TAMPERE UNIVERSITY
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OPTIMIZING FORECASTING TECHNIQUES FOR PROCUREMENT SAVINGS

The Case of BuyIn GmbH

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ABSTRACT

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The need for this thesis emerged from a specific working life problem, desire for more accurate and efficient forecasts at the case company. This thesis has been done specifically for the case company's purposes, to optimize the procurement savings forecasting techniques.

The preliminary purpose of this bachelor's thesis was to gather information on the forecasting techniques employed at the case company. The utmost aim of this thesis was to yield development proposals for improving the individual forecasting techniques and the overall forecasting process at the case company.

The researched materials were combined to form a framework and used to reflect and compare the techniques employed at the case company. These materials were gathered through extensive research and analysis of the available academic literature and studies. The case company knowledge was acquired through participant observation and analysis of internal documents. The forecasting techniques employed at the case company were reflected and analytically analyzed based on the researched and combined literature.

The findings of this thesis are presented as development proposals for the case company, to improve the individual forecasting techniques and the overall forecasting process. The findings suggested that implementation of the forecast value added method would improve the forecast performance.

The findings indicate that there is no one optimal way to forecast, and thus the importance of testing and measuring the different forecasting techniques is emphasized. Forecasts are also never perfect and thus it is important to count for the risks and uncertainties in the forecasts. Additional quantitative research would have to be conducted to conclude if the development proposals yielded in this thesis improve the forecast performance, and what are the sectors for further improvements.

Key words: business forecasting, forecasting techniques, forecast accuracy, Monte Carlo simulation

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1 INTRODUCTION

1.1 Thesis topic

The broad topic of this thesis will be business forecasting, more specifically forecasting of the procurement savings at the case company. The need for this thesis emerged while the author was working as a Controlling and Finance -department intern at the case company. The research problem, and the need for this thesis is the case company's desire to produce more accurate and efficient procurement savings forecasts. The research will be done specifically for the case company's purposes, nevertheless the findings of this thesis could also be applied to other companies in different fields using similar forecasting techniques.

This thesis will be done in a form of a case study, and as a background research to assist with the working life problem of the case company. The case company of this thesis will be BuyIn GmbH. BuyIn is a procurement alliance founded in 2011 by Deutsche Telekom and Orange (France Telekom), and it is operating in the telecommunications and information technology -business area. The case company, BuyIn will be introduced in more detail later, in the case study chapter of this thesis.

The more general topic of this thesis will be business forecasting. In more detail, the research will concentrate on the different forecasting methods and techniques, which are currently implemented at the case company to forecast the procurement savings. The researched methods will include qualitative and quantitative forecasting methods, with an emphasis on quantitative, simulation based approach to forecasting. The background research done for this thesis, will help to reflect, analyse and compare the forecasting methods and techniques which are employed at the case company. Based on the methods and framework, which will be presented in the following chapter of this thesis, development proposals will be yielded aiming to optimize and advance the forecasting techniques and process at the case company.

Forecasting the procurement savings presents a large part of the daily activities in the Controlling and Finance -department within the case company. As a procurement alliance, forecasting the procurement savings is an essential part of the case company's monthly, quarterly and yearly performance reporting. Besides this department, the topic of this thesis also has an extensive business significance for the entire case company. In addition to providing valuable insight for the Controlling and Finance -department, the findings and development proposals which will be generated in this thesis, could also be exploited in other departments within the case company.

In this thesis the topic of forecasting, developing the different forecasting techniques and the overall forecasting process will be narrowed down to forecasting the secured procurement savings within the case company. Although, the item being forecasted in the case study will be specific, the findings and the development proposals discussed later in this thesis could also be applied to different types of forecasted items and to different areas of business.

Forecasting as a strategic tool is highly essential in many different business areas, and thus makes this topic to be professionally widely interesting and relevant. Not only does a well-made forecast help the companies to estimate where they might land in regards of the forecasted item, but it enables the companies to make better informed decisions and implement corrective measures accordingly. The themes of this thesis are certainly topical, since forecasting can be utilized in unlimited ways by different business fields for different purposes. Furthermore, being able to produce reasonably accurate forecasts can provide companies with a notable business advantage.

1.2 Objectives and purpose

The more general purpose of this thesis is to provide the case company with more clarity and insight regarding its current procurement savings forecasting techniques, and the advantages and disadvantages or problems connected to these forecasting approaches. The purpose is to fully identify the differences of each of these procurement savings forecasting techniques and to clarify what are the different benefits and drawbacks these forecasting approaches present, and what kind of results they generate for the case company.

The purpose of this thesis is to do a background research on the different forecasting methods and techniques, which will provide the basis for the comparison and analysis of the techniques employed at the case company. The purpose is to describe and compare the different features of these methods and techniques, and to distinguish the connected advantages and disadvantages. The overall objective is to discuss and conclude actions the case company could implement to optimize and develop the specific procurement savings forecasting techniques and the overall forecasting process.

Apart from providing the case company with an assessment on its procurement savings forecasting techniques, the main objective of this thesis is to yield development proposals on how to develop and improve, not only specific forecasting techniques but also the complete procurement savings forecasting process. These development proposals will be aimed to improve the performance of the forecasts in the sense of improving the forecast accuracy of the forecasting models employed at the case company. In addition, the development proposals will be targeted to enhance the overall procurement savings forecasting process and the quality and reliability of the forecasts. Additional objective will be to analyse and discuss if one of the forecasting techniques at the case company would be applicable to other departments within the case company.

1.3 Concepts and theory

Forecasting methods and forecast performance measuring form a part of the provided framework. These concepts help in distinguishing differences between the forecasting techniques employed at the case company, and provide framework for measuring and evaluating the forecast performance. Risk and uncertainty assessment together with Monte Carlo simulation approach to forecasting present another part of the framework of this thesis. Based on these concepts, the different features of the forecasting methods and techniques will be presented. Furthermore, the case company’s forecasting techniques will be reflected, and the development proposals yielded based on the presented concepts.

Future as it is cannot be predicted perfectly, what has happened in the past and the present is known, but for businesses it is important to be able to estimate what will happen in the future. In the business environment forecasting and being able to produce reasonably accurate forecasts is highly important, and a significant factor in many types of business decision-making and planning processes. (Montgomery, Jennings & Kulahci 2015, 3.)

Forecasting can be said to be a process of predicting future outcomes, and a forecast a prediction of what happens in the future. Because the reality is so complex and ever changing, there is no single optimal way for producing the forecasts. Since there is no single optimal way, it is desirable to test, measure and evaluate different forecasting methods and thus models. This enables obtaining a view on the methods or techniques which perform accurately and efficiently in the desired cases. (Carnot, Koen & Tissot 2005, 9–12.)

Forecasts are almost never perfect, and even highly accurate forecasts are extremely hard to obtain. Thus risks and uncertainties are closely related with forecasting. It is important to be able to quantify these risks and uncertainties related to the forecast. Three different approach to forecasting will be introduced in the framework part of this thesis. These approaches will present the differences on how the uncertainty and the related risks and opportunities are counted in different forecasts. (Gilliland & Sglavo 2010.)

1.4 Working methods and data

The two basic approaches to business research are the quantitative and the qualitative approaches. Quantitative research is used when the phenomena being observed can be quantified and subjected to quantitative analysis via mathematical or statistical techniques. Qualitative research on the other hand aims more to discover the qualitative phenomenon for example human behaviour, opinions or motive and examines the why's and the how's. (Kothari 2004, 3–5.)

In this thesis mainly the qualitative approach to research will be employed. To be able to statistically analyse the different forecasting techniques which are currently employed at the case company, the actual values of the procurement savings for the year 2016 would need to be available. Since these values are not yet available, it is impossible to analyse, compare or yield reliable development proposals based on statistics. Thus this thesis will be done mainly as qualitative research, and the development proposals yielded will be based on this qualitative research rather than statistics. Nonetheless a small section will be included, where statistical methods to measure the forecast accuracy will be presented.

The data for the framework of this thesis will be collected from a variety of academic sources. The literature selected for the framework will generally consist of business forecasting related literature, case studies and findings regarding the different forecasting methods and techniques. In more specific the selected literature will have an emphasis on the forecasting techniques which are currently being employed at the case company. In addition, the framework will combine literature on risk and uncertainty assessment and on the simulation approach to forecasting.

The author of this thesis has worked as a Controlling and Finance -department intern in the case company, and thus has been deeply involved in the procurement savings forecasting process. The acquired knowledge has been gathered through participant observation during the author's internship. In addition, document analysis has been performed on the case company's internal materials regarding the different forecasting techniques. Furthermore, the author has been substantially involved in the process of introducing and modelling the simulation forecast at the case company. This new simulation based forecasting technique was introduced during the author's internship as a new approach to produce the procurement savings forecasts and assess the forecast related risks and uncertainties.

This thesis will not include specific data collection and thus secondary data will be used. The secondary data which will be used in this thesis, will be the acquired working knowledge of the case company's forecasting techniques and processes and the studied and combined academic literature based framework. In the last parts of this thesis the case company's techniques will be reflected to the framework and analytically analysed.

1.5 Thesis structure

Simplistically explained research can be said to be a search for knowledge, and thus it is an author's original contribution to the existing knowledge of the researched topic. Even though research process has several connected activities, these can be seen as more overlapping and continuous rather than strictly individual and distinctive. Kothari (2004, 1, 12) presents a procedural guideline concerning the research process, where the first step of the research process is the formulation of the research problem. (Kothari 2004, 1, 12.)

In this thesis the research problem or the reason for conducting the research is the case company's desire to identify ways to develop and improve the procurement savings forecasting techniques, emphasis on the simulation based forecast model. Thus in this thesis the research objective is to identify and discuss possible approaches to optimize and develop the forecasts, mainly in sense of the forecast accuracy.

After the formulation of the research problem and the definition of the objectives, the available literature and other materials will be reviewed and combined. In this thesis the following chapter, forecasting methods and framework, will present the reviewed, selected and combined literature. Since forecasting is not an exact science, the framework provided in this thesis will be used to assess the different features of the forecasting techniques and their compatibility for the case company's purposes. Fundamentally the case study, the overall research and the development proposals will be reflected and analyzed through the reviewed literature and materials.

After presenting the framework, the following chapter of this thesis will introduce the case study. In the case study chapter of this thesis the case company, BuyIn, will be introduced in more detail. The procurement savings forecasting techniques and the process of producing the savings forecasts at the case company will also be presented in this part of the thesis. The author will present each of the methods and techniques employed at the case company, with an emphasis on the new simulation based forecast model.

After presenting the forecasting techniques employed at the case company, the following chapter will concentrate on comparing and evaluating the forecasting techniques and the different features of these techniques. This analytical analysis and comparison will aim to identify the differences of these techniques and what are the benefits or drawbacks they present for the case company. In addition, this chapter will include discussion and analysis of the applicability of the simulation forecast to other departments within the case company.

After presenting the case study and the comparison of the forecasting techniques, the following chapter will discuss the yielded development proposals. These proposals will be made for individual forecasting techniques and models, and for the complete process of producing the procurement savings forecasts at the case company. In addition, this chapter will include suggestions on new, not yet utilized methods and techniques the case company could test, measure and evaluate, to possibly improve the quality and reliability of the procurement savings forecast.

The final chapter of this thesis will be the summary and conclusion on the provided forecasting framework, the presented case study and comparison, and on the yielded development proposals. In this part the author will shortly summarize what has been done in this thesis and will conclude on the overall forecast related findings. In addition, any open or unanswered research questions will be discussed in this part of the thesis, together with possible further research studies related to this case study.

2 FORECASTING METHODS AND FRAMEWORK

2.1 Forecasting methods

According to Harris (2014, 16) forecast can be said to be any statement concerning the future. The future is always unpredictable, but being able to produce fairly accurate forecasts is an important part in helping the companies to function and perform effectively and efficiently. Forecasts are made to estimate some activity level in the future for example inventory levels, demand, sales volume or in the case company of this thesis, the forecasts are produced to estimate the secured procurement savings value in a calendar year. (Harris 2014, 16; Samonas 2015, 88.)

There are various ways to divide and group different forecasting techniques, but according to Mun (2010, 371–372) the forecasting methods can broadly be divided into two categories, qualitative forecasting methods and quantitative forecasting methods. These qualitative and quantitative forecasting methods can then be further divided into a vast number of different forecasting techniques. This is presented in figure 1. (Mun 2010, 371–372.)

Qualitative approach to forecasting is seen as subjective in nature and it is also referred as judgemental forecasting. This method is purely based on individuals' or groups' opinions, expertise and judgement on the topic at hand, to turn qualitative information into quantitative estimates. For the most parts this method is used when there is only limited amount or no historical data available on the item being forecasted. Even though some analysis of the possibly available data may be performed in the qualitative approach, the basis of this forecasting method is subjective judgment. (Chambers, Mullick & Smith 1971; Mun 2010, 371–372; Montgomery et al. 2015, 4.)

On the other hand, quantitative approach to forecasting uses the available historical data and a forecasting model of some kind, in producing the forecasts. The quantitative forecasting method is based on the assumption that the past and the current data can be used in estimating the future activity levels. According to Mun (2010, 371–372) the quantitative forecasting method can be further divided into three main quantitative forecasting techniques, which can be identified in figure 1. These three techniques include time-series methods, which use the available historical data in a chronological order, cross-sectional methods in which the values of the historical data are time-independent and mixed panel methods which are a mixture between panel data or external data and time-series data. (Mun 2010, 371–372; Montgomery et al. 2015, 5.)

