on one to three potential suppliers which then receive an “official” RfQ. The time frame in this process step is affected by the potential customers’ premises and the suppliers’ solutions. It can further be mentioned that the time for completion of this process step diminishes as the product life cycles of the automobiles and therefore the future development phases do also shrink.

(2) RfQ income: The second step in the defined customer-supplier interaction is that as soon as the RfQ or invitation to a tender is received by the potential supplier, the sales back office prepares an official and specific offer for the tender, based on the customer specifications of the problem or product. The development of the product or the concept for the problem solution is nearly finished in this phase and only a few suppliers (depending on the purchase strategy of the OEM) are invited to tender to proceed into detailed negotiations about technical and commercial issues until the potential customer decides on some products/ solutions (customers).

The potential supplier had to update the offer several times during the negotiation process, especially in terms of technical solutions and price (please refer to the introduction “power of the Automotive OEMs” on page 2-

3). In parallel, raw material had to be procured (if it is not in stock), the production means had to be established (tools, machines, devices) and were inspected by an auditor of the OEM. This time is mostly influenced by the potential customer (who schedules and defines the negotiation phases), the number of competitors, the complexity of the product and production process, the buying volume and intended lifetime of the product.

(3) Final offer sent out: As soon as the negotiation phase was successful and the production process was audited by the OEM, a final offer is sent out to the potential customer who accepts it by submitting a framework agreement which is signed by both parties. The framework agreement includes the technical specifications, prices, quantities and even descriptions of the production process, by which the product had to be manufactured. This indicates that the potential supplier already had to invest a large sum of money to establish production means and the production process. As soon as the framework agreement is established, the process need to be secured, raw material purchased, capacities available and ready for the first request by the OEM. This time frame is determined by the customer to process the final offer and establish the framework agreement.

(4) “Order” / Call income: As soon as the first call is done by the OEM customer, the supplier produces the requested number of products and delivers it on the requested time (just-in-time) and place (sometimes even directly to the assembly line) (just-in-sequence). For this reason, the supplier had to store all the capacity, raw material and production means for the indicated number of products as defined in the framework agreement, to be able to deliver after request just-in-time or just-in-sequence. This state lasts as long as indicated in the framework agreement.

(5) Sales turnover increase: The final step in the customer-supplier interaction is the payment (depending on the payment terms established in the framework agreement) of the customer and the sales turnover increase at the supplier’s side. The payment is usually done after every call depending on the requested quantity of the products. In the Automotive Tier 1 Industry sector, the payment for the delivery of the products (for a specific call) is usually done two weeks after the delivery of the requested products.

The time frames of the whole sales process of the Automotive Tier 1 supplier are about 139 weeks (see figure 44, page 143) in total. This is the investigated MRT for the researched Automotive Tier 1 cases.

Concluding it can be stated that the sales process in this industry sector is very long and affected by a large number of customer and supplier driven factors that need to be taken into account. This implies long-term planning of future sales. As it is indicated in section 1.3.1 (page 9) that the success of the plan depends on the precision of prediction of the customer-supplier interaction, the developed diagram supports to anticipate the future sales turnover increase by better planning activities. It is therefore recommended to implement the MRT as well as the investigated factors that influence the sales process in order to support better planning and forecasting capabilities/ performance.

6.1.3. Automotive Tier 2 Supplier Industry

The companies acting as Tier 2 suppliers are able to deliver identical products to different customers, markets and even to different prices in large quantities. The Tier 2 suppliers have a large number of possible customers and can reduce the grade of competition by specialisation of their product portfolio. The process to generate a customer-supplier relationship is less complicated than it is for a Tier 1 supplier. The Tier 2 supplier has a shorter information horizon about the future development of the market (see figure 30, page 130) and a shorter sales planning horizon (see figure 31, page 131) compared to the Tier 1 supplier. This is because the products of the Tier 2 supplier are eventually assembled in a large number of aggregated products unknown to the Tier 2 supplier.

To indicate the future sales turnover, the Tier 2 supplier could calculate the average sales turnover decrease according to the product lifetime of the products delivered to the Tier 1 supplier. If the average product lifetime of the products is, for example, five years, the theoretical sales turnover decrease is 20% p. a. This indicates the necessary new order income volume per year. As it seems very difficult for the Tier 2 supplier to forecast future sales, it seems obvious that most of the cases apply extrapolation methods, especially simple moving averages (see figure 35, page 135).

Most of the cases also internally adapt their capacities if the order income measure decreases (see figure 34, page 134) and forecast accuracy is only measured by 50% of the investigated cases (see figure 37, page 137). Some of the top performance category cases plan their sales annually, based on single (key) customer developments, their key parts (highest contribution cost) and the stage of the key parts in the product life cycle. Most of the cases stated that there is a trend that planning becomes more and more unsafe, framework agreements are only indications (despite of penalties) and not a true indication for sales turnover as was the case five years ago. Tier 2 suppliers (n = 8) experience a large number of difficulties in establishing plans for future sales turnover, therefore they tend to make use of the top-down planning method because top management is more knowledgeable than sales employees (see attachments *sales planning approach*, page 206).

The researcher developed a diagram of the sales process (figure 49, page 159) to better plan the several process steps for the Automotive Tier 2 sector to enable those companies acting in this industry sector to plan better and more accurately for the future.

This customer-supplier interaction for planning and forecasting future sales can be described as follows:

(1) First contact: The time from the first contact between the potential supplier and the potential customer to RfQ income at the potential supplier’s side depends on the potential customer. In the Automotive Tier 2 Supplier Industry, the response time depends mainly on the demand of the Tier 1 supplier, whether it is a customer-defined (most of the time) or a supplier-defined product and the level of repetition of the sales action between the potential customer and supplier. Either it is a new investment, a reinvestment or a reinvestment with several changes. If the interaction will be about a new customer-defined investment, time further depends on the complexity of the product.

Figure 49: Customer-supplier interaction and the MRT in the Automotive Tier 2 Supplier Industry

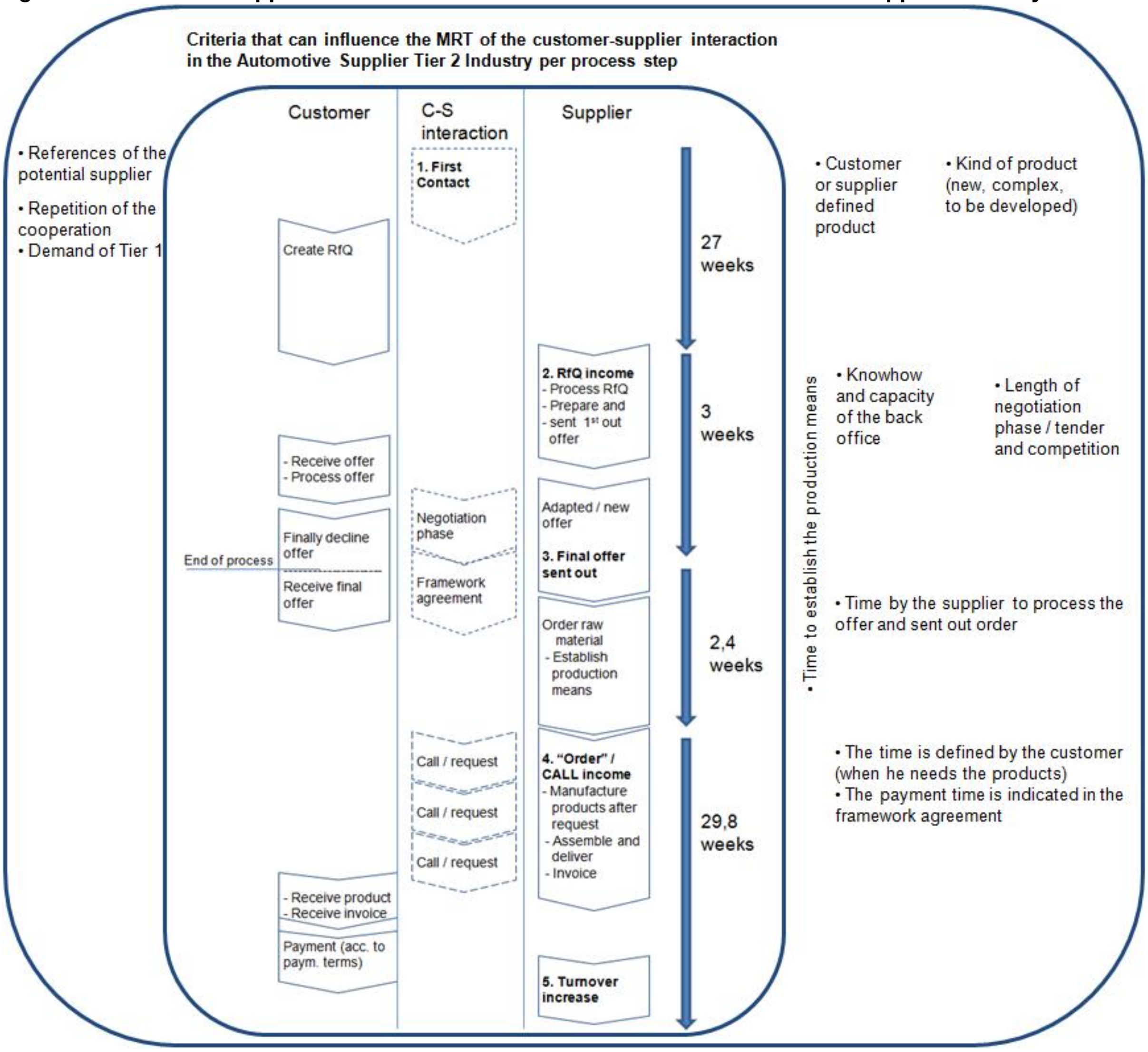


Figure: Developed by the researcher

(2) RfQ income: The second step in the defined customer-supplier interaction is that as soon as the RfQ or the invitation to a tender (which is seldom) is received by the potential supplier, the sales back office prepares an offer or prepares for the tender, according to the customer specifications. If the offer is established, it is sent out to the potential customer or presented at a meeting scheduled by the potential customer. At that meeting, the potential customer has to decline it, accept it or invite the presenters again. The negotiation is mostly about prices, as the technical details are set out in the specification document of the potential customer. This time is mostly influenced by the potential customer, as the demand depends on the customer (OEM).

(3) Final offer sent out: As soon as the negotiation phase is successfully completed, a final offer is sent out to the potential customer who accepts it by

submitting a framework agreement which is signed by both parties. The framework agreement includes the technical specifications, prices and quantities. As soon as the framework agreement is established, raw material is procured (if it is not in stock), the production means are established (tools, machines, devices, if not already placed).

(4) “Order” / Call income: As soon as the first call (order) is completed by the Tier 1 customer, the Tier 2 supplier produces the requested number of products and delivers it on the requested time (just-in-time) and place (sometimes even directly to the assembly line) (just-in-sequence). For this reason, the supplier had to store all the capacity, raw material and production means for the indicated number of products as defined in the framework agreement to be able to deliver after request just-in-time and just-in-sequence. This state lasts as long as indicated in the framework agreement.

(5) Sales turnover increase: The final step in the customer-supplier interaction is the payment (depending on the payment terms established in the framework agreement) of the customer and the sales turnover increase at the supplier’s side. The payment is usually done after every call depending on the requested quantity of the products.

The time frames of the whole sales process of the Automotive Tier 2 Industry are about 62 weeks (see figure 44, page 143) in total, which is the investigated MRT. As a result it can be stated that the length of the sales process in this industry sector is quite similar to the Machinery & Equipment Industry and the activities of the sales process itself are quite similar to the Automotive Tier 1 Industry, however less complex. The several conclusions already stated for the Machinery & Equipment as well as for the Automotive Tier 1 sector can therefore be applied in this case as well. It is recommended to implement the MRT as well as the investigated factors that influence the sales process in order to support better planning and forecasting capabilities/ performance.

6.2. THE INFLUENCE OF MARKET INFORMATION AND PLANNING HORIZON ON SALES FORECAST ACCURACY

6.2.1. Information horizon about the market development in the context of forecast accuracy

As indicated in the conceptual framework (figure 20, page 102) it is estimated that sales (the customer's decision to make an investment) is dependent on environmental conditions. If the economy is growing, customers intend to buy more (because customer's demand is higher), if the economy is stagnating or shrinking, customers intend to buy less. It could be stated that if companies have a specific information horizon (for defined years) about the market development for the next (x) years (for the sales turnover relevant years), the best forecast accuracy can be achieved (see figure 50 below). This is because the companies can plan their capacities according to the market development and prospective future sales turnover. In parallel, the question arises of how far ahead of time should companies have information about future market developments.

Figure 50: Information horizon in the context of forecast accuracy

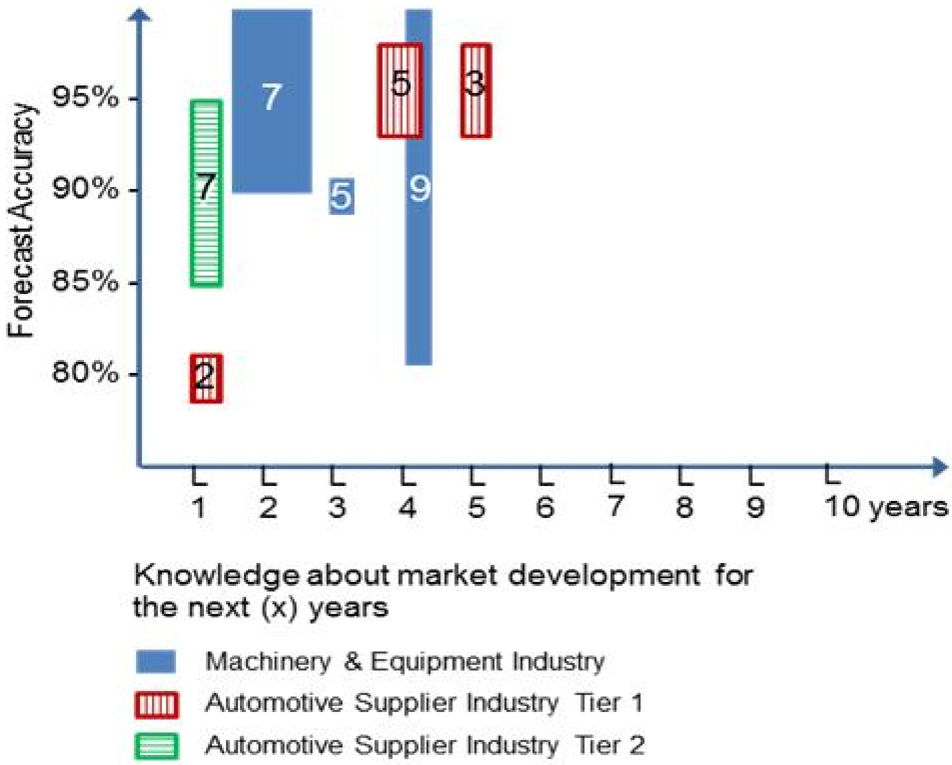


Table: Developed by the researcher

The figure indicates that there is a relation between the information horizon and forecast accuracy. In the Machinery and Equipment Industry the information horizon varies from two to four years. For the companies planning with a three year information horizon the accuracy is below 90%. For those who plan with a four year horizon the accuracy varies from below 80% to almost 100%. For the companies planning with a two year information horizon the accuracy shows the highest level varying from 90 % to 100 % (with less variance). It can therefore be stated that the best information horizon for planning for this industry sector is two years.