From the two presented forecasting methods the case company of this thesis is utilizing both the qualitative and the quantitative approaches to forecasting. More specifically the forecasting techniques currently being used at the case company are the qualitative experts' opinions approach and the quantitative cross-sectional Monte Carlo simulation approach. These can be identified in figure 1.

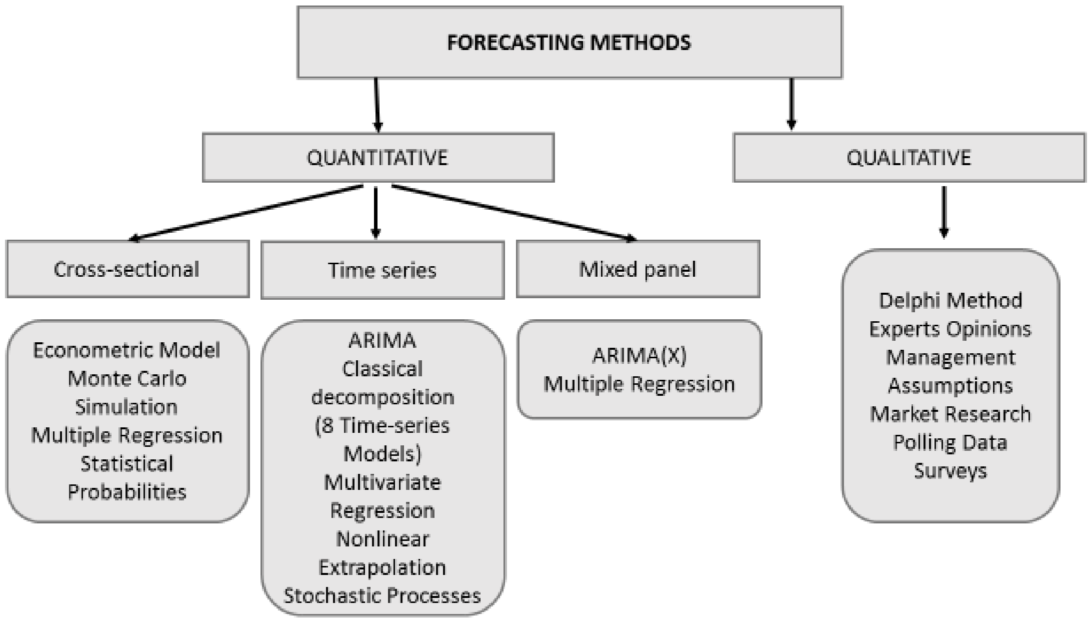

FIGURE 1. Forecasting methods (Mun 2010, modified)

Literature can be found for and against both quantitative and qualitative forecasting methods. According to Harris (2014, 28–31) there have been researches which indicate that forecasts which are judgmentally adjusted tend to perform more accurately compared to pure statistical models. This also means that instead of making biased assumptions or overrides to the forecast, the importance is in applying unbiased judgement. Supporting this Chase (2013, 8) introduces a concept of domain knowledge, which means the use of impartial business and market knowledge and experience when making qualitative assumptions or overrides. (Chase 2013, 8; Harris 2014, 28–31.)

On the other hand, Chase (2013, 82–83) claims that quantitative methods tend to perform better compared to qualitative methods. This is claimed mainly because in the judgmental forecasts individuals or groups tend to implement biased judgement and thus the produced forecasts are not accurate nor consistent over time. Because there is no distinct optimal way to produce the forecasts, in most cases, the best approach to forecasting is to test and measure both qualitative and quantitative techniques and investigate how the different forecasting methods perform. In many cases, companies or forecasters implement a forecasting model which utilizes parts from both qualitative and quantitative methods. (Chase 2013, 82–83.)

There are a number of problems related with the judgmental forecasting method. According to Montgomery et al. (2015, 542–543) humans are inconsistent in choosing the input factors for the forecast, and in the way those factors are weighted. This is one possible source of error in judgemental forecasting. Another problem comes from humans usually highlighting the most recent events, again if those events are random in nature and not consistent this might lead to an error in the forecast. Too optimistic or pessimistic thinking is one of the main sources of forecast errors in addition to humans' poor ability to forecast variability or uncertainty. Since there is no historical data employed in the judgmental forecast, the accuracy of the forecast depends only on the human made input assumptions. (Montgomery et al. 2015, 542–543.)

In the quantitative methods, the approach to forecasting is to use historical and current data as basis to forecast the future. This is a relatively good starting point, but leads to the problem of history not always repeating itself or even rhyming. Just because something happened in the past, does not mean that it will happen in the future. The forecast models purely based on historical data are also weak in considering sudden changes in the overall business environment or the forecasted area. Thus forecasting models that rely purely on the historical data available, might not be so accurate in the long run. According to Gilliland and Platt (2010, 32) even if there are historical data points available, which can be used as input assumptions or to build a forecast model, this does not ensure that the model based on historical data will deliver good and accurate forecasts. (Gilliland & Platt 2010, 32; Harris 2014, 10.)

2.2 Measuring forecast performance

One of the most important parts of a successful forecasting process is the measuring of the forecast performance. The forecast performance has to be measured, so corrective actions can be taken and the forecast performance can be improved. Forecast performance cannot be improved if the current forecast is not measured and benchmarked during the forecasting process.

Chase (2013, 106–107) provides two specific objectives as to why measure forecast performance. The first reason is to measure how well the actual outcome of what is forecasted, can be estimated. This can also be seen as the accuracy of a specific forecasting technique or a model on a specific time. The second reason is to compare the different methods and techniques being used for forecasting, to see which of these is the best technique to predict the future outcome. Because the forecast performance cannot be improved unless it is measured, the process of measuring the forecast performance should be an ongoing learning process rather than a one-time occurrence to evaluate the performance of one technique on a given time. (Chase 2013, 106 – 107.)

In this thesis the objective is to yield development proposals to improve the performance of the different forecasting techniques, in the sense of improving the accuracy of the forecasts. The term forecast accuracy refers simply, to the accuracy of the produced forecast. In other words, how precisely some future event can be estimated. Forecast accuracy is one way to measure the overall forecast performance, and it can be measured in variety of ways.

When measuring the forecast accuracy only in the aggregated, overall level of the forecast, the lower levels' plus and minus errors cancel each other out, making the overall forecast accuracy seem much better. Thus it is advised to measure the forecast performance also in the lower, disaggregated levels of the forecast, since all the improvements made in these lower levels will also improve the accuracy of the aggregated overall forecast. (Chase 2013, 103–104.)

According to Chase (2013), the best way for a company to start the process of improving the forecast performance, is not always to set a forecast accuracy target. Companies are likely to be overoptimistic in regards of their original forecast accuracy goals, which might lead to failure in the continuous process of forecasting. Instead it is suggested that a better approach would be to set a target for improving the accuracy of the forecast. This can be done by measuring the current forecast accuracy, benchmarking it and then setting a percentage target to improve this forecast accuracy. (Chase 2013, 104–105.)

2.3 Forecast accuracy

2.3.1 Forecast error

Forecast accuracy can be measured in various ways. To evaluate the accuracy of the forecasting techniques it is important to use genuine forecasts. This means that the forecast accuracy can only be defined when evaluating how well the forecast model performs on new data, which are not used for the model. Even if a model fits to the historical data, this does not always indicate that it will forecast accurately in the future. Thus to obtain a view of the accuracy, the forecasted and the actual data are needed. (Hyndman 2014, 1.)

No forecast is perfect and thus, forecast errors will always occur. To improve the forecast, the purpose is to minimize these errors. The measuring of the forecast accuracy in relation to measuring the forecast performance, always starts at the measuring of the forecast error. The forecast error can be determined as the difference between the actual value and the forecasted value for a specified time period. Thus the forecast error is displayed in unit terms for the forecasted period. The equation for the forecast error calculation can be written as follows. (Chase 2013, 107–108.)

$$\text{Error} = e_t = F_t - A_t \qquad (1.)$$

Where e_t = error for time period t

F_t = forecast for time period t

A_t = actual value for time period t

A positive forecast error indicates that the produced forecast for a specified time, for example forecast on the sales of a company for the next six months, was larger than what actually happened, the actual sales of the company during that six months. This is also called as “over-forecasting”. A negative forecast error on the other hand indicates that the forecasted value was smaller than the actual value. This is also called as “under-forecasting”. This way of calculating the forecast error is preferred as it compares the actual values to the forecasted values and in further error calculations this approach seems to be more unbiased. (Chase 2013, 107–110.)

2.3.2 Forecast percentage error

The unit error values are in many cases converted into a percentage form. This is also known as the forecast percentage error or PE. To display the error in the forecast as a percentage error, instead of unit terms is favored since it is more descriptive and scale-independent. The forecast percentage error, if calculated similarly from different forecasts, can be used to compare the accuracy of the different forecasts. It is more understandable and comparable to conclude that the forecast percentage error was 13% instead of the forecast error being 3,2 million euros. (Hyndman 2014, 3.)

There are different ways to calculate the forecast percentage error, but following the already established forecast error approach it can simply be calculated as the difference of the forecasted value and the actual value, the already introduced forecast error, divided by the forecasted value and, and to turn it into percentage multiplied by hundred. According to Chase (2013) this way of calculating the forecast percentage error is preferred, since it seems to be more unbiased towards over-forecasting and under-forecasting compared to other ways of calculating the percentage error. In addition, in business environments the actual values are normally compared to the forecasted values. This approach will also clearly indicate if the error in the forecast was positive or negative. The equation for the forecast percentage error can be written as follows. (Chase 2013, 108–110.)

$$\text{Percentage error} = PE = (F_t - A_t) / F_t \times 100 \qquad (2.)$$

Where e_t = error for time period t

F_t = forecast for time period t

A_t = actual value for time period t

2.3.3 Measures of bias

The first important aspect of forecast accuracy measurement is the possible bias, the direction of the forecast error. There are two common measures to evaluate if the forecast is biased, the mean error or the ME and the mean percentage error or the MPE. These measures can be used to evaluate if the employed forecast model is biased, and has a tendency to under-forecast or over-forecast. (Taming Uncertainty… no date, 3, 8.)

The mean error can be measured by summing up all the forecast errors of specific forecasting technique and computing the mean. The mean percentage error is similarly the average of the percentage errors. The ME and MPE are not accurate measures to evaluate the magnitude of the forecast errors occurring in the time period, since the negative and the positive errors cancel each other out when calculating the ME or the MPE. Thus this method works as a measure of bias in the forecast. Following the already presented equation to calculate the forecast error (1.) and the forecast percentage error (2.), a positive ME or MPE indicates that the forecasting model tends to over-forecast, whereas negative ME or MPE indicates that the forecasting model tends to under-forecast. (Chase 2013, 112; Taming Uncertainty… no date, 3, 8.)

2.3.4 Measures of precision

The second important aspect of forecast accuracy measurement is precision, the magnitude of the forecast error. There are two common measure to evaluate the forecast precision, the mean absolute error or MAE and the mean absolute percentage error or MAPE. These measures can be used to evaluate the overall magnitude of the errors in a specific forecasting technique. (Taming Uncertainty… no date, 3, 10.)

The mean absolute error and the mean absolute percentage error are calculated similarly as the already presented ME and MPE, but from the absolute forecast error and absolute forecast percentage error values, disregarding the minus and plus signs. Thus a view can be obtained of the average magnitude of the error occurring in the forecast. In other words, the lower the MAE or the MAPE the lower the average error and the higher the precision or the accuracy of the forecast. However, unlike the measures used to evaluate the forecast bias, the MAE and the MAPE do not give any indication on the direction of the error. (Chase 2013, 112–113; Taming Uncertainty… no date, 3, 10.)

2.4 Measuring forecast process performance

According to Chase (2013) companies tend to measure the forecasts mainly on the aggregated levels, and only few companies measure the lower level forecast performance on all the branches of input. Measuring the lower level performance as well would be critical for identifying the points or inputs in the forecast which do not add value to it. If these points, actions or inputs in the forecast can be identified, they can either be improved, or preferably eliminated completely to improve the overall forecast performance in the sense of accuracy and efficiency. (Chase 2013, 118–119.)

Forecast value added or FVA is a methodology which is used to measure the forecasting process performance and efficiency. Simply, in the forecast value added method the focus is on the change in the forecast accuracy after each step or change done during the forecasting process. In other words, are the efforts during the forecasting process adding value to the forecast or making it worse. Thus FVA is the change in some selected performance metric, which can be assigned to a particular participant or step in the forecasting process. (Gilliland 2015, 1.)

FVA can be implemented by using any selected forecast performance measurement, such as the already introduced percentage error, to measure how the different steps in the forecasting process change the overall accuracy of the forecast. Thus with a selected performance metric, it can be measured if specific activities or input assumptions have a positive FVA and are increasing the accuracy of the overall forecast or have a negative FVA and are decreasing the overall forecast accuracy. (Chase 2013, 120; Gilliland 2015, 1.)

Being able to implement the forecast value added requires the companies to record the forecast before and after every new input during the forecasting process. By recording the forecast after each touch point it is possible to measure if the activities or inputs completed during the forecasting process are value-adding or not. According to Chase (2013, 122) companies that utilize forecast value added method have been able to improve their overall forecast accuracy. If the non-value adding actions or inputs cannot be improved, by eliminating these factors completely the forecast accuracy will automatically increase and the forecasting process will get more efficient and effective. (Gilliland & Platt 2010, 23; Chase 2013, 122.)

2.5 Risk and uncertainty assessment

According to Gilliland and Platt (2010, 25–26) a practical approach to forecasting is to identify that forecast accuracy has its limits. Even though there is a forecast that does not eliminate all the uncertainties and thus the risks of the situation. Forecasts are never perfect, hence it is important to prepare for some uncertainties and risks regarding the forecasted item. (Gilliland & Platt 2010, 25–26.)

Uncertainty can be explained as a possibility or a probability of some event occurring, and risk as the consequence of such an event. Thus risk is the outcome of some uncertain event happening. For example, if you bet 5€ that with a single coin toss you will get tail, the related uncertainty is head appearing instead of tail, and the risk is you losing the 5€. On the other hand, even if there are uncertainties in some situations, there might not be any risk at all, and thus uncertainty does not equal to risk. Risks and uncertainties can decrease and increase independently and resolve through the passage of time. (Mun 2010, 12–14.)

There are variety of ways to measure risks. Some of the more frequently used measures are the probability of occurrence, how likely it is that some event occurs. This probability of occurrence can be obtained through risk analysis, for example by employing the Monte Carlo simulation. Another commonly used method to measure risk is the standard deviation, which is the average of each data point’s variance from the mean. The standard deviation can be obtained from a given data set by computing it, but many statistical or software tools can calculate this automatically. The higher the standard deviation the wider the range and the higher the risk. By quantifying and analyzing the risks in a given situation, companies are able to make better informed business decisions. (Mun 2010, 42–43.)

When talking about the risks related to some situation, or in the case of this thesis the risks related to the value of the secured procurement savings, if there are opportunities these can be seen as “positive risks” with the same kind of uncertainty related qualities. At the case company Monte Carlo simulation, a simulation based approach to forecasting, was introduced as a new technique for producing the procurement savings forecast. Besides further developing the forecasting techniques, Monte Carlo simulation also enables the quantification of the risks, opportunities and uncertainties via the probabilistic simulation functions.

There is no guarantee for a perfect, or even for a highly accurate forecast (Gilliland & Sglavo 2010). Thus it is important to be able to quantify the risks and uncertainties related to the forecasted value. Instead of producing a single value forecast output, by implementing the Monte Carlo simulation, which uses the method of probability of occurrence, a more wide-spread and descriptive picture of the forecast related risks and uncertainties can be obtained.

2.6 Single value forecast approach

A single value forecast is a forecast which only produces one output or forecast value. For example, the sales of a company for the next six months are 3,5 million euros, would be a single value forecast. According to Chase (2013, 17–18) the idea of a one-number forecast is too simple. As forecasts are usually more wrong than right and almost never perfectly accurate, a sole one number is too naïve approach to forecasting. Instead, the forecast output should consist of several numbers, providing more descriptive picture of the forecast. (Chase 2013, 17–18.)

A single value forecast can be obtained from almost every forecasting model. The problem with this approach is that companies tend to rely too much on this one number, and not consider the possibility of risks occurring. If there is no indication on the possible risks and uncertainties related to this single value forecast, the actual values might end up being something completely different. These kind of errors, looking only at a single value forecast and not considering other possibilities, can easily lead to poor decision making within the company. (Chase 2013, 17–18; Moore & Haran 2014.)

Usually forecasting starts with the creation of the most likely case, the most probable values for each input factor, which gives a single value forecast output. In addition to this single value approach, a what-if analysis provides simple insight to the sensitivity of the forecast. By changing one or several input parameters, a view can be obtained on how these changes affect the output of the forecast. (Charnes 2012, 1.)

2.7 Scenario forecast approach

Another common approach to forecasting is to calculate a what-if or a scenario analysis. One of the most common scenario forecasts consists of the best case, the worst case and the most likely case. These scenarios can be produced by calculating the best, the worst and the most likely values for the different input factors of the forecast. After allocating the different values for the input factors, it is rather simple to calculate the values for each of these three cases. By creating the scenario forecast of the best case, the worst case and the most likely case a range of the possible outcome values can be obtained. (Charnes 2012, 1.)

The scenario analysis or scenario approach to forecasting gives a spectrum of possible outcomes instead of a single value. This approach has some kind of quantification of the possible risks, the worst case scenario, and the possible opportunities, the best case scenario. For companies and decision makers the scenario forecast, providing a range of possible outcomes, is more informative than a single value forecast. On the other hand, if the range is too large, counting for all the extreme possibilities from catastrophes to lottery wins, the forecast is not very informative. Similarly, if the range between the worst case and the best case scenarios is too narrow it might not be accurate, and it might miss the actual value. (Moore & Haran 2014.)

Even though adding more spread and being more informative compared to the single value forecast, there is criticism against this approach as well. According to Charnes (2012, 1) it is unlikely for all the input values to be either the best possible or the worst possible at the same time, the problem with informativeness. On the other hand, Moore and Haran (2014) claim that even more often, the range between the worst case and the best case is too small, and the actual value does not land between the produced scenarios. Besides the accuracy-informativeness trade off problem, another fallback of this approach is that it does not quantify the uncertainties. Even though there are the most likely case and the best and the worst cases, this approach does not give any indication regarding the probabilities, the likelihoods of any these scenarios occurring. (Charnes 2012, 1; Moore & Haran 2014.)

2.8 Monte Carlo simulation approach

2.8.1 Monte Carlo simulation

Monte Carlo simulation simply put, is a random number generator for the uncertain input factors. The method of simulation can be used among other things for forecasting, risk analysis and risk quantification. In a way Monte Carlo simulation is like a scenario analysis, but instead of calculating three different scenarios it can be used to calculate even tens of thousands of different scenarios. (Mun 2010, 81–82; McLeish 2011, 78.)

In Monte Carlo Simulation the uncertain variables or input factors for the forecast, can be replaced with assumptions, predefined probability distributions, instead of single value assumptions. Thus the single value input estimates can be changed to be a range of possible values for each uncertain forecast input. When running the simulation, it the randomly picks a value from the predefined range, from the probability distribution, to be the input parameter for the forecast. By employing a range of possible values as input instead of a single value, a more realistic picture of the future can be obtained. (What is… no date, 1; Mun 2010, 82.)

For example, if a forecast has five uncertain input factors, all these can be replaced with probability distributions, so with a range of values. When the simulation is run for example ten times, the outcome would be ten different scenarios, so ten different forecasts, where the individual input values have been picked from the distributions assigned to them. All the produced scenarios would then accumulate to the outcome of the simulation forecast, which would also be in a form of probability distribution. Thus Monte Carlo simulation uses probability distributions and the probability of occurrence in quantifying the risks and uncertainties in the overall forecast. (What is… n.d., 1-3; Mun 2010, 81–85.)

By analyzing the output of the forecast, the probability distribution statistically, conclusions can be made regarding the riskiness of the simulated situation. Thus simulation based approach provides the ability to quantify and analyze the risks and uncertainties related to the forecast, which then helps the companies to make better informed business decisions. (Charnes 2012, 2–4.)

There are many different software programs providing Monte Carlo simulations. At BuyIn Oracle Crystal Ball was selected as a software tool to introduce and develop the simulation based forecast, and run the Monte Carlo simulation. Hence this was a completely new technique, implemented to forecast the procurement savings and to quantify the related risks, opportunities and uncertainties.

2.8.2 Benefits and limitations of Crystal Ball

As Crystal Ball is only a software tool providing support for the process of forecasting and risk analysis, besides the benefits it yields, there are some limitations associated with this software program. According to Charnes (2012, 9) some benefits related to Crystal Ball are the built in sensitivity-analysis tools, which aid in discovering the key input factors, as well as the graphs and the statistics the program automatically provides for the forecast output. Moreover, Crystal Ball can be installed to personal computers as an Excel add-in which makes it wildly accessible, in addition to its user friendly features and easy to use functions. (Charnes 2012, 9.)

On the other hand, as it is an analytical tool, the input data validity is a critical factor for success. Like in any other technique used to creating forecasts, the output is only as good as the input, and thus if the input assumptions are not valid neither is the forecast output. One of the main benefit of the tool is also one of the main limitation of Crystal Ball – as it is an Excel add-in, if a model cannot be built in Excel, Crystal Ball cannot be used to simulate it. Thus Crystal Ball is subjected to the limitations of Excel. Additionally, there is some academic criticism in regards of Crystal Ball giving an approximate solution with the simulation, rather than an exact one. (Charnes 2012, 9–10.)

2.8.3 Simulation process

When building a simulation model, the process usually begins with building a deterministic model in Excel of the situation being forecasted or analyzed. In deterministic model all the input factors or assumptions are fixed and thus it produces only a precise outcome, so a single value output.

After a model is created, Crystal Ball can be used to add stochastic or probabilistic assumptions to the uncertain variables, or the inputs of the model. In a straightforward way the simulation modelling process consists of four activities. Creating a model and adding probabilistic input variables, running trials to learn how the simulation model behaves, continuously customizing the model until it is credible, and finally analyzing the forecast or the output graphs and statistics to help in decision making or in identifying points for further improvement. (Charnes 2012, 29.)

One of the most important elements in the forecast model building process is the documentation of the model and the input assumptions. It is crucial to keep track of the model, the input assumptions and the changes made during the forecasting process to be able to correctly analyze and measure it later. In addition, to avoid mistakes and make the simulation process clearer and easier, it is advised to have different worksheets for inputs, calculations and results or outputs of the model. (Mun 2012, 56, 59, 62.)

2.8.4 Simulation input

To take advantage of the simulation based forecasting technique, assumptions have to be set for the uncertain variables or the inputs of the forecast. Crystal Ball provides a variety of probability distributions which can be defined and selected as the input assumptions for the forecast. In the following the basic probability distributions provided by Crystal Ball (figure 2) will be introduced together with presenting how to incorporate the available historical data to create an input assumption for the forecast.

Yes-No distribution (figure 2), also known as Bernoulli distribution is perhaps one of the simplest probability distributions. In this distribution the random variable has only two possible outcomes, zero or one. This distribution can be used for example to represent a simple coin toss, where the 0 is "head" and the 1 is "tail". (Charnes 2012, 37.)

With Discrete Uniform distribution (figure 2) equal probabilities can be assigned to all integer numbers between the selected values. This distribution can be used for example to mimic a fair rolling of dice. All the numbers from one to six have an equal probability to be on the top of the dice when rolling. (Charnes 2012, 41.)

Uniform distribution (figure 2) is used when the maximum and the minimum values are known, but the likeliest value or other specifics are not known. With this probability distribution equal likelihoods can be assigned to all values between the minimum and the maximum, not only for integer numbers. This is called a continuous probability distribution. If more information becomes available, uniform distribution should be changed to a more specific probability distribution to attain more accurate results. (Charnes 2012, 45.)

Triangular distribution (figure 2) is as its name indicates a triangular shaped probability distribution, to which the minimum, the maximum and the likeliest values need to be known. It is also a continuous distribution, but compared to uniform distribution one more data point, the likeliest value is needed to specify it. Compared to normal distribution, which is introduced next, the tails are over emphasized and the middle values are under emphasized in a triangular distribution, and thus it should be replaced if more accurate estimates become available. (Charnes 2012, 46–47.)

Normal distribution (figure 2) is also a continuous probability distribution and it characterizes many natural phenomena. It is symmetrical and only two parameters are needed to specify a normal distribution – mean and standard deviation. In normal distribution mean also equals to median and mode because of the symmetry of the distribution, and standard deviation is a measure that quantifies the amount of variation in the data. For example, the rate of return on stocks or sales revenue might be modelled with normal distribution. Even though not all random variables are normally distributed, for stochastic assumptions it usually works rather good as a first input assumption. (Charnes 2012, 47–48.)

Lognormal distribution (figure 2) is a continuous probability distribution and it also needs two parameters, mean and standard deviation, to specify it. Lognormal distribution characterizes a random variable which has a normally distributed logarithm. A random variable which is lognormally distributed can only have positive values, hence the lognormal distribution is bound to zero on the left side. Many variables can be modelled with lognormal distribution for example, stock prices or salaries in an organization. (Charnes 2012, 53–55.)

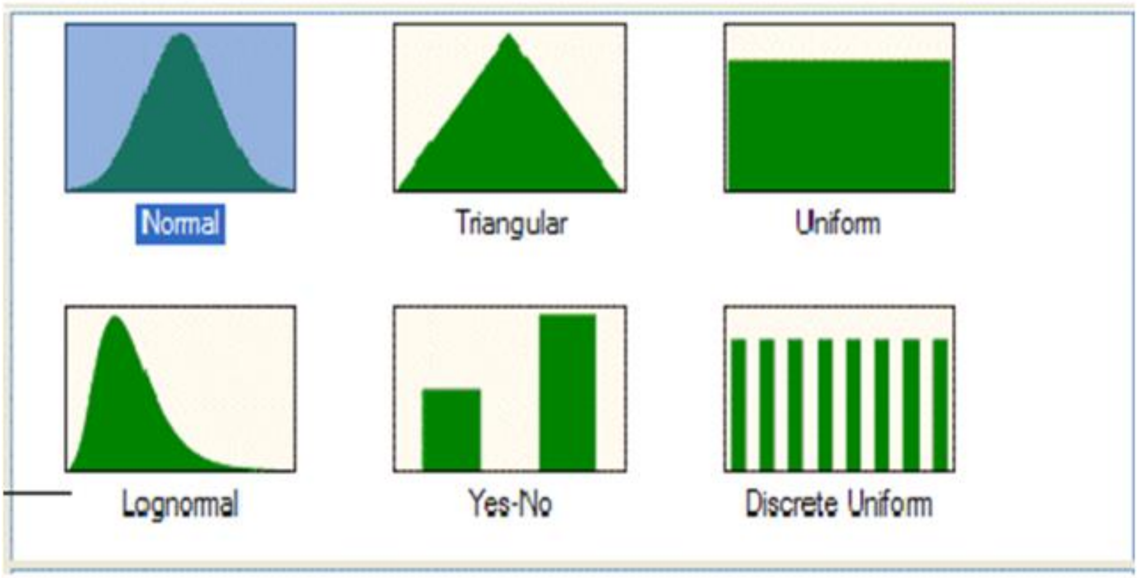

FIGURE 2. Basic probability distribution of Crystal Ball (Oracle)

If historical data are available on the uncertain input factors of the model, this can be utilized in Crystal Ball. There are two ways to employ historical data to create the input assumptions, direct sampling and sampling from a fitted distribution. Direct sampling method uses the historical data values directly in the simulation. This means that the simulation can only use the exact values which are in the given historical data set. Besides this, another downside of using direct sampling is that the amount of historical data values available is usually smaller compared to the number of times the simulation is run. This leads the simulation to pick the same values for several times, which might lead to decreased forecast accuracy. (Charnes 2012, 55–58.)