Clearly, a four to five year information horizon is the best option for the Automotive Tier 1 suppliers. A one year information horizon seems to be sufficient for planning of the investigated Tier 2 suppliers.

This relation between the market information horizon and forecast accuracy level indicates the importance of knowledge about time in sales planning and forecasting. It seemed that capacities can be saved with an adequate information horizon (for the industry sector) to achieve a high level of forecast accuracy.

6.2.2. Sales planning horizon in the context of forecast accuracy

As discussed in the figures 47, 48 and 49 (pages 150, 154 and 159), the customer-supplier interaction is affected by industry characteristics, and figure 50 (page 161) indicated that there is a relation between the information horizon of market development and forecast accuracy. Therefore the questions arise of how the sales planning horizon affects the forecast performance in terms of forecast accuracy. The sales planning horizon is in this context defined as the planning time span into the future as displayed in table 4 on page 163.

Table 4: Sales planning horizon in the context of forecast accuracy

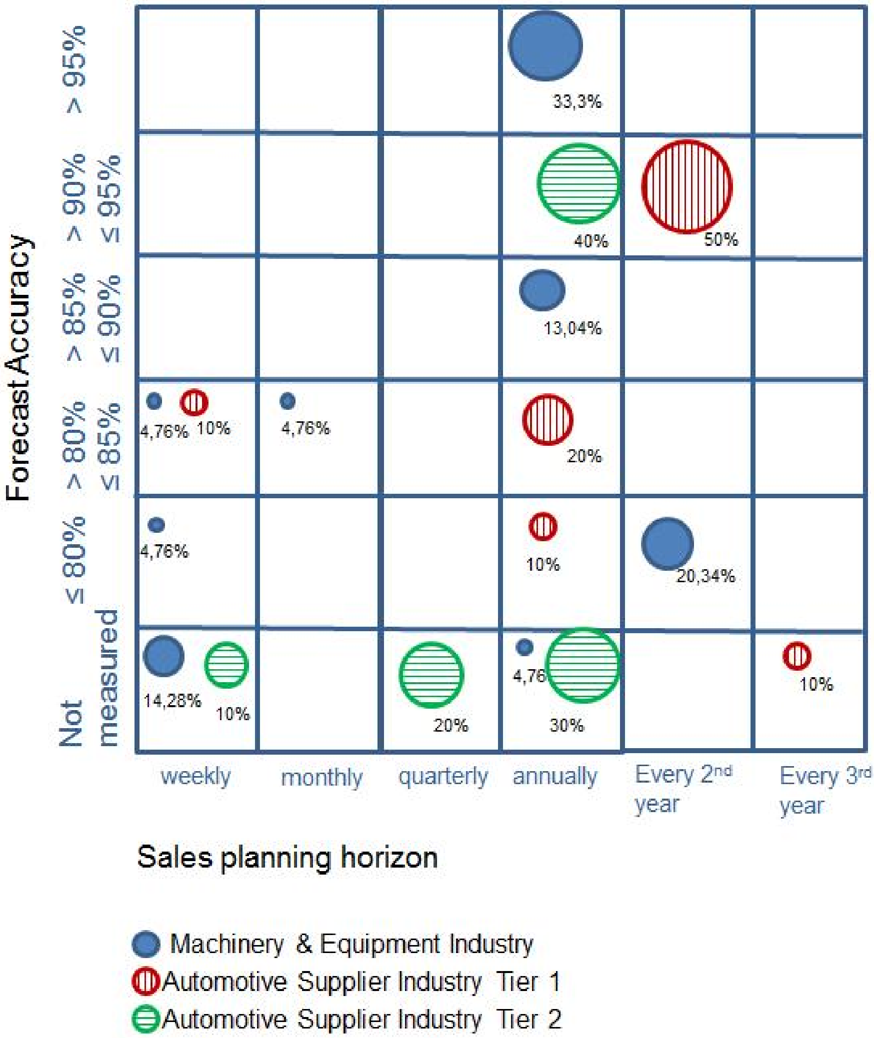


Table: Developed by the researcher

The highest forecast accuracy was measured in the Machinery & Equipment Industry where 33.3% of the respondents maintained an accuracy rate of 95% and more. All of these respondents use an one year planning horizon. A planning horizon of more or less than one year (every 2nd year, monthly and weekly) only achieved accuracies of 80% to 90%. Fourteen percent of the machinery cases did not measure forecast accuracy. It is therefore clear that sales planning and forecasting is less accurate if the planning horizon drop below and above one year.

In the Automotive Tier 1 Supplier Industry, the highest forecast accuracy with 90% to 95% was achieved by 50% of all respondents in this sector using a planning horizon of about two years. If the planning horizon was annually or weekly, the accuracy was measured at 80% to 85% or less. 10% of the cases did not measure their accuracy with a three years planning horizon. Concluding it can be stated that the best planning horizon in terms of forecast accuracy for the Tier 1 Industry is every 2nd year. In the Automotive Tier 2 Supplier Industry, the highest forecast accuracy (by 40% of the investigated cases) with 90% to 95% was measured at companies that had an annual planning horizon. The other investigated cases (n = 60% = 6) did not measure forecast accuracy. Therefore, the most accurate accuracy can be achieved with an annual planning horizon.

The cross-case conclusions indicate that, first of all, the sales planning horizon is influenced by time aspects, secondly that these time aspects are industry specific and thirdly, such time aspects are ignored by some companies which do not measure accuracy and that demonstrates their ignorance in this regard.

6.3. THE INFLUENCE OF SALES PLANNING AND FORECAST ACCURACY ON SALES PERFORMANCE

6.3.1. Planning approach in the context of sales performance

In one of the latest investigations into the distribution of information in American, German, French and English companies, Newman (2010: 1286-1312) mentioned that information management is a core competence of the company. However, different information is available in different information centers within the company (Ehsani, Makui and Sadi Nezhad, 2010: 853-863). This indicates that different information is distributed in the company hierarchies. A sales employee can, for example, know its current customers and their needs very well; its information however may not be available in assessing the future market development for the next years. This indicates that a company's performance is influenced by the company's approach to plan future sales turnover. As already discussed (see section 2.4, pages 34-36), there are three approaches to elaborate the sales plan: The bottom-up, the top-down and the mixed approach. The results of the empirical study indicate that there is a relation between the companies' planning approach and their performance (see table 5, page 165).

Table 5: Sales planning approach in the context of sales performance measures

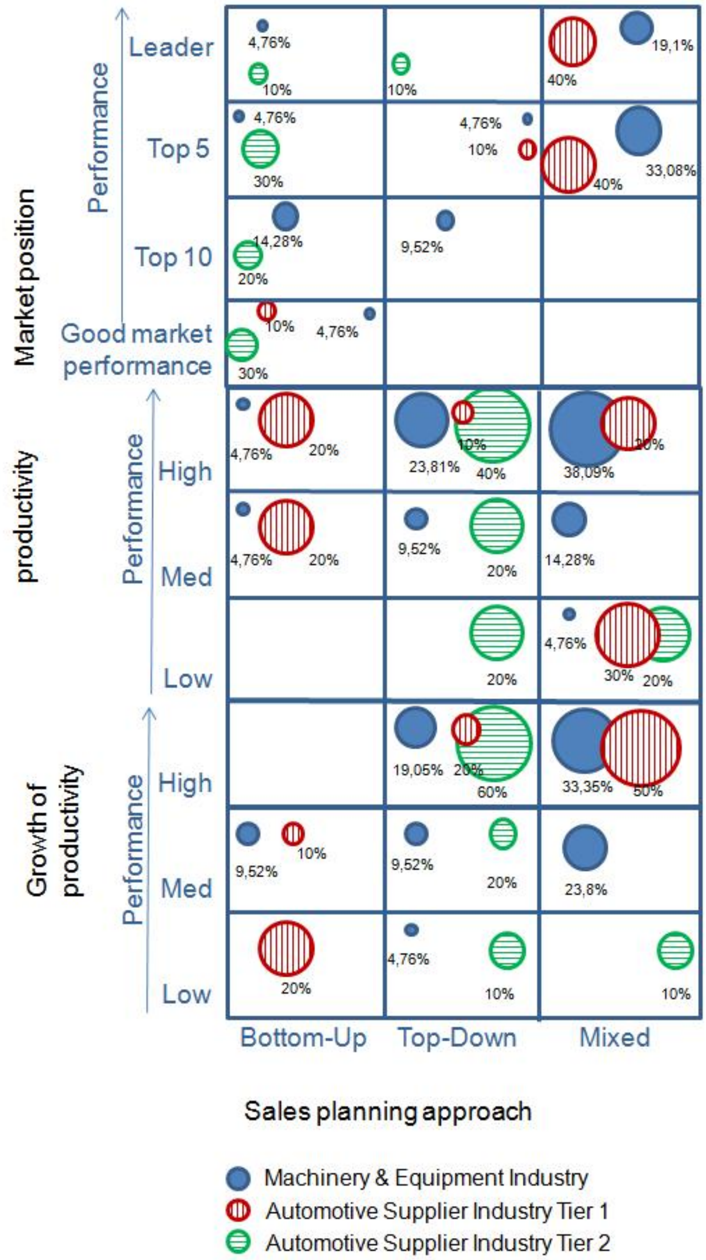


Table: Developed by the researcher

For the investigated market position of the cases it can be stated that 51.15% of the Machinery & Equipment companies achieved a market position as market leader or top five company in the machinery sector if the mixed-planning approach was applied. In contrast, only 28.56% of the researched companies that used the top-down or bottom-up planning approach and could achieve a top 10 position or good market performance. Eighty percent of the investigated Automotive Tier 1 supplier companies achieved a market leader position or top 5 position if the mixed planning approach was applied. The situation of the Automotive Tier 2 supplier in terms of market position is that most of the investigated Tier 2 participants (90%) used the bottom-up approach, however, with different market positions. Ten percent achieved a market leader position, 30% a top 5 position, 20% a top 10 position and 30% a good market performance.

It can be concluded from table 5 that for the Machinery & Equipment as well as Automotive Tier 1 Industry sectors the mixed planning approach supports the improvement of the market position. It is therefore recommended that companies acting in these industry sectors follow the mix planning approach. It is even more important for those companies which do not plan, to take note of the market position advantages of this method of planning. Unfortunately, it seems that companies in the Automotive Tier 2 sector do not make use of the mixed planning approach at all. It would be interesting to see that if more of these companies would make use of the mixed planning approach instead of only the bottom-up approach, more of them would be in a market leader position.

For the investigated performance measure productivity the situation for the Machinery & Equipment cases is that about 52.37% did achieve a high or medium sales performance when the mixed panning approach was applied. If top-down planning was applied, only 33.33% achieved a high or medium sales performance. Some machinery companies (9.52%) that applied the bottom-up planning approach achieved a high or medium productivity performance. Concluding it can be said that the mixed-planning approach supports the performance in terms of productivity for the Machinery & Equipment cases. The recommendation is also to apply mixed planning in this industry sector.

For the investigated cases of the Automotive Tier 1 Supplier Industry, the situation is that all companies achieved a high performance in terms of productivity if the mixed (20%) or the bottom-up (20%) approach was applied. Ten percent of the Tier 1 companies achieved a high productivity with the top-down approach. Surprisingly, 30% of the Tier 1 companies that applied the mixed planning approach only achieved low productivity performance. For this situation a clear conclusion cannot be stated; it is estimated that the situation appears because of industry specific characteristics, such as the framework agreements. This agreement, as indicated in section 6.1.2 (pages 152-157), is usually set with sales volumes (quantities and prices) and for several years which could make the planning approach for the Tier 1 supplier less important. This is because the planning figures are given by the OEM and are not planned in detail internally. However, the framework agreement is going to be a less reliable order income indicator and therefore the planning approach should be further investigated to recommend the most successful one.

The investigated cases in the Automotive Tier 2 Supplier Industry mostly applied the top-down approach (n = 8). This approach was the most successful in terms of productivity. Sixty percent of the Tier 2 companies achieved high or medium performance by the top-down planning approach and only 20% a low productivity performance. Concluding it can be said that the top down approach supports the performance in terms of productivity for the Automotive Tier 2 Industry. The recommendation is to apply this approach in order to achieve a high productivity performance.

For the sales performance measure productivity growth, most of the investigated Machinery & Equipment cases (57.15%) achieved a high or medium productivity growth performance by the mixed planning approach. In contrast, only 28.57% of the investigated Machinery & Equipment cases achieved a high or medium sales performance by the top-down approach but 4.76% achieved an even lower sales performance. If the bottom-up sales approach was applied, only medium sales performance was achieved by 9.52% of the cases. It is therefore concluded that the mixed-planning approach is the most successful one to achieve a high growth of productivity which is therefore recommended to apply in the Machinery & Equipment sector.

A nearly similar result to the Machinery & Equipment Industry was achieved by the Automotive Tier 1 supplier: Fifty percent of the Tier 1 supplier cases used the mixed planning approach and did therefore achieve a high sales performance in terms of growth of productivity. In contrast, 30% of the companies that used the bottom-up approach did achieve a medium or low sales performance and 20% using the top-down approach did achieve a high performance measure. It is concluded that the mixed planning approach achieved the best productivity growth measure if it is applied. Therefore this approach is recommended.

For the investigated Automotive Tier 2 cases it can be stated that most of them (90%) used the top down approach and 80% achieved a high or medium performance in using this approach. It is concluded that this approach achieved the best performance measure in terms of growth of productivity and it is recommended for this industry sector to apply the top-down approach.

Summarised, these results indicate that a mixture between the bottom-up and the top-down planning approach combines both advantages and eliminates most of the disadvantages of this planning approaches. Another interesting conclusion is that the planning approach strongly depends on the industry the approach is applied in. Industry characteristics should be taken into account for sales planning and forecasting.