Crystal Ball can also be used to fit a continuous distribution to the historical data available. The process of fitting and selecting the distribution is almost automatic. Of course some judgment and working knowledge is required to use this method efficiently, and to ultimately select the most suitable probability distribution. This method is favored over direct sampling because of its continuous and smooth nature. A downside is that to utilize this method, a good enough distribution needs to be found. Crystal Ball has a built in goodness of fit assessment but it is also recommended to visually compare the historical data points to the distribution suggested by the program. Not always is the highest ranking distribution the best and not always can a distribution be fitted to the available historical data set. (Charnes 2012, 58–63.)

2.8.5 Simulation output

When the model is ready and the simulation is run, Crystal Ball automatically calculates and collects each of the trial values and displays the statistics and graphics of the outcome. Like the input assumptions, the outcome of the simulation forecast is also in a form of probability distribution, this can be seen on the left in figure 3. In addition to the probability distribution Crystal Ball also provides other graphics such as the cumulative and reverse cumulative distributions.

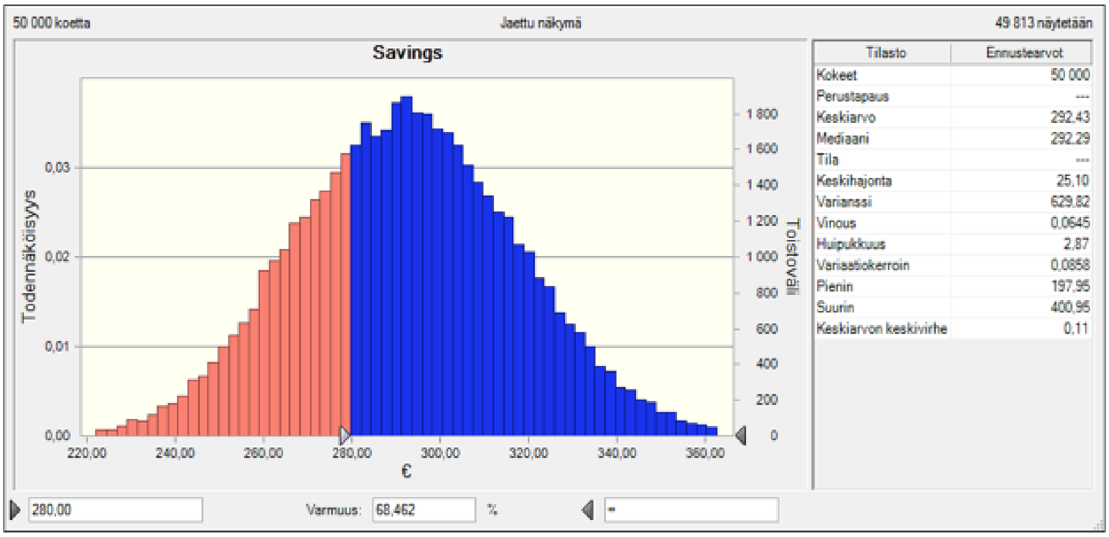

FIGURE 3. Simulation forecast output

In addition to the forecast output graphics, Crystal Ball also provides the most important statistics related to the forecast output. This can be seen on the right in figure 3. These statistics are produced automatically, and generate a more descriptive picture of the forecast output compared to a single value or a three-point scenario. The statistics window summarizes the key performance indicators of the forecast. (Mun 2010, 105–106; Charnes 2012, 27–28.)

In the statistical view the key performance indicators are displayed according to the following four moments. The first moment according to Mun (2012, 37–41) is the measurements for the center of the distribution – mean, median and mode. In the second moment the spread of the distribution is measured, this can also be seen as the measure of risk. Standard deviation, variance and volatility can be used to measure the width or risk of a variable. The third moment measures the skewness of the distribution. This indicates the asymmetry of the distribution to either left or right. In a skewed distribution the mean is always closer to the tail of the distribution. In the fourth moment kurtosis, or the tailedness of the distribution, is measured. High kurtosis indicates thicker tails and thus a higher probability for extreme events on the left and right side of the distribution. All these statistics are automatically provided by Crystal Ball, and help in analyzing the forecast output. (Mun 2012, 37–41.)

Even though Crystal Ball automatically provides the key statistics regarding the forecast output, the results still need to be analytically analyzed. For example, the mean of the output distribution cannot be expected to be the actual value occurring. Instead of looking the individual values provided by the tool, the output should be seen and analyzed as a whole. All the information, the complete output probability distribution, should be seen as the end forecast, and the decisions or actions taken based on the forecast output should be done accordingly.

3 THE CASE OF BUYIN GMBH

3.1 Case company introduction

The case company of this thesis is BuyIn GmbH. BuyIn is a procurement alliance founded in 2011 by Deutsche Telekom and Orange (France Telekom) and it operates in the field of telecommunications and information technology. BuyIn, as a procurement alliance provides strategic procurement services to its mother companies and customers. Headquartered in Brussels Belgium, BuyIn has over 400 employees with over 25 different nationalities. Currently BuyIn operates in more than 40 different countries in four continents, with the main procurement activities being done across Europe and Africa. (BuyIn.)

When providing strategic procurement services and bundling the procurement power of 40 countries, BuyIn can combine over 25 billion euros of annual spend of its mother companies and customers. By leveraging these economies of scale in delivering the procurement services, BuyIn can increase the competitiveness and generate substantial procurement savings to its stakeholders. In just over three years BuyIn has been able to generate savings totaling in over 1 billion euros. (BuyIn.)

BuyIn’s annual spend and business activities are divided into four central business areas. These four different domains within the company are Information Technology, Digital Home and Platforms, Network Technology and Customer Equipment domains. Thus BuyIn aims to generate procurement savings in these different domains by combining the spend of its mother companies and leveraging the economies of scale. (BuyIn.)

BuyIn has the before mentioned four different domains within the company, and the author of this thesis has worked as a Controlling and Finance intern within one of these domains. This thesis is concentrated to this one specific domain, its forecasting techniques and the overall forecasting process. The author has been deeply involved in the process of producing the forecasts within this domain and furthermore, in the process of building the simulation based forecasting model.

In this domain the procurement activities are done in a variety of different regions. Thus the procurement savings are calculated, reported and forecasted individually for every region. From these different regions, the case study describes and concentrates on the procurement savings forecasting on one specific region within the domain. Nonetheless, the qualitative forecasting techniques employed at BuyIn, presented later in this chapter, are similar for all the regions within this domain. In addition, similar qualitative forecasting techniques are employed in three out of four of the already mentioned domains at BuyIn.

The specific domain of this thesis consists of five smaller categories, to which all the procurement projects within this domain can be allocated. Further there are two different engagement models specifying BuyIn's level of involvement in these procurement projects. Thus all the projects within this domain can be divided into five categories and further into two types of engagement models.

Although this thesis has the emphasis on only one of the domains, and on one of the regions within this domain, the next introduced procurement savings are calculated similarly for all of the regions within this specific domain. In addition, the procurement savings are calculated similarly in three out of four of the domains within BuyIn.

3.2 Procurement savings at BuyIn

In this thesis the forecasted item and thus the importance is on the secured procurement savings at BuyIn. Instead of sales or income, BuyIn is steering with the procurement savings it provides for its stakeholders. Therefore, BuyIn has a procurement savings target for a calendar year, against which these savings are calculated and reported each month. In this thesis, the concentration is on forecasting these secured procurement savings for a calendar year.

The procurement savings come from variety of different procurement projects, which are all displayed and tracked in BuyIn's internal project management tool. In this tool, all the projects regardless of status, draft, cancelled, planned, started and already signed and secured are in. During the business year new projects are coming in to the project management tool and the statuses of the projects change accordingly during the year. Planned projects get started and started projects get signed and secured, and sometimes already started projects get cancelled or put to on-hold. Thus the project management tool tracks all the projects within the tool on a continual, real time basis.

At BuyIn the procurement savings are calculated within the domain from these domain projects against a pre-defined procurement spend baseline. Against this spend baseline, all the projects have either zero, negative or positive savings which are, besides savings as a unit figure, also displayed as a savings ratio. Thus all the projects in the project management tool, regardless of status, have a spend baseline, procurement savings and savings ratio value. The savings ratio at BuyIn is calculated as the value of the savings divided by the value of the spend baseline. For example, a project which has a spend baseline of 2500€ and estimated savings of 500€ has a savings ratio of 0,2 or savings percentage of 20%.

The project management tool consists of a vast number of projects. All these projects are grouped as either secured projects, planned projects or other projects according to the status of the project in a given time. The different project statuses and the grouping of the projects are presented in figure 4. The secured projects group consists of projects which have already been approved or secured, whereas the planned projects group consists of to be analyzed or ongoing projects, where the negotiations have not yet been finalized. The other projects group consists of projects which have been cancelled, put to on-hold or are still at draft status. Later in this thesis the projects are referred as group, either secured projects, planned projects or other projects.

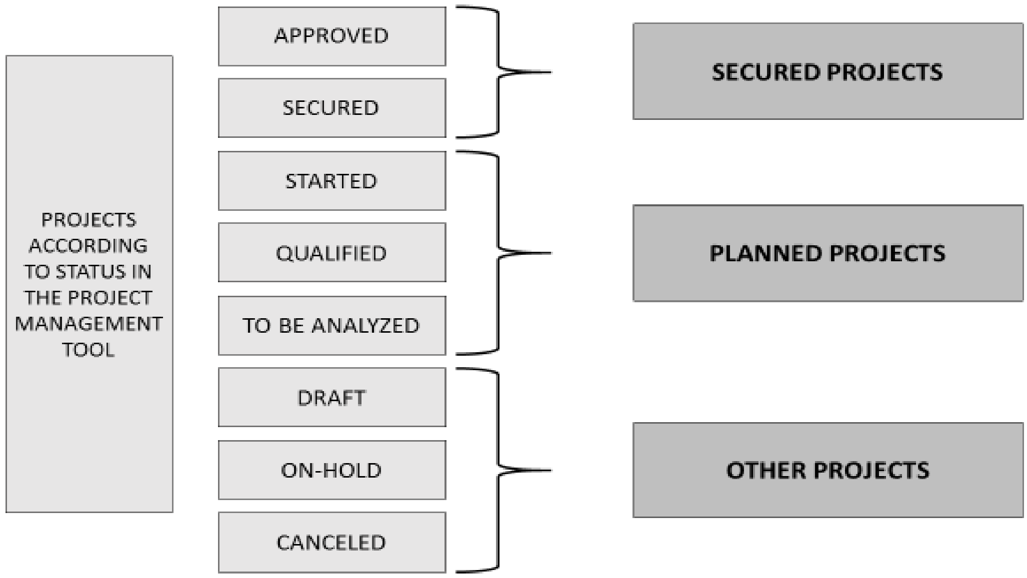

FIGURE 4. Secured projects, planned projects and other projects at BuyIn

3.3 Forecasting process at BuyIn

At BuyIn, the process of forecasting can be said to be an ongoing one. The secured and the planned procurement savings are calculated and reported every month, for the ongoing calendar year. New forecasts are also prepared each month, after getting a new data extract from the project management tool. Thus the forecast interval, the density of new forecasts prepared, is one month. The forecasts at BuyIn are always prepared in the beginning of a new month, with new complete data coming from the previous month. For example, the “June forecast” at BuyIn is the forecast prepared in early July with complete data from June. (Montgomery et al. 2015, 6.)

The forecast horizon or the forecast lead time is the number of periods in the future for which the forecast is produced. Because the procurement savings at BuyIn are calculated and reported in the end for a calendar year, and new financial reports and forecasts are produced each month, the forecast lead time at BuyIn is decreasing every month. For example, when creating the June forecast the forecasted part is only the remaining part of the calendar year, so the lead time would be six months or six periods in this example. On the other hand, when creating the September forecast the forecasted part is only the remaining three months. Thus the lead time is decreasing every month going forward in the year, and it is the number of remaining months in that calendar year. (Montgomery et al. 2015, 6.)

The forecast lead time is closely related to the accuracy of the forecast. It is easier to forecast something happening in three months compared to three years. At BuyIn the lead time in February's forecast is ten months compared to the three months in September's forecast. Thus in BuyIn's case the forecast accuracy should increase during the year. In BuyIn's case, to be able to validly and reliably compare the different forecasting techniques it is important to compare the forecasts produced in the same month, so that the lead times in the compared forecasts are the same.