6.3.2. Forecast accuracy in the context of sales performance

The question about the importance of forecast accuracy and its methods to improve forecast accuracy was discussed in chapter two. However, literature fails to prove if forecast accuracy influences the performance of a company. This question was qualitatively investigated in this research project and evaluated as follows (table 6, page 169):

Table 6: Sales forecast accuracy in the context of sales performance measures

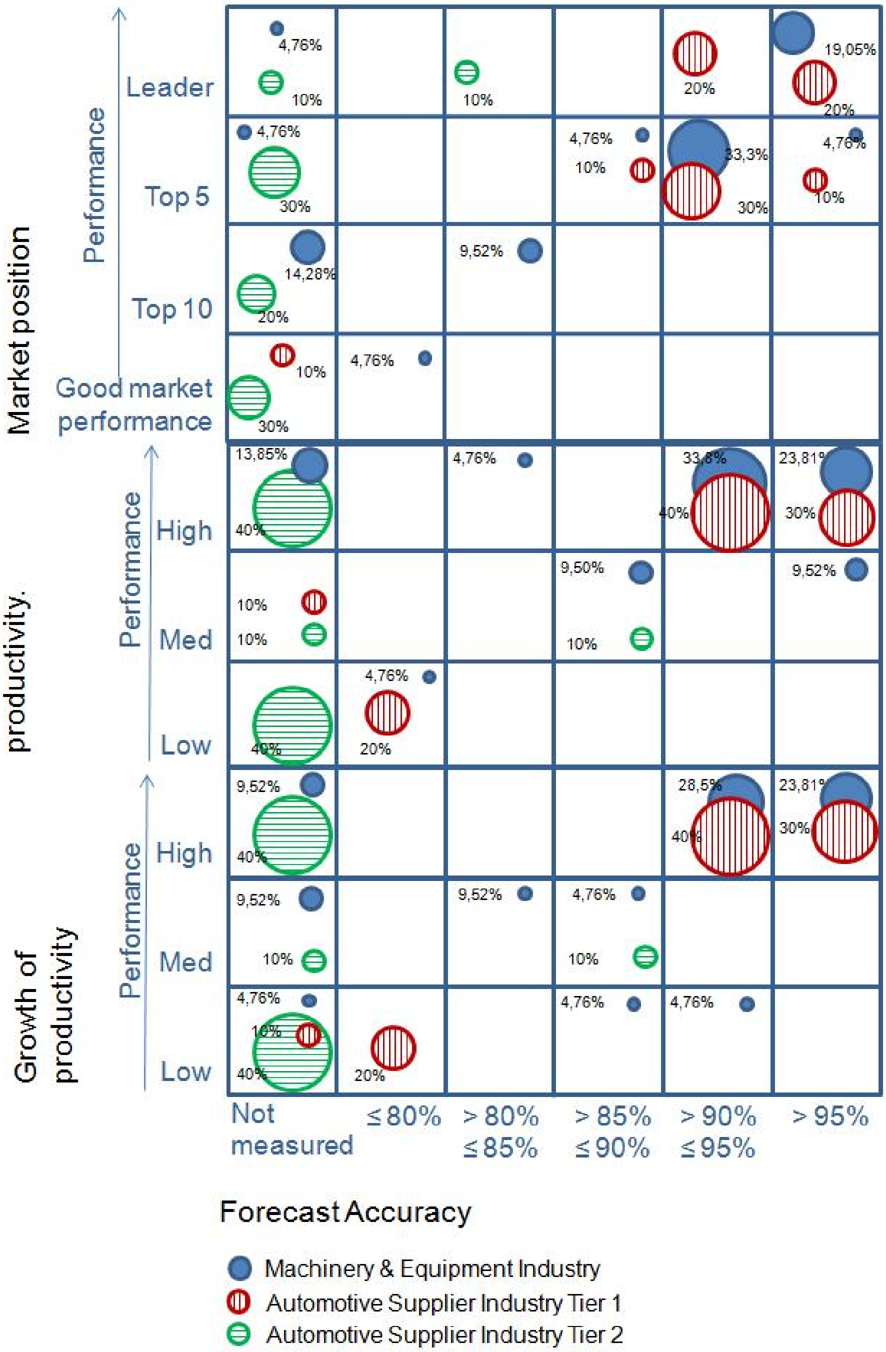


Table: Developed by the researcher

The investigation about forecast accuracy and sales performance measures, such as market position, productivity and growth of productivity indicated that the better the forecast accuracy the better the sales performance of a company (except for Tier 2 suppliers, they mostly do not measure forecast accuracy (n = 9)).

For the investigated Machinery & Equipment Industry, it can be stated that in terms of market position, 57.11% of the investigated Machinery & Equipment companies with a forecast accuracy of more than 90% are ranked as market leaders or ranked as a top 5 market position company. For the sales performance measure productivity, 67.13% of the investigated cases with a forecast accuracy of more than 90% sample achieved a high or medium performance. This situation is similar to the performance measure growth of productivity: 52.31% of the cases with a measured forecast accuracy of more than 90% achieved high performance. A similar indication can be made for the investigated Automotive Tier 1 Supplier Industry. Eighty percent of the Automotive Tier 1 companies with a similar forecast accuracy of 90% or more were ranked as market leaders or top 5 companies in the market they are acting in. For the performance measure productivity, 70% of the Tier 1 supplier cases that had a forecast accuracy of more than 90% achieved high performance. In terms of the performance measure growth of productivity, 70% of the Tier 1 cases that had a forecast accuracy of more than 90% were high performing.

Concluding it can be said that for the Machinery & Equipment as well as Automotive Tier 1 Industry, adequate sales planning with high forecast accuracy seems to be very important; at least measured by the three performance measures and the participants answers as investigated in this research project. The better the forecast accuracy is, the better the performance measures are. It is therefore recommended to pay good attention to forecasting methods to achieve high forecast accuracy; this can be, among others, achieved by taking the discussed customer-supplier interactions, time frames and influencing factors in figures 47, 48 and 49 into consideration.

No conclusion could be made for the Automotive Tier 2 companies, because most of the sample (n = 9, 90%) did not measure their forecast accuracy. This fact can be explained by the Tier 2 suppliers industry characteristics as already indicated in section 1.1 (pages 1-6).

6.4. THE INFLUENCE OF MRT

This research project detected for the investigated industrial markets, namely the Machinery & Equipment, the Automotive Tier 1 Supplier and the Automotive Tier 2 Supplier cases that these markets react with a time lag, called MRT, of about one to three years (see figure 44, page 143). Therefore, the investigated companies in these markets cannot correct any decrease in sales immediately by additional sales efforts. The turnover takes too long to follow (because of these time lags). The reason for this is that new turnover can only be achieved by either new customers or new products sold to existing customers. It can therefore be stated that industrial markets are different from consumer markets regarding the sales planning and forecasting process. This is because the reliability of sales planning and forecasting depends on the outcome of customer-supplier relations, thus the sales process itself. In fact, these sales processes in the investigated industry sectors have such a long duration, that it is not possible for sales managers to immediately compensate low sales figures by increased sales efforts. The turnover raise will come in a later period and thus simply too late for the current one. This results in the fact that the reliability of the sales forecast (for the established sales plan) is reduced, if industry characteristics and special time aspects of the sales process are not taken into consideration. This time aspects can be described best (among others) by the *Market Response Time* (MRT).

The MRT is defined as the time lag between the start of an *increase of sales efforts by the supplier* (first contact) and *the market response* in terms of increased purchase. This is when the customer starts to financially respond to the customer with the result of a *sales turnover increase* at the supplier's side. If the MRT is long, sales planning and forecasting has increased importance, because sales efforts need to be planned a long time in advance. For this reason, response times are major elements in planning and forecasting. The investigated companies showed that these three industry sectors have different MRTs (see figure 44, page 143), such as 68 weeks in the Machinery & Equipment Industry, 138 weeks in the Automotive Tier 1 Supplier, and 62 weeks in the Automotive Tier 2 Supplier Industry. These different MRTs influence the companies planning and forecasting processes in different ways.