If using the June forecast at BuyIn as an example, the following can be stated regarding the forecasting process. Since the forecasted item is the secured procurement savings, the secured projects and thus the secured savings from the first six months of the year are already known. Thus the forecast lead time is the remaining six months. At BuyIn the procurement savings in the already secured projects are taken in at face value for the forecast. This is because changes in the savings of the already secured projects are not extremely probable and at the same time if changes do occur those are rather small in scope. Thus the forecasted item is the amount or value of the procurement savings which will be secured during the rest, six months of the year.

3.4 The bottom-up forecast at BuyIn

BuyIn has implemented a straightforward way to forecast the procurement savings. Simply this so called "bottom-up forecast" at BuyIn is done by calculating all the already secured procurement savings and all the planned procurement savings from the project management tool, in a given month. This is also displayed in the figure 5. For example, the June forecast equals to the procurement savings from the already secured projects until June plus the procurement savings from the planned projects at that time.

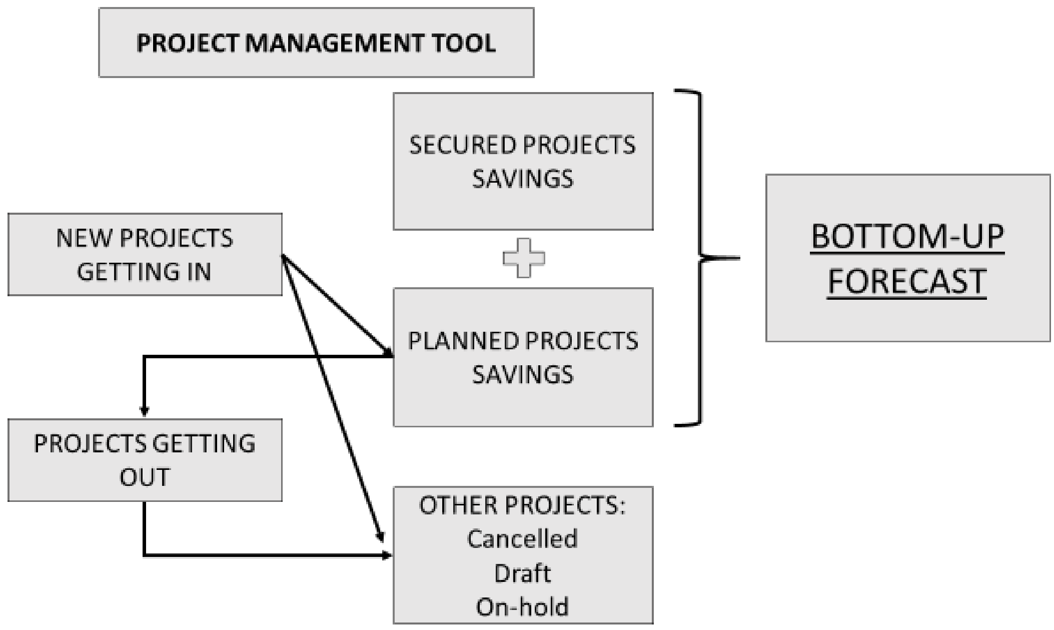

FIGURE 5. Bottom-up forecast structure at BuyIn

The bottom-up forecast at BuyIn is purely judgmental, since the project savings in the project management tool for planned projects are generally estimated by the person negotiating the project. In addition, the controlling team is supporting and challenging the negotiators with their savings estimates to ensure that the data in the project management tool would be as accurate as possible. Moreover, the major projects are reviewed on a regular basis to ensure that the baselines and the savings estimates are up to date and the data in the project management tool of high quality.

The negotiators undoubtedly have the domain specific knowledge and the knowledge of the specific category, for which they negotiate the projects within this domain. Furthermore, the negotiators are aware of the project specific features, baseline and scope when estimating the savings in the project management tool. Regardless of this, the baseline, scope or features of an ongoing project can always change. Thus the estimations made by the negotiators together with the controlling team are always just the best subjective assessment of the project savings at the moment.

In this bottom-up forecast approach, the forecasting is done by the many negotiators for their own projects with the support of the controlling team. This entirely judgmental way of producing the forecast is remarkably quick for the controlling team, since the negotiators are producing a large part of the savings estimates for their own projects. In this type of a forecast the controlling team will gather up the data from the project management tool and calculate the savings from the already secured projects and the planned projects to create the bottom-up forecast.

Even though remarkably easy and quick, this way of producing the procurement savings forecast has some problems. If the negotiators do not update the project management tool with the newest information on their projects, this automatically leads to an error in the forecast. Besides not keeping the tool up to date, errors can emerge from misunderstood or unrecorded changes in the project financials or the project features. In addition, the pitfall of qualitative methods, poor or biased use of judgment while estimating the savings will also result in forecast errors.

Essentially as this way of producing the forecast is judgmental, all the problems related to the qualitative forecasting methods can occur. In addition to these problems, this bottom-up approach to forecasting does not consider the procurement savings from new projects, not in the project management tool at the time of forecasting, but coming in later in that year. In the same way it also does not consider that the savings in the projects, which might get cancelled later in the year, will not contribute to the overall year end secured procurement savings value, even though forecasted so at the time. The planned projects, which do not get secured during the rest of the year and stay as planned until the next year, will also present a similar problem. This means that there is always a certain value that is forecasted but will not be actualized, and another value that is actualized but was not forecasted. Thus these present another source for errors in the bottom-up forecast.

In the end this bottom-up forecasting technique at BuyIn produces only a single value forecast output. Even though this forecast is the product of experts' best estimates on their own projects, it is unrealistic to expect that this single value forecast would be accurate. In addition, this kind of a single value approach to forecasting does not quantify any uncertainties, risks or opportunities related to this forecasted single value. Thus it does not give any indication to which direction and how wrong the forecast might be.

3.5 The scenario forecast at BuyIn

The scenario approach to forecasting is employed at BuyIn at its most known version of the worst case, the most likely case and the best case scenario. This approach was introduced to add more spread and count for the possible risks and opportunities on top of the most likely case, the bottom-up forecast. Essentially the bottom-up forecast is the most likely case, since the procurement savings inputs in the project management tool for individual projects, are the best subjective estimates available.

At BuyIn the scenario approach to forecasting is also purely judgmental, and the worst case and the best case scenarios are produced by using subjective judgment. If the negotiators have information that one or some of their planned projects include possible risk or upside potential is this integrated to this forecasting approach. In addition, the controlling team's information of possible risks and/or opportunities on the planned projects, or information regarding new not yet in the project management tool, or getting cancelled projects is also integrated to create these scenarios.

At the end the worst case and the best case scenarios are produced by the controlling team. This is done after assessing all the information available, coming from the negotiators and acquired by the controlling team. These scenarios, produced by the controlling team, are done by allocating the estimated risk and/or opportunity values for a number of individual projects, and then calculating the worst case and the best case scenarios.

The scenario approach to forecasting adds more spread to the forecast output. Instead of having a single value, there are three outcome values for the forecast, the worst case, the most likely case and the best case scenarios. Thus compared to the single value forecast this approach enables some quantification of the potential risks, the worst case scenario and the opportunities, the best case scenario, related to the forecasted secured procurement savings value. However, in practice the risks and/or opportunities at BuyIn are allocated only to a rather limited number of projects, depending on the information available. Thus this approach does not count for all the potential risks and opportunities related to the forecast and the range between these two cases is generally not exceedingly large.

Even though this approach enables some quantification of the possible risks and opportunities it fails in the quantification of the uncertainty. The three-point scenario gives only the values of the possible outcomes, but does not include nor indicate any probabilities related to these values. Even though there is a scenario forecast it does not give any indication of where the actual value might land, nor guarantee that the actual value will even land in between the produced range.

Naturally in this approach the same problems with the forecasted but not actualized and actualized but not forecasted savings for new, cancelled or not secured planned projects will emerge. Besides this, as a qualitative forecasting method, this approach is also subjective to all the problems related with judgmental forecasting. Too optimistic or pessimistic allocation of the potential risks and/or opportunities can lead to distorted, uninformative and inaccurate range in the scenario.

Overall this forecast is relatively uncomplicated and quite quick to produce for the controlling team. Of course more effort and resources are needed from the negotiators to provide the information, and from the controlling team to compile and assess the available information, to produce the scenario forecast. On the other hand, if produced with high quality information and using impartial judgment, this scenario approach increases the forecast value considerably with the quantification of the potential risks and opportunities. Thus if information is available on the potential risks and opportunities, it would be value adding to employ that information to generate the scenario forecast instead of only a single value.

3.6 The simulation forecast at BuyIn

3.6.1 Simulation forecast structure

The simulation based forecasting technique was introduced at BuyIn to enable the use of historical data in forecasting, and to better quantify the risks and uncertainties related to the forecasted procurement savings value. At BuyIn Oracle Crystal Ball was chosen as the software tool to utilize Monte Carlo simulation in the forecasting process. This simulation based approach to forecasting was entirely new technique at BuyIn and was introduced the first time in June, 2016.

This simulation based forecast model consists of four different main building blocks which all include several different input assumptions. The four main blocks of the simulation forecast are the already secured projects, the individually assessed projects, the remaining planned projects and an assumption regarding the vouchers. These blocks are presented in figure 6.

The first block (figure 6) is the already secured projects. In this block the procurement savings from these already secured projects are taken in at face value from the project management tool. In these projects, since already secured, little to no changes are expected in the savings and thus no simulation or probabilistic input is assigned to this overall secured procurement savings value.

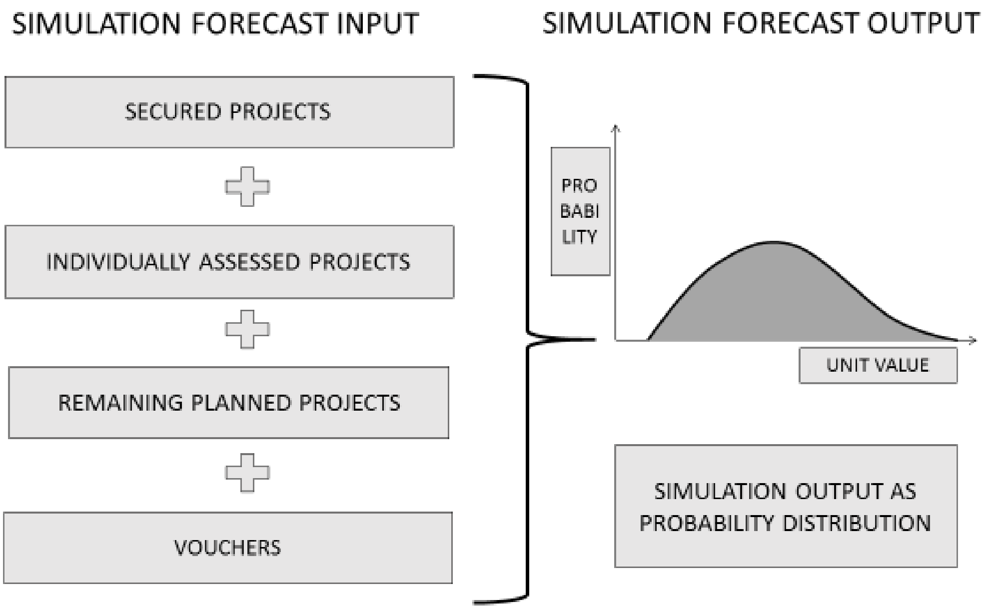

FIGURE 6. Simulation forecast structure at BuyIn

The following block (figure 6) is the individually assessed projects. This block consists of individually selected projects where information is available on the possible risks and/or opportunities. Like in the scenario forecast, the information provided by the negotiators and acquired by the controlling team is put to good account for these individually assessed projects. Instead of having a single value like in the bottom-up forecast, or the worst and the best possible values like in the scenario forecast, the simulation approach enables the replacement of these values with a probability distribution.

To choose the probability distributions for all the selected projects individually, the available information is assessed and analyzed by the controlling team. With the information available subjective judgment is used by the controlling team to choose the distributions for all individual projects. Uniform and triangular probability distributions were mainly selected as the input probability distributions for the individually assessed projects. In addition, depending on the available information, for some projects custom distributions were used to assign a certain probability for one value and a certain probability for another value. For example, 30% probability of zero and 70% probability of thousand.

The historical data were utilized in the third block (figure 6) of the simulation model, for the remaining planned projects. The remaining planned projects being the ones not included in the individually assessed projects block. The historical data were collected from this specific domain and region projects from two previous years, 2014 and 2015, where good quality information was available. To obtain more detailed results, besides collecting the overall domain and region specific historical data, the data were also divided and documented for all the five different categories and the two engagement models. Thus ten sets of data were created based on the category and engagement model.

The historical data were utilized in the simulation model in two different ways. The first points of interest were the changes in the spend baseline of these created ten data sets. The change in the spend baseline meaning what was the spend on the planned projects according to the forecast for example from June to the end of the year, compared to what was the actual spend on the projects which were secured during that time. These changes were the outcome of a number of planned projects not getting secured during the year and new projects that were not known at that time of the forecast, but got secured by the end of the year.

The problem of the forecasted but not actualized and actualized but not forecasted savings was tackled via the changes in the spend. Thus the changes in the planned spend versus the secured spend for the two previous years, where data were available, were calculated and “change ratios” were created for all ten data sets. For example, if the planned spend was forecasted to be 100€ but only spend worth of 50€ was secured, the change ratio would have been 0,5. On the other hand, if 100€ was forecasted and 120€ was secured the change ratio would have been 1,2. According to these two points obtained from the historical data, how much the spend did change in 2014 and in 2015, an assumption was made that the change in the spend for 2016 would land somewhere in between these two points. Thus a uniform probability distribution was applied to the planned spend values of the ten different data sets to simulate the spend.

The other point of interest in the historical data were the historical savings ratios of these ten different data sets. The savings ratios were of interest, because that enabled the allocation of the historical savings ratios to the planned spend to create savings. For example, if there was 600€ of planned spend and a historical savings ratio of 0,15 or 15%, this could be used to forecast 90€ of savings.

Essentially all the judgmental savings estimates in the project management tool for the remaining planned projects were ignored and replaced with the savings ratios according to the historical data. The allocation of the historical savings ratios was done through the direct sampling method provided by Crystal Ball. This was the method where the simulation was picking the exact values, in this case the savings ratios, from the given historical data set. Thus this method was used to allocate the historical savings ratios of the ten different data sets to the spend of the same data sets to forecast savings for all ten groups.

Thus in the third block (figure 6), the historical data were used to simulate the savings for the remaining planned projects in the already described two ways. Firstly, the spend of the different groups were simulated according to the obtained historical data points by using a uniform distribution. Secondly the savings were created for the remaining planned projects by simulating the historical savings ratios of the different groups via the direct sampling method, and applying those to the already simulated spend. Thus savings values were generated for the remaining planned projects in ten different groups.

The final block (figure 6) in the simulation model is an assumption regarding the procurement savings coming from vouchers. Shortly, vouchers at BuyIn comprehend no-spend but positive savings projects. For example, additional discount coupons or benefits coming from the suppliers on top of the project savings. These vouchers are included as zero spend but positive savings projects in to the project management tool, to differentiate the savings coming from vouchers and the savings coming from the procurement projects. Because of this, they were not included in the remaining planned projects block, but were analyzed and simulated separately. Both historical data regarding the year end voucher values in 2014 and 2015, and subjective judgment were used in defining a uniform distribution for the voucher savings.

3.6.2 Simulation forecast output

After the simulation model was built from these four different blocks, some including several individual input assumptions, the simulation was run to generate the procurement savings forecast. The output or the forecast of the simulation is in a form of a probability distribution. The probability distribution can then be used to analyze the riskiness of the simulated situation. In addition to quantifying the risks and the opportunities in the forecast the probability distribution displays the uncertainties related to the forecasted values. Besides the probability distribution Crystal Ball provides graphics of the cumulative and the reverse cumulative probabilities.

In addition to the graphics, Crystal Ball automatically provides the most important statistics on the forecast. These statistics display the key performance indicators, measured as the four moments of the distribution. The first moment is the center of the distribution, describing the expected secured procurement savings at the end of the year, for example mean, median and mode. The second moment describes the spread of the distribution or the related risks, for example standard deviation and variance. The third moment describes the skewness or the direction of the most probable events in the forecast. The fourth moment describes the thickness in the tails or the probability of extreme events (lower or high) occurring. In the end Crystal Ball provides an extremely large amount of descriptive and detailed information regarding the forecast, which all need to be analyzed by the controlling team to make the most out of this software tool. (Mun 2010, 37–41.)

In the following chapter the already introduced forecasting techniques will be further compared and analyzed. This chapter will concentrate on the forecast output, what kind of information the forecasts generate for BuyIn, the resources needed to produce and analyze the forecasts, and on the accuracy of the employed forecasting techniques. In addition this chapter will include discussion regarding the applicability of the simulation forecast to other domains within BuyIn.

4 COMPARISON OF THE FORECASTING TECHNIQUES

4.1 Forecast output

When looking at the outputs provided by the different forecasting techniques, substantial differences can be identified between the judgmental forecasting approaches and the simulation forecasting approach. This is presented in figure 7. The judgmental bottom-up forecast providing only a single value forecast output is the simplest approach. The scenario forecast provides three possible values as an output, the worst, the most like and the best case values. Even though also a rather simple approach, the scenario forecast provides more information on the possible forecast outcome, compared to the single value bottom-up forecast.

The simulation forecast on the other hand provides a wide range of outputs (figure 7). The probability distribution and other graphics provided by Crystal Ball are extremely valuable in assessing the uncertainties and risks related to the forecast. In addition, the remarkably good coverage of all the important statistics related to the forecast, provide immediately a descriptive picture of the complete overall forecast, not just of a single value or the mean of the forecast.

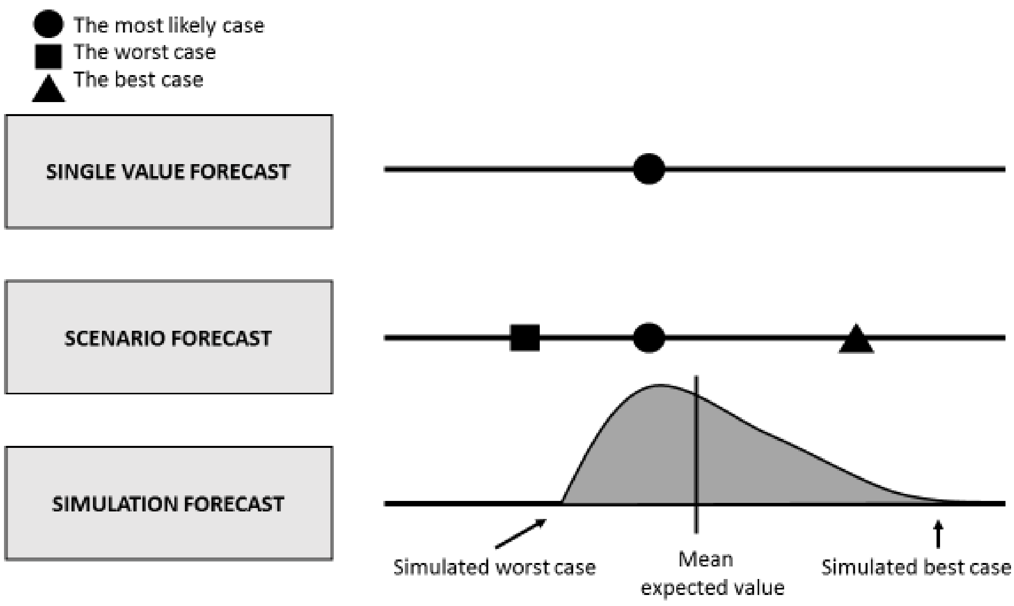

FIGURE 7. Single value, scenario and simulation forecast output

Compared to the single value approach, which only produces one forecast output value and does not quantify any risks nor opportunities, the scenario approach enables the quantification of the potential risks and opportunities in a rather simple manner. By producing the worst case and the best case scenarios, it is possible to obtain some quantification of the possible risks and opportunities. In addition, a view of the range between these values can be obtained, indicating if there is more potential risk or more potential opportunity. However, both of these approaches fail to quantify the uncertainties or the probabilities related to the forecast output. Both the single value and the scenario approaches do not give any indication on the likelihoods of any of these values occurring.

With the simulation based forecast it is possible to quantify the uncertainties and the related risks and opportunities. Instead of providing a single value or a range of possible values, with the simulation based approach, the output will be in a form of probability distribution. This can be used to quantify both the uncertainties or probabilities and the risks and opportunities related to the forecast output. Furthermore, the automatically provided additional graphics and statistics can be utilized when analyzing the forecast output distribution. Compared to the two previous forecasting approaches at BuyIn, the simulation forecast produces a large amount of explanatory information regarding the forecast output. However, to best benefit from the simulation tool and from the provided graphics and statistics, those should be analyzed as a whole instead of looking only single values like mean or standard deviation.

4.2 Resources needed

When creating the forecasts, the bottom-up approach is definitely the most time efficient. The relatively small contribution needed from the controlling team is to support the negotiators when needed, and to compile the correct, domain and region specific data in Excel to produce the bottom-up forecast. Thus only few resources are needed to generate the bottom-up forecast, which can be done in a matter of minutes.

Time wise, to generate the risks and opportunities on top of the bottom-up forecast takes a little bit longer because more input is needed from both the controlling team and the negotiators of the projects. The possible risk and opportunity factors have to be identified, quantified and recorded to enable the creation of the scenario forecast. Regardless, this way of producing the forecast is also comparatively quick, since the bottom-up forecast is produced each month and thus the most likely case is already available. In addition, at its current form the risks and opportunities are allocated only to a limited number of projects, where and if additional information is available. Thus the additional amount of resources and time needed to produce this type of a forecast are not substantial.

The simulation based forecasting technique is by far the most time consuming of these three forecasting techniques. A lot of time and resources were assigned to building the model and to obtain and analyze the needed historical data. On the other hand, if there is no need to significantly modify the model structure, not a lot of resources need to be allocated on these actions anymore. Then again, if the model is not performing as expected, the model structure and the input assumptions might need further analyzing and modifying, which will again need more resources.

In addition, to update the historical database when more projects get secured and to modify the individually assessed projects list every month takes time. Furthermore, the probability distributions on the spend changes, also have to be modified according to each months' historical data values. Altogether, to produce the procurement savings forecast with the simulation model every month, requires considerably more resources compared to the simple bottom-up forecast or to the scenario forecast.

Besides the resources needed to produce the forecast, the simulation approach also requires more time in analyzing the forecast output. Compared to the previous forecasting techniques, producing only one and three output values, the simulation forecast produces tremendous amount of information. This information needs to be analyzed, to properly benefit from the simulation tool and from all the information it provides.

When evaluating or comparing the efficiency of the forecasts, it is good to note that for the forecasting process to be effective, the forecast that takes more resources to produce, should also yield more benefits. However, the amount of resources spent on forecasting do not always equal to the benefits obtained. In addition, no matter how much resources are allocated to the forecasting process, a perfectly accurate forecast might never be obtained, and thus it is good to internalize that forecasting has its limits. (Gilliland & Platt 2010, 1–2.)

4.3 Forecast accuracy

Besides the resources needed and used for creating and analyzing the forecasts, it is also important to compare the forecasting techniques in the sense of the forecast accuracy. Technically the bottom-up forecast and the scenario forecast are always as accurate or inaccurate, since the bottom-up forecast equals to the most likely case in the scenario forecast. Thus to further analyze the scenario forecast accuracy, it could be measured, how accurate were the worst case and the best case scenarios, and if the actual values did land between the produced scenarios or not.

However, in this thesis the further analyzed value is the single value bottom-up forecast, which is also the most likely case in the scenario forecast. To obtain a better view of the accuracy of the forecasting techniques at BuyIn, the measure next used for comparison is the forecast percentage error. Thus the comparison of the accuracy is done by comparing the forecast percentage errors in the individual forecasts. The forecast percentage error was selected as the measure for the comparison because its simplicity, comparability and because the forecasted and actual values of the procurement savings cannot be disclosed for confidentiality reasons.

Furthermore, in BuyIn's case to correctly compare the available data, the accuracy of the forecasting techniques, the compared forecasts need to be produced in the same month. This is because the forecast lead time affects the forecast accuracy, and thus results obtained by comparing forecasting techniques with different lead times might not be valid. In this thesis, the compared forecasts are the June forecasts, meaning that the forecasts were prepared in early July with the complete data from June and the lead time in the compared forecasts is six months.

The bottom-up forecast percentage error can be calculated for the two previous years, 2014 and 2015 where the data are available. The forecast percentage error in the June bottom-up forecast in 2014 was -32% and the forecast percentage error in the June bottom-up forecast in 2015 was -35%. The percentage errors obtained from the bottom-up forecasts can be said to be rather large but also strikingly close to each other. Both values are negative, meaning that the forecasted values were smaller than the actual year end values. Thus it can be said that the bottom-up approach tends to be negatively biased and "under-forecast".

The simulation based approach to forecasting was introduced at BuyIn in June 2016, and while the secured procurement savings are reported for a calendar year, there are yet no actual procurement savings value available. Hence there is yet no result, on how accurate this forecasting technique actually is. Thus when implementing the approach there was a want to back-test the simulation model to obtain a view if the model structure and the simulation process work, and how accurate it possible could be.

Thus after the simulation forecast model was built, it was back-tested with the data from the two previous years. In short, the June data from 2014 and 2015 were used to create the June simulation forecasts for these years. The model structure and the input assumptions were otherwise the same, excluding the individual project assessment block, because no such information was available. Thus the structure consisted of the already secured project savings and the remaining planned projects, including all planned projects when back-tested. Here the historical data were used for the spend changes and for the savings ratios in the earlier described ways. In addition, voucher assumption was included based on the available historical data and subjective judgment. With these adjustments the simulation was run to generate back-tested June simulation forecasts for 2014 and for 2015.

When the back-testing was done, it was possible to obtain the June simulation forecasts for 2014 and 2015, and thus it was possible to calculate the forecast percentage errors for these back-tested simulation forecasts. The forecast percentage error in the June simulation forecast in 2014 was +3% and the forecast percentage error in the June simulation forecast in 2015 was -5%. The percentage errors obtained from the simulation forecasts through back-testing could be said to be extremely small and also strikingly close to each other. In addition, it could be said that the simulation approach is more unbiased compared to the bottom-up approach, which seemed to under-forecast.

The results obtained from this back-testing indicated, that the model structure and the simulation process would work, and that this technique can be utilized in forecasting the year end procurement savings. However, the forecast percentage error results, and thus the sense of accuracy,obtained through the back-testing are not reliable. Since the input assumptions, the historical data for the remaining planned projects block already included the actual year end values of the back-tested years, this might distort the results and make them seem more accurate. In addition, this back-testing could be seen more as a “model fitting” to the historical data rather than actual forecasting of the future. (Hyndman 2014, 1.)