It is not only important to plan and anticipate sales; it is also an indication of how to increase sales (Morlidge and Player, 2010: XV). The ability to increase sales depends on two factors: Either to sell something “better” than before or improve the quality of the sales process (Monroe and Cox, 2004: 10). It is proved in this research project that knowledge of the MRT enhances the quality of the sales process by taking notice of the factors that influence this process (see figure 47 on page 150, figure 48 on page 154 and figure 49 on page 159).

To sum up, the sales process is most important for a company’s success because selling is a process that can be studied, controlled, planned and forecasted (Monroe and Cox, 2004: 13). In other words it can be said that a salesman’s job is to manage a number of customers step-by-step through the sales process which is a unique combination of product category, market segments and sales resources for each company (Kahle, 2007: 21-23). If MRT/ time is kept in mind and included in planning and forecasting, the sales process can be done much more efficiently (see figure 50 on page 161, table 4 on page 163). Furthermore, it is expected that knowledge of MRT will have an impact on sales force thinking, on sales recruiting and leadership as well as on manufacturing times (time-to-market).

6.5. CONCLUSIONS

As it is stated in the problem statement in section 1.4 (page 15) that MRT is ignored during industrial sales planning and forecasting in different industry sectors leading to inefficient planning, this paragraph points out the contribution of this research project to the solution of this problem. This paragraph further points out the fulfilment of the primary and secondary research aims as stated in section 1.7.2 on page 19.

6.5.1. Conclusions to the problem statement

The problem statement indicates that MRT is ignored during industrial sales planning and forecasting in different industry sectors leading to inefficient planning. This research project has proved that such time aspects are not taken into consideration and that with the consideration of MRT in the sales process, sales planning and forecasting can be done more successful. In turn, it is showed that the ignorance of MRT resulted in inefficient planning.

- This research project proved that there are different time lags in the sales processes of the investigated Machinery & Equipment, the Automotive Tier 1 Supplier and the Automotive Tier 2 Supplier Industry. These time lags are called MRT and for the mentioned industry sectors equals 68 weeks, 139 weeks and 63 weeks (see figure 44, page 143).

- This research project showed that such time aspects are not taken into consideration in the investigated cases (industry sectors) leading to inefficient planning:
    - Most of the managers increase sales efforts if the order income situation gets worse (see figure 34, page 134), this is however the wrong approach and causes in inefficiency (see section 6.4, pages 171-172);
    - The prediction of future development of the business by early indicators is disregarded by a large number of the investigated cases in all investigated industry sectors which leads to inefficiency (see figures 32 and 33, pages 132 and 133);
    - Managers are not aware of time aspects in sales planning and forecasting that influence future sales and impact on sales performance which leads to inefficiency (see figures 45 and 46 on pages 144 and 145); and
    - A large number of companies do not measure accuracy. This demonstrates the companies' ignorance in this regard, resulting in inefficient planning and forecasting behaviour (see figure 35, page 135).

- This research project showed that if time aspects were taken into consideration in sales planning and forecasting, forecast accuracy could improve (and therefore sales performance could improve) (see figure 50 on page 161 and table 4 page 163):

  - It seemed that capacities can be saved with an adequate information horizon of one to four years (see figure 30, page 130) with a high level of forecast accuracy (figure 50, page 161).
  - The cross-case conclusions indicated (see table 4, page 163) that the sales planning horizon of one to two years (see figure 31, page 131) is the proper planning horizon for the investigated cases.

- This research project showed that an adequate sales planning approach could improve sales performance (measured by the performance measures market position, productivity and growth of productivity) (see table 5, page 165):
  - It can be concluded from table 5 that for the Machinery & Equipment as well as Automotive Tier 1 Industry sector the mixed planning approach supports the improvement of the market position. Unfortunately, it seems that companies in the Automotive Tier 2 sector do not make use of the mixed planning approach at all. It would be interesting to see that if more of these companies would make use of the mixed planning approach instead of only the bottom-up approach, more of them would be in a market leader position (see *further research implications*, pages 178-179).

- This research project showed that the better the sales forecast accuracy the better the sales performance (measured by the performance measures market position, productivity and growth of productivity) (see table 6, page 169):
  - It can be said that for the Machinery & Equipment as well as Automotive Tier 1 Industry sector, adequate sales planning with high forecast accuracy seems to be very important: The better the forecast accuracy is, the better the performance measures are.
  - No conclusion could be made for the Automotive Tier 2 companies, because most of the sample (n = 9, 90%) did not measure their forecast accuracy. It would therefore be interesting to further investigate the Automotive Tier 2 supplier’s performance of companies that measure forecast accuracy (see *further research implications*, pages 178-179).

- The overall conclusion of this research project is that the implementation of MRT in sales planning and forecasting can increase sales performance. In turn, the problem statement can be proved that if MRT is ignored during industrial sales planning and forecasting, it can lead to inefficient planning. This is true for the Machinery & Equipment Industry because of the developed relation between order income and acquisitions: The order income is constant, if the current sales in Euro is equal to the sum of new acquisitions expressed in Euro. The order income and the sum of new acquisitions depend on the investigated MRT. Therefore MRT is highly important.

  For the Automotive Tier 1 and Tier 2 suppliers, the situation is as follows: The sales turnover of a series supplier only decreases if a framework agreement is fulfilled. It is usually fulfilled when the product lifetime of the product (this is in the investigated cases an automobile), which is manufactured by the OEM, ends. The product lifetime for an automobile is usually calculated as five to six years. Mathematically, however, and this is not recognized by a large number of the investigated automotive cases, the sales turnover situation gets worse every year if no new framework agreements can be closed by the supplier. This is because the sales loss can be displayed as the quotient of total sales and average lifetime of the products currently manufactured. Therefore it is important to balance the theoretical sales loss (e.g. 20% p. a. if the product lifetime of the product is expected to be five years and no new acquisitions are done).

6.5.2. Conclusions to the primary and secondary objectives

This paragraph concludes the fulfilment of the primary and secondary objectives of this research project as follows:

- The primary research objective is to investigate the sales planning and forecasting behaviour in the Machinery & Equipment, the Automotive Tier 1 Supplier and Tier 2 Supplier Industry was done (see chapter five and six as well as secondary aims as follows);

- The sales process, its time frames and influencing factors as well as the MRT in the three selected industry sectors were investigated (see figure 44 on page 143, figure 47 on page 150, figure 48 on page 154, figure 49 on page 159);
- The state of sales planning and forecasting in the three selected industries was investigated, especially in terms of
    - information horizon (see figure 30, page 130), sales planning horizon (see figure 31, page 131), early indicators for order income (see figures 32 and 33, pages 132 and 133), managers reactions on sustainable order income decrease (see figure 34, page 134), sales forecasting methods (see figure 35, page 135), sales forecast accuracies (see figure 37, page 137 and forecast accuracy measures (see figure 36, page 136);
- The effects of time aspects on the planning horizon were investigated (see table 4, page 163); and
- The effects of forecast accuracy on sales performance were investigated (see table 6, page 169).