It could be said that the simulation forecast model functions and based on the back-testing the simulation forecast could be expected to yield more accurate results compared to the bottom-up forecast. However, it cannot be said that the simulation forecast will yield as accurate results as obtained through the back-testing. When the actual year end procurement savings value for 2016 becomes available, only then can the actual forecast error and the forecast percentage error be measured, and a sense of the accuracy of the simulation forecast obtained.

When comparing different forecasts, in the sense of forecast accuracy, there are some important points to remember. Firstly, to be able to validly compare the accuracy of the forecasts, the forecasted values and the actual values for the same time period have to be available. Secondly the same kind of measure has to be used for the comparison, for example the forecast percentage error can be used as a measure for the comparison. Thirdly the lead time in the compared forecasts should be the same. In BuyIn’s case this means that the forecasts are produced in the same month, for example the June bottom-up forecast is compared with the June simulation forecast. (Clements 2016.)

4.4 Simulation forecast applicability

At BuyIn the already introduced bottom-up forecasting technique, is applied similarly in all the regions in the domain of this thesis. Moreover, the bottom-up forecasting technique is applied across the domains, and it is currently utilized in three out of four domains at BuyIn. Thus the bottom-up forecast is already applied in other regions within this domain and in other domains at BuyIn. Nevertheless, the accuracy of the bottom-up forecast in other regions and domains is not known, and not a part of the research of this thesis.

The application of the simulation forecast model to other regions within the domain of this thesis has already been done. When applied to other region, the structure of the simulation forecast model was the same as described in this thesis. Of course the historical data used for the input assumptions were collected from the region specific data. It could be assumed that within this domain, the same structure in the simulation forecast model could be applied for other regions as well. However, nothing can be said for certain regarding the accuracy of this forecast model for another region. If there are some region specific factors, trends or other knowledge, these should be integrated and counted separately for every individually produced forecast. Thus after testing and measuring the forecast model for a different region, it can be evaluated, if the model generates accurate results as it is, or could it be modified to generate even better results.

The application of the simulation forecast approach to other domains has not been done yet. If in other domains, the bottom-up approach to forecasting also generates forecast percentage errors of around +/-30%, the simulation based forecasting technique could also be applied to these domains to improve the forecast performance. Since in three out of four of Buyin's domains the procurement savings are calculated similarly, and the bottom-up forecast approach is already in use, the same kind of structure to building the simulation forecast model for other domains could also be leveraged. Of course the author, not having experience of these other domains at BuyIn, cannot say if the exact same structure would be applicable for other domains or if some modifications would be needed.

Overall the simulation based approach to forecasting provides a variety of new features and functions compared to the single value bottom-up forecasting approach. Thus if the accuracy of the currently utilized forecasting technique is not satisfying in other domains at BuyIn, the simulation forecast approach provides the possibility to boost the forecast performance, and the possibility to quantify the uncertainties, risks and opportunities related to the forecast.

In a general way it could be said that the simulation forecasting technique is applicable to other domains and regions where improvements to the forecast performance are wanted. Nevertheless, no certainty can be given regarding the applicability of the model as it is. Of course it could be applied, but no indication can be given regarding the performance of this model in other regions and domains. To build a good forecast model, which generates reasonably accurate forecasts the specific domain knowledge is required. In addition, the model structure and the input assumptions would need to be tested and evaluated by the domains to obtain the best results possible.

In the following chapter, development proposals are yielded regarding the already presented forecasting techniques employed at BuyIn. These development proposals are targeted to improve the accuracy of the individual forecasting techniques. In addition, new forecasting approaches are introduced that BuyIn might want to consider evaluating and implementing. Moreover, the development proposals include suggestion for improving the forecast process performance and the overall forecasting process.

5 DEVELOPMENT PROPOSALS

5.1 The bottom-up forecast

Of the three forecasting techniques now employed in this domain, the bottom-up technique has been utilized the longest, and it is an already established way to produce the procurement savings forecast. Being a purely judgmental method, this way of producing the forecast can only be improved by improving the quality of the judgmental inputs, the savings estimates on the planned projects, if no quantitative methods are desired to be included.

To improve the forecast quality, the project management tool should be updated regularly with complete and the newest information available. Besides this, instead of using biased judgment, the negotiators and the controlling team should aim to use impartial domain knowledge and experience when estimating the procurement savings. When improving the quality in the disaggregated levels, the quality of the individual project savings estimates, the overall aggregated quality of the forecast also increases.

If the quality of the bottom-up forecast can be improved, all the input assumptions are made by using unbiased domain knowledge and updated with the newest information, this way of producing the forecast could generate more accurate forecasts than currently. On the other hand, although the input assumptions would be of high quality, this technique still does not count for the new, cancelled or not secured projects and thus there would always be an error in the forecast. Hence there is a limit to the accuracy of this forecasting technique, but it might be possible to increase it from the current percentage error of around -30%. When selecting the techniques to be employed in the future, even though rather inaccurate it is also good to note, that this way of producing the forecast is extremely time efficient.

If the bottom-up forecasting technique is wanted to be kept as purely judgmental, it is important to highlight the involvement of the negotiators. They are in the role of making many individual estimates or forecasts, which then are compiled to the overall procurement savings forecast by the controlling team. Thus the negotiators should always aim to make the individual estimates as impartial and as accurate as possible, utilizing all the information available, to improve the overall quality of the bottom-up forecast.

On the other hand, it might be considered to include some quantitative techniques to the bottom-up forecast to possibly improve the forecast accuracy. The selected techniques could be implemented only in Excel as single values, or those could also be simulated to add the probabilistic functions. For example, if it is desired not to include the historical data on the savings ratios, but rather assume that the assumptions made by the negotiators are more accurate, only the historical data on the spend changes could be included. This way the forecast would include both qualitative and quantitative methods, and it could be tested and measured, if including the spend changes results in more accurate forecast or not.

Another way to include some historical data to the bottom-up forecast could be, instead of implementing the spend changes, to create similar savings changes for the five different categories and two engagement models. This could be implemented in a similar way like the already done and presented spend changes. Of course, this approach would also need to be tested, measured and evaluated to conclude if it adds any value to the forecasting process. Then again, since the bottom-up forecast is purely judgmental and extremely quick as it is, it could be evaluated if there is any need to modify this approach. It could be discussed, should there be an additional “modified bottom-up forecast” or should the concentration solely be on developing the simulation forecast model.

5.2 The scenario forecast

The scenario method is somewhat more complicated in a manner of developments. Essentially the improvements in the quality of the judgmental assumptions made to the bottom-up forecast, will also be automatically reflected to the most likely case of the scenario method, since these two cases here are the same. Thus when improving the bottom-up forecast quality, the scenario forecast will automatically improve on the side.

In this scenario approach the improvements could be concentrated to the estimates for the possible risk and opportunity factors. In these estimates, produced by the controlling team together with the negotiators, it is also important to internalize the notion of impartial approach to defining the parameters. The way this method is currently implemented by the domain, the risks and/or opportunities are allocated only to a rather limited number of projects. Thus the number of these individual project assessments could be increased to attain a wider range of the related risks and opportunities.

However, increasing only the number of the individual project assessments, would not change the accuracy of the most likely case, but rather the point values of the worst case and the best case scenarios. Thus the increase in the number of project assessments done, would lead to a wider range between the worst and the best case scenarios, but would not change the accuracy of this forecast method, if only the most likely case is measured. A wider range between the scenarios might give a better picture of the possible extreme values, but presents the problem with informativeness. To obtain a good scenario forecast, a balance should be found between the accuracy and the informativeness in the produced range.

Considering that the new simulation based approach to forecasting has been implemented, it could be evaluated if this scenario approach to forecasting adds any value to the overall forecasting process at BuyIn. If the worst case and the best case scenarios are not measured and evaluated, this approach to forecasting adds only little value compared to the bottom-up forecast. Moreover, the simulation approach to forecasting enables the quantification of the risks and opportunities in a more sophisticated way, and it also quantifies the uncertainties related to the forecast. Thus it might be considered, if there is at all need for the judgmental scenario forecast.

5.3 The simulation forecast

The simulation based forecasting technique is new at BuyIn and since there are no actual values yet available from this year, nothing can be said for certain regarding the accuracy of the currently used model. It could be assumed that the simulation forecast would be more accurate compared to the bottom-up forecast, but the results would need to measured and evaluated when available. Thus it is rather complicated to generate concrete development proposals for this forecast model, since the performance of the aggregated forecast or the disaggregated levels are not yet known. In principle, the same approach of using impartial domain knowledge applies also to this forecasting technique, in points where judgment is used for the input assumptions instead of historical data.

Besides the subjective assumptions, other sector where improvements to the simulation model could be possible, is the replacement of the direct sampling method, in the selection of the historical savings ratios, with the fitted distribution method. According to Charnes (2012, 58–63) this method is more favorable, and is known to produce more accurate results. Thus if a suitable distribution curve for the historical data sets can be found, it could be examined if this way of employing the historical data would result in more accurate forecast in BuyIn's case. (Charnes 2012, 58–63.)

In the simulation based forecast model, the individual project assessment block mainly consisted of projects where the input assumptions were either triangular distribution, uniform distribution or custom distribution. The first two distribution curves are rather simplistic, and could be replaced with either normal or lognormal distribution curves to attain more accurate results if appropriate. For example, by testing with different means and standard deviations it is relatively easy to attain a normal distribution similar to isosceles triangle. Of course this should also be tested to discover if the accuracy increases or decreases, to know which assumptions are the most appropriate to employ. (Charnes 2012, 45–48.)

Since there is some criticism against the judgmentally adjusted forecasts, it could be tested if the simulation forecast would yield more accurate results without the individually assessed projects. Since this block consisted of number of projects, where the input assumptions were judgmentally selected, it could be considered to move these projects as part of the remaining planned projects block, where the historical data are applied. This kind of modification might improve the accuracy of the simulation forecast. At the same time, it would also make the process of producing the simulation forecast more time efficient, since no additional information would need to be identified, quantified and recorded for individually assess the projects. Then again this also needs to measured and evaluated, if the historical data would outperform the judgmental input assumptions in these individually assessed projects. (Chase 2013, 82–83.)

Based on the data obtained through the back-testing, even though not completely reliable in the sense of the forecast accuracy, it could be assumed that the simulation forecast model structure is comparatively good. Thus if assuming that the model structure counts for all the important sectors which are needed, but nothing redundant on top of that, the place for improvements would be the input assumptions instead of model structure. According to Fairhurst (2015, 78) the output of a forecast model, or the accuracy of it, is only as good as the input assumptions made during the forecasting process. “Garbage in, Garbage out” means that the quality of the forecast is dependent on the quality of the input assumptions made. Thus for BuyIn to improve the quality of the simulation forecast it would be extremely important to measure and evaluate the quality of the input assumptions. (Fairhurst 2015, 78.)

Especially for the simulation forecast model, as it consists of both qualitative and quantitative methods and of so many different input assumptions, it would be highly important to implement the forecast value added method. By measuring and benchmarking the accuracy of the forecast inputs, the input points which are inaccurate can be identified and either improved or deleted. This would be exceedingly valuable to further develop and improve the accuracy of the simulation forecast model as well as the efficiency of producing such a forecast.

5.4 Implementing the forecast value added

To develop the simulation based forecast model and the forecasting process, the forecast value added method could be introduced. By introducing the forecast value added method it would be possible to identify the points or input assumptions in the forecast which add value, in sense of forecast accuracy. On the other hand, the points or input assumptions which do not add value or decrease the value of the forecast, can also be identified. After identifying these kind of value decreasing points, those can be singled out, and either improved or eliminated completely. (Chase 2013, 118–119.)

To appropriately utilize the forecast value added, the overall forecast and all the input assumptions in the forecast, should be benchmarked and recorded. In reality, it is ineffective to benchmark all the individual input assumptions, but some sort of division to lower levels should be possible to conduct. When breaking down the aggregated forecast to these lower levels, the performance of these levels can be measured and benchmarked.

Negative and positive forecast errors in the lower levels cancel each other out when calculating the overall, aggregated forecast error. Thus the aggregated forecast error might seem to be much smaller, than the forecast errors that occur in the lower levels. Hence, the lower levels are a good place for improvements, since improvements made in these levels will also improve the quality of the overall forecast. (Chase 2013, 103–105.)

To measure the lower level performance in the simulation forecast, the following blocks could be identified as these lower levels. The individual project assessments block, if not many projects, preferably measured individually to attain a better picture of the accuracy of the judgmental input assumptions, or if not possible, this could also be measured as a block. The historical savings ratios for the ten different groups or data sets, the changes in spend baseline for these same groups, and the voucher assumptions could also be benchmarked and measured individually. When the actual year end procurement savings value becomes available it will be possible to compare the aggregated overall forecast together with the lower levels to study how this simulation based forecast model actually performed, and what are the sectors which need improving.

The forecast value added method could also be implemented to the bottom-up forecast. Even though there are many individual projects and it would be inefficient to measure and benchmark all of these, the projects could be grouped similarly to the five categories and to two engagement models. Another way to group, measure and evaluate the projects would be to group them by negotiator, although this would create even larger amount of different groups. By implementing the forecast value added to the bottom-up forecast, ways to improve the accuracy and the process performance could be identified.