6.6. RECOMMENDATIONS

The following aspects are the recommendations of this research project:

- Apply the frameworks (figure 47, 48 and 49) of the research project: Figure 47 is developed by the researcher so that companies in the Machinery & Equipment Industry sector can use it to better understand the criteria that influence the sales process and how long its sales force need to generate new turnover (compare the developed relation/ equation between order income and acquisitions on page 175 and MRT). Figure 48 and figure 49 were similarly developed for the Automotive Tier 1 and Automotive Tier 2 Supplier Industry sector. If companies use this diagram, it will be able to develop better plans for the future and do better forecasting (compare the developed equation of sales loss as the quotient of total sales and average lifetime on page 175 and MRT);
- Use an adequate information horizon: For the Machinery & Equipment Industry and the Automotive Tier 1 Supplier Industry it is recommended to

have an information horizon of two to four years. For the Automotive Tier 2 Supplier Industry it is recommended to have information about the market development for the next year;

- Use an adequate sales planning horizon: A sales planning horizon of about one year seems to be sufficient enough for all investigated industries. If resources are available, the Automotive Supplier Tier 1 Industry sector may have a sales planning horizon of about two years;
- Use an adequate sales planning approach: It is recommended that companies acting in the Machinery & Equipment as well as Automotive Tier 1 Supplier Industry sector apply a mix planning approach. It is even more important for those companies which do not plan, to take note of the sales performance advantages of this sales planning method. It is recommended for the Automotive Tier 2 suppliers to apply the top-down sales planning approach in terms of the performance measures productivity and growth of productivity;
- Implement the MRT as an early indicator for order income: To anticipate the future order income situation it is recommended to implement the investigated MRT into sales planning. Sales force indications in the Machinery & Equipment Industry sector or framework agreements in the Automotive Supplier Industry sector are not sufficient and reliable enough;
- Use simple sales forecasting methods: It is recommended to pay good attention to forecasting methods and use simple forecasting methods, such as extrapolation and expert opinions, instead of complex ones; and
- Achieve a better sales forecast accuracy than 85%: It is recommended to measure the sales forecast accuracy and achieve better than 85% accuracy. This can be achieved, among others, by taking the discussed customer-supplier interactions, time frames and influencing factors in figures 47, 48 and 49 into consideration. Furthermore it is recommended to follow the investigated information and planning horizon to reduce the problem of less accuracy.

6.7. LIMITATIONS OF THE RESEARCH RESULTS

The following aspects indicate the limitations of this research project:

- Research context: This research project only investigated the industrial context, especially the Machinery & Equipment and the Automotive Supplier Industry. Its results can only be applicable to this research context;
- Research Methodology: The underlying research methodology of this research project is a qualitative one. The qualitative approach is the only suitable approach for the research context explained afore. The emphasis is placed on collecting individual, detailed, in-depth information and the qualitative rather than the quantitative element of the information is important. It is therefore the intention to investigate a representative subsection of a specific population in order to make assumptions about the whole population. However, statistical generalisation could not be given.

6.8. FURTHER RESEARCH IMPLICATIONS

The following aspects indicate ideas for further research implications:

- As this research project was an exploratory study about a topic that was not investigated before, further research could be done to statistically generalise its results;
- Statistical generalisation should be done especially for the time frames of the sales process steps as well as for the investigated MRT per industry sector;
- It should be statistically investigated, whether the MRT can be used as pre-indicator for the order income situation, especially in the Machinery & Equipment Industry sector, to better plan capacities;
- Furthermore, the detected clusters per industry sector should be investigated in depth, as it is estimated that several characteristics in the sales planning and forecasting process are determinable;
- The indicated relation between information horizon and forecast accuracy should be further investigated (figure 50, page 161);
- Based on the results of this study, it can be estimated that the forecast accuracy is the highest if the company's knowledge horizon is equal to the

product life cycle time of the products. This indication also needs statistical prove. If it could be proved, systems could become relevant for the industry how to effectively detect market developments;

- As it seems that a large number of the Automotive Tier 2 companies do not measure their forecast accuracy (see figure 37, page 137), it would be interesting to further investigate the Automotive Tier 2 supplier's performance of companies that measure forecast accuracy; and
- Last of all, the statement by Leeflang and Hunneman (2010: 75), that there are less research papers delivered at research conferences for the industrial context regarding market response models, should be further investigated. This investigation could be done in terms of the reasons why there are obviously less papers in B2B and how time aspects have further impact, not only on sales, but on the in the industrial business at a glance.

MOTIVATION FOR USING OLD SOURCES

The topic of industrial sales planning and forecasting is not researched very well and some parts of this study discuss historical aspects.
As such, sources that are from that time period are used to support the history and sometimes this sources are the only available ones.

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ATTACHMENTS

<u>Original attachment to the eMail sent out by the researcher to potential participants after the first telephone contact:</u>

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Interviews zur Dissertation

Ihr Win: **Anonymisierte Darstellung der Interview- und Forschungsergebnisse zur Vertriebsplanung im Automobilzulieferbereich Tier 1/ Tier 2 und Maschinenbau Mitte 2011**

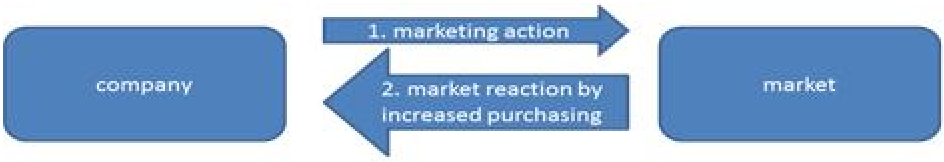
Mein Win: Ihre Antworten im Interview

Thema: Einfluss der Markt-Reaktions-Zeit auf die Vertriebsplanung im Maschinen- und Anlagenbau und im Automobilzulieferbereich

Interviewpartner: Automobilzulieferer und Maschinen- und Anlagenbauer an OEM und Tier 1 Automotive

Dauer: ca. 60 Minuten, persönlich

Zum Inhalt: Fragen zur Firmensituation i. A., zur Marktsituation, zur Wettbewerbssituation, zur Kundensituation, zum Vertriebsmanagement, zur Betriebs- & Vertriebsplanung, zu den Vertriebszielen, zu den Prognoseinstrumenten, Vorhersagegenauigkeit, Sales - Buying Stages, etc.



Markt-Reaktions-Zeit

Interview guide:

Industry sector of the investigated company (case)
Company name
Participant information
Name, position and department of the interview participants and contact details

Company facts & figures (double checked with external sources, if deviations appeared, external sources were used):
Sales turnover of the company in the automotive sector (must be more than 80%)
Number of sales employees
Market position of the company in the investigated industry sector

Market:
How long is your information horizon of the company about the future market development?
Where do you get your knowledge from?
Do you have performance indicators to appraise the future demand for your products?

Sales planning:
How do you plan your sales for the next year?
Which sales approach do you use (top-down, bottom-up, mixed-planning)?
How do you solve the top-down vs. bottom-up problem?
How long is your sales planning horizon?
Do you have early indicators for "order income"?
What do you do if order income decreases sustainable?

Time aspects:
How long is the time of your company from the first contact with a customer (about a defined project/ product) until RfQ Income?
-Predefined time frames in 2-week steps from 0 - 2 weeks until 140 -142 weeks
What factors do affect this time frame?

How long is the time from RfQ income final offer sent out to the customer?
-Predefined time frames in 2-week steps from 0 - 2 weeks until 20 - 22 weeks
What factors do affect this time frame?

How long is the time from final offer sent out to the customer until order income?
-Predefined time frames in 2-week steps from 0 - 2 weeks until 12 - 14 weeks
What factors do affect this time frame?

How long is the time from order income until sales turnover increase?
-Predefined time frames in 2-week steps from 0-2 weeks until 60 - 62 weeks
What factors do affect this time frame?

Do you know something about the Market Response Time?
Do you implement factors of time in sales planning?

Cross-check:
Explain the definition of MRT to the participant (s)
How long is your MRT and on what factors does this MRT depend on?

Sales forecasting:
What forecast method do you use?
What forecast accuracy do you have?
How do you measure your forecast accuracy?
What do you do if you become aware of deviations from your forecast and plan?

Sales planning approach:

Machinery & Equipment Industry: Planning approach			
Company	Bottom-Up	Top-Down	Mixed
M1			x
M2			x
M3			x
M4			x
M5			x
M6	x		
M7			x
M8			x
M9			x
M10		x	
M11		x	
M12		x	
M13			
M14			x
M15			x
M16		x	
M17	x		
M18			x
M19		x	
M20			x
M21		x	
Sum	**2**	**7**	**12**

Automotive Tier 1: Planning approach			
Company	Bottom-Up	Top-Down	Mixed
A1	x		
A2			x
A3			x
A4	x		
A5	x		
A6			x
A7		x	
A8	x		
A9			x
A10			x
Sum	**4**	**1**	**5**

Automotive Tier 2: Planning approach			
Company	Bottom-Up	Top-Down	Mixed
AS1			x
AS2		x	
AS3		x	
AS4			x
AS5		x	
AS6		x	
AS7		x	
AS8		x	
AS9		x	
AS10		x	
Sum	**0**	**8**	**2**

Chapter 5: Classification into low, medium and high performance regarding productivity:

Taken the statistical data into consideration, the classification into low, medium and high performance regarding productivity was done by the following formulae:

$$\text{low performance} = \textit{all companies with turnover per sales employee less than } (\text{mean of the cluster} - \text{standard deviation of the cluster})$$

This results for the Machine Tool Manufacturer for instance that all companies with less than 136.1 T€ sales turnover per sales employee (201.5 T€ - 65.4 T€) are classified as companies with low performance. This calculation is similar to all other clusters.

$$\text{medium performance} = \textit{all companies with turnover per sales employee less than } (\text{mean of the cluster}) \text{ but more than } (\text{mean of the cluster} - \text{standard deviation of the cluster})$$

This results for the Machine Tool Manufacturer for instance that all companies with less than 201.5 T€ sales turnover per sales employee but more than 136.1 T€ are classified as companies with medium performance. This calculation is similar to all other clusters.

$$\text{high performance} = \textit{all companies with turnover per sales employee more than } (\text{mean of the cluster})$$

This results for the Machine Tool Manufacturer for instance that all companies with more than 201.6 T€ sales turnover per sales employee are classified as companies with high performance. This calculation is similar to all other clusters.

Chapter 5: Classification into low, medium and high performance regarding productivity growth:

Machinery & Equipment Industry:

For the performance dimension productivity growth, the calculation system was more simple and based on the mean of the whole Machinery & Equipment cases (as well as Automotive Supplier Tier 1 and Tier 2 cases) which was m = 2.9%. The standard deviation of the sample was 2.1 with a standard error mean of 0.473%. The 95% confidence interval for the true value of the mean was bounded between 1.89% and 3.86%. Based on the mean, it was decided that all the companies that achieved a better growth rate as the average growth were classified as high performer. The companies that achieved a growth rate of less than the mean but better than 0% were classified as medium performer and companies that achieved negative growth were classified as low performer.

Automotive Tier 1 and Tier 2 Supplier Industry:

For the performance dimension productivity growth, the calculation system was more simple and based on the mean of Automotive Tier 1 and Tier 2 sample, which was for the Tier 1 suppliers m = 1.19% and for the Tier 2 suppliers m = 1.01%. The standard deviation of the Tier 1 sample was 1.87 with a standard error mean of 0.59%. The 95% confidence interval for the true value of the mean was bounded between -0.15% and 2.53%. For the Tier 2 sample, the standard deviation was 1.81 with a standard error mean of 0.57. The 95% confidence interval for the true value of the mean was bounded between -0.22% and 2.38%. Based on both means, it was decided that all the companies that achieved a better growth rate as the average growth were classified as high performer. The companies that achieved a growth rate of less than the mean but better than 0% were classified as medium performer and companies that achieved negative growth were classified as low performer.

Statistical information to section 5.3.1. and 5.3.2.: Machinery & Equipment Industry

The mean and standard deviation for the Machinery & Equipment cases (n = 21) in terms of productivity was 191.9 T€ and 60.8 T€. A deeper insight into the company structures of the investigated machinery cases resulted into several clusters according to what the companies manufactured. The investigated clusters were Machine Tool Manufacturer (n = 13), Measurement Equipment Manufacturer (n = 1), Automation System Manufacturer (n = 5), and Paint Shop Manufacturer (n = 2).

Based on these clusters, the mean of the Machine Tool Manufacturer (n = 13) was 201.5 T€ with a standard deviation of 65.4 T€ (standard error mean = 18.1T €) and the 95% confidence interval for the true value of the mean was bounded between 162.0 T€ and 241.1 T€. For the Automation System companies (n = 5), the mean was 172.0 T€ with a standard deviation of 59.7 T€ (standard error mean = 26.7 €) the 95% confidence interval for the true value of the mean was bounded between 97.8 T€ and 246.2 T€. For the Paint Shop Manufacturer (n = 2), the mean was 200.0 T€ (standard error mean = 40.0 T€) with a standard deviation of 56.6 T€ and the 95% confidence interval for the true value of the mean was bounded between -308.2 T€ and 708.2 T€. The Measurement Equipment Manufacturer (n = 1) was classified as a medium performer because of the lack of comparability.

Statistical information to section 5.3.3. and 5.3.4.: Automotive Supplier Industry

As the mean for the whole Tier 1 supplier cases regarding productivity was 152.5 T€ with a standard deviation of 52.0 T€ and the mean for the Tier 2 cases was 149.0 T€ with a standard deviation of 74.9 T€. A deeper inside into the company structure resulted that the investigated companies could be summarised into clusters according to what they manufactured. The investigated clusters for the Tier 1 were Steering Component Manufacturer (n = 2), Stamping Parts Manufacturer (n = 1) and Motor Component Manufacturer (n = 7). For the Tier 2 the sample consisted of Motor Component Manufacturer (n = 2), Stamping Parts Manufacturer (n = 6), Steering Component Manufacturer (n = 1) and Electronic Component Manufacturer (n = 1).

Based on these clusters, the situation regarding productivity for the Tier 1 suppliers was as follows: The mean of the Steering Component Manufacturer (n = 2) was 197.5 T€ with a standard deviation of 24.7 T€ (standard error mean = 17.5 €) and the 95% confidence interval for the true value of the mean was bounded between -24.9T T€ and 418.9 T€. For the Motor Component Manufacturer (n = 7) the mean was 146.3 T€ with a standard deviation of 63.2 T€ (standard error mean = 22.4 T€) and the 95% confidence interval for the true value of the mean was bounded between 93.4 T€ and 199.1 T€.

The sample of the Tier 2 suppliers consisted of Motor Component Manufacturer (n = 2), Stamping Parts Manufacturer (n = 6), Steering Component Manufacturer (n = 1) and Electronic Component Manufacturer (n = 1). The statistical data for the Motor Component Manufacturer were a mean of 145.0 T€ with a standard deviation of 106.1 T€ (standard error mean = 75.0 T€) and a 95% confidence interval for the true value of the mean that was bounded between -808.0 T€ and 1 098.0 T€. For the Stamping Parts Manufacturer, the mean was 163.3 € with a standard deviation of 82.6 T€ (standard error mean = 33.7 T€) the 95% confidence interval for the true value of the mean was bounded between 76.6 T€ and 250.0 T€. The Steering Component Manufacturer as well as the Electronic Component Manufacturer (n = 1) were classified as medium performer because of the lack of comparability.