In addition, if decided to implement some quantitative methods to the original bottom-up forecast, it could be easily measured, if these quantitative methods are value adding or not. If the possibly added quantitative methods do not add value to the bottom-up forecast, those can then simply be deleted. On the other hand, if the added quantitative methods do add value and provide a more accurate forecast, they could be implemented to the techniques used at BuyIn to create the procurement savings forecast. Some simple quantitative methods on top of the bottom-up forecast might evolve into forecasting technique, which is relatively accurate and also highly time efficient.

5.5 Implementing pure statistical model

Seeing that the aim at BuyIn is to improve the accuracy of the forecasts, compared to the accuracy yielded by the bottom-up forecast, all methods should be in the end compared to this. Since not always does a statistical model outperform experts' opinions, the bottom-up forecast is a good fallback and a benchmark for all further developments. On the other hand, since some researchers claim that pure statistical models perform better compared to judgmental ones, it might also be considered to examine this approach as well. (Chase 2013, 82–83.)

To implement a simple, pure statistical model could be done by using the simulation based approach, or if not a lot of resources are wanted to be allocated, even simpler approach would be to use Excel. To correctly implement a pure quantitative forecasting technique, only the historical data would be used, and no judgmental adjustments would be done in any point of the forecast.

If utilizing similar structure, like the current simulation forecast, only the historical data on the savings ratios and on the changes in the spend baseline would be implemented. Thus no individually adjusted projects nor vouchers would be included, unless clear historical data on the vouchers could be obtained, and it would not be judgmentally adjusted. Measuring the performance of a pure statistical model gives the opportunity to compare this with the pure judgmental model, the bottom-up forecast, and with the simulation based forecast model employing both qualitative and quantitative methods. By doing so, more information can be attained regarding which method used in producing the forecasts yields the most accurate results in BuyIn's case.

5.6 Time series data

Time series techniques are one sub-category of the quantitative forecasting methods identified in the beginning of this thesis. Time series data are collected on the variable of interest in a chronological order on equally spaced, consecutive, time periods. For example, daily, weekly or monthly collected data may be used. In addition, the data can be instantaneous, cumulative or any kind of statistics that represent the activity of the variable during that time. (Montgomery, Jennings & Kulahci 2011, 2.)

Time series methods are based on the assumption that the future mimics the past and thus the past can be utilized to forecast the future. This method relies on the identification of patterns in the historical data, and assumes these patterns will continue similarly into the future. The patterns are for example seasonality, randomness, trend and cycles. Chase (2013, 84) applies this time series method to forecast sales and demand, but this technique, or at least parts of it could also be utilized in forecasting the procurement savings at BuyIn. (Chambers et al. 1971; Chase 2013, 84.)

The time series forecasting technique although out of the scope of this thesis, would need extensive research to conclude, if applicable and value adding to BuyIn. However, some parts of this technique could already be applied and evaluated, if value adding or not. To create time series data, the selected variable, for example savings or savings ratios, would have to be put to chronological order first, for example by week or by month. This could be done for the complete domain and region specific data, or this could be divided in to the categories and engagement models to generate more specific data sets.

The interest in this approach is to identify patterns, for example seasonality or trends, in the created chronological time series data. If such patterns can be identified, it could help to qualify and modify the input assumptions in the simulation forecast to be more accurate. By utilizing the time series technique, if seasonality in the data can be identified indicating for example that the savings ratios tend to be higher during the last couple of months of the year, this information could be implemented when producing the simulation forecast in the last months. If there are patterns or trends found in the data, the information could be implemented to the simulation model.

Overall there are various techniques to produce time series forecasting, from naïve models to extremely complicated and sophisticated ones. To implement a completely new forecasting technique at BuyIn, right after introducing the simulation based approach, might not be the most efficient and effective. However, simply creating a time series data could help to identify, if there are visible patterns in the data. If such patterns can be identified, the information could be utilized in the already existing forecasting techniques, to further improve and develop these.

5.7 Forecasting process

To improve the forecasting process, the forecast value added method should be introduced. This way it would be possible to evaluate the performance of the simulation forecast and identify the parts where improvements could be done. If some of the forecast input assumptions are decreasing the forecast value, by eliminating these inputs the forecast would automatically get more accurate and the process of producing the forecast more time efficient.

Since the simulation forecasting technique has now been established, it sould be continuously developed. Probably the first year's forecast accuracy result might not be the best that can be obtained, and thus further development could always be done. For the next years, the target for the forecasting process could be, not to set a specific target for the forecast error or accuracy, but rather to set a target for continuously improve the accuracy of the simulation forecast. Usually when setting an exact target for the forecast accuracy, companies tend to be overoptimistic which then leads to missed target, disappointment and doubt towards the forecasting process. It is unrealistic to expect superior results from the newly introduced model, and thus resources could be allocated towards improving it even further. (Chase 2013, 104–105.)

As a new procurement savings forecast is produced each month, it might be good to evaluate and consider what is the best way to employ these techniques to the monthly forecasting process in the future. It might be desired to discuss and evaluate, if the simulation forecast should be produced each month or to save some resources, for example only quarterly. The accuracy results obtained from the different forecasting techniques and the resources needed to create and analyze the forecasts have to be considered when evaluating and deciding, how to progress with the monthly utilization of the different forecasting techniques. It is also good to remember that regardless of forecasting technique, the forecast lead time affects the forecast accuracy. Thus the forecasts produced in the beginning of the year will always be less accurate compared to the ones produced closer to the year end.

Moving forward, it might be discussed, what is the level of forecast accuracy which would be acceptable or desirable during the business year. To reach and then maintain this level of accuracy, the selected forecasting technique(s) should be reviewed and the inputs should be validated on a regular basis. Obtaining a good result once, does not imply that the forecasting technique or a model would work well long into the future. Additionally, it is good to remember that to achieve the desired level of accuracy is not always possible, and if achieved once it does not mean that it can be maintained. The forecast accuracy has its limits and in some cases it cannot be controlled. Then again the techniques used and resources spend to the forecasting process are controllable. (Gillaland & Platt 2010, 1–2.)

There are already two completely different ways, the qualitative bottom-up and scenario, and the simulation approach, to produce the procurement savings forecast. Besides these approaches, the negotiators best estimates coupled with the historical data on spend changes might be considered. In addition, a pure statistical model could be implemented as well. If implementing different approaches it could be discovered, if there are any extremely accurate or inaccurate ways to produce the procurement savings forecast and if new techniques or assumptions could be incorporated to the already established models.

Because there is no single optimal way to produce a forecast, different methods and techniques should be implemented, tested and evaluated. It cannot be said for certain which technique is the most accurate, and if it continues to be as accurate into the future. Thus in forecasting it is important to test, measure and evaluate the different techniques to obtain a view which technique or model performs the best. Furthermore, it is good to remember that forecasting is an ongoing process, thus the forecast performance should be continuously measured and recorded so it can be evaluated and developed. (Montgomery et al. 2015, 16.)

6 SUMMARY AND CONCLUSION

This thesis was conducted in a form of a case study. The case company of this thesis was BuyIn GmbH, and the more general research topic was business forecasting. In more detail, this thesis concentrated on the forecasting methods and techniques which are currently employed at the case company. The research was conducted mainly as qualitative research, and the method used to acquire the needed data for the framework of this thesis was academic research on the available literature. In addition, document analysis was performed of the case company's internal materials, and the author has also obtained data regarding the case company through participant observation.

The purpose of this thesis was to do a background research to provide the case company with information regarding its forecasting techniques and to identify the differences, and advantages and disadvantages connected to these approaches. The objective of this thesis was to yield development proposals aimed to improve the forecast performance of the individual forecasting techniques as well as the overall forecasting process. In addition, another objective was to discuss and analyse if the simulation forecast would be applicable to other domains within the case company.

The forecasting methods presented in this thesis were the qualitative and quantitative forecasting methods. Qualitative methods rely on subjective judgment of a person or a group whereas quantitative methods utilize the past and the current data in forecasting the future. At BuyIn both qualitative and quantitative methods are being employed to forecast the procurement savings. Furthermore, two completely different forecasting techniques have been identified at BuyIn, purely qualitative bottom-up and scenario forecasts, and simulation based forecast, which utilizes both qualitative and quantitative methods.

Besides the different methods, differences have been identified in other sectors of the forecasts as well. The bottom-up forecast was the most time efficient, but only produced a single value output, and thus did not quantify any forecast related risks or opportunities. The scenario approach was comparatively time efficient as well, and produced the best case the most likely case and the worst case scenarios. Thus this approach enabled a simple quantification of the potential risks and opportunities related to the forecast.

Many differences have been identified between the simulation forecast and the purely qualitative techniques. Besides utilizing the historical data available, the simulation approach enables the quantification of both risks and opportunities, and the uncertainties related to the forecast. By providing a probability distribution as an output, a good view of the forecast risks and opportunities can be obtained. In addition to the probability distribution, the software tool used at BuyIn also automatically provides a variety of graphics and statistics of the key performance indicators related to the forecast, which can be utilized when analysing the forecast output.

The findings of this research indicated that forecasting is not an exact science and that there is no proven optimal model, technique or even a method for producing forecasts. Thus testing, measuring and evaluating the different methods and approaches to forecasting has been highlighted as an important factor in identifying the best or the most appropriate ways to produce the forecasts. The findings also pointed out that forecast accuracy has its limits and perfectly accurate forecasts may never be obtained.

The discoveries expressed that the accuracy of a forecast model is never fixed, and thus continuous development and modification might be needed to obtain the desired level of accuracy. In addition, it is pointed out that in some cases the desired level of accuracy might be obtainable, and thus it would be good to compare the resources needed to the forecasting process with the benefits the forecast provides. The accuracy of the forecast may not be controllable but the resources spend to the forecasting process can be controlled.

Even though no certain improvement factors could be stated without throughout testing and measuring, some techniques have been identified, to possibly improve the forecast performance, in the sense of improving the forecast accuracy. These development proposals were yielded for the individual forecasting techniques BuyIn is currently employing, and for the process of producing the procurement savings forecast. In addition, new approach to forecasting have been identified and proposed in this thesis.

The development proposals yielded in this thesis included the notion of impartial domain knowledge for all the judgmental forecasting approaches or inputs included in the forecasting process. According to this, all the assumption which are not based on historical data, should always be made as unbiased as possible. In addition to this to improve the bottom-up forecast as it is, the project management tool should be updated with the newest data available on all projects. To also potentially improve the bottom-up forecast accuracy it could be considered to implement, test and measure some quantitative techniques on top of the purely qualitative bottom-up forecast.

To possible improve the simulation forecast, the research findings suggested that the historical data should be implemented through the fitted distribution method instead of the direct sampling method. Also for the individually assessed projects the rather simple probability distributions could be replaced with more sophisticated distributions such as the normal distribution or the lognormal distribution. Since the individually assessed project inputs were also based on judgment instead of historical data, it would be highly essential to remember the use of impartial domain knowledge when selecting the probability distributions.

Another proposal yielded by the author was to implement a purely quantitative model, which would only use the available historical data. Again, it cannot be said if this technique would yield better results than the techniques already implemented at the case company, but it might be interesting to test, measure and compare how this technique would perform in comparison to the techniques being currently used. Again, the findings highlighted that there is no one optimal way to forecast, and underlined the importance of continuous measuring and evaluation.

One influential discovery was the forecast value added method, which could be used to measure the forecast process performance. The importance of this method is to identify the forecast input points and their value to the overall forecast performance. During the forecasting process, all the input assumptions made should be benchmarked, so when the actual values become available it could be measured if the input assumptions made during the forecasting process are adding value to the overall forecast or not. Implementing this method allows the identification of the input points in the forecast, which do not add value or decrease the value of the forecast. Thus the findings suggested that implementing the forecast value added method would increase the forecast accuracy and make the forecast more effective.

The objectives set for this thesis have been mainly achieved. The main objective, yield development proposals for the individual forecasting techniques and for improving the overall forecasting process has been achieved for the most parts. Development proposals have been yielded for all individual forecasting techniques and for the forecasting process. On the other hand, it would have been interesting to statistically analyse these proposals to be able to conclude, if and which of these proposals would have actually improved the forecast performance. Thus the testing and measuring of the proposals yielded in this thesis will need further quantitative research.

The other objective set for this thesis, to discuss and analyse the applicability of the simulation forecast model was only partially achieved. In the end nothing definite could have been said about the applicability of the currently used simulation forecast model as it is. The findings suggested that the simulation as a forecasting technique would be applicable, but to obtain the best possible results the model and the inputs would need to be defined separately for all individual forecasts.

The research need or problem of this thesis remains partially open, and further quantitative testing and measuring would be needed to identify the best ways to improve the forecasts. Thus it would be highly interesting to research this topic and the case study even further. While the nature of this thesis was qualitative research, all the development proposals yielded were also qualitative in nature. Thus quantitative testing and measuring would be needed to evaluate if the proposals yielded in this thesis actually generate improvements regarding the forecast accuracy.

The quantitative testing and measuring of the different forecasting techniques and the development proposals yielded has been left open, and as a further research to be studied. When the actual values for the procurement savings at the case company become available in early 2017 it would be possible, for the first time, to acquire reliable results regarding the simulation based forecast model performance. The actual procurement savings value would also enable the quantitative comparison of the different forecasting techniques as well as the measuring on of the forecast process performance by implementing the forecast value added method. Thus quantitative research of this case study would be further required, to enable the performance evaluation and comparison of the different forecasting techniques, and for yielding more concrete development ideas for improving the forecast accuracy.

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