Aalto University
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Profit Driver Based Forecasting, Case Rautaruukki Oyj

Accounting

Master's thesis

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PROFIT DRIVER BASED FORECASTING

CASE: RAUTARUUKKI OYJ

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Janne Nikkola
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AALTO UNIVERSITY SCHOOL OF ECONOMICS ABSTRACT
Research on Accounting
Janne Nikkola

PROFIT DRIVER BASED FORECASTING, Case Rautaruukki Oyj

Purpose of the thesis

The purpose of this thesis is to find suitable forecasting methods and possible profit-loss drivers for profit-loss forecasting. The second purpose of the thesis is to review the profit forecasting process of a case company and propose actions to improve the performance of the forecasting.

Research material

In the empirical part of the thesis, a case company's profit forecasting accuracy is examined. The selected data consists of statistical forecasts for case company's profit-loss statement items (net sales, cost of goods sold and operating income) for year 2009. The drivers used in this thesis were selected from company's possible market drivers list.

Research Methods

Forecasting accuracy is studied by using different forecasting methods which are selected from the literature of statistical forecasting. In addition, different time series methods are used to simulate profit-loss forecasting processes and behaviour of selected drivers in profit forecasting process.

Results

The results showed that there are not unambiguous number of drivers in profit forecasting, which could improve by themselves the profit forecasting accuracy. Furthermore, better forecasting accuracy is achieved when combining several methods. The result for the case company is the numbers of drivers to be used in profit forecasting are dependent on the market segments that the divisions operate.

Keywords

Forecasting, judgemental forecasting methods, statistical forecasting methods, forecast error measures, drivers

AALTO-YLIOPISTON KAUPPAKORKEAKOULU TIIVISTELMÄ
Laskentatoimen tutkielma
Janne Nikkola

INDIKAATTORI POHJAINEN TULOKSEN ENNUSTAMINEN

Tutkielman tavoitteet

Tutkielman tavoitteena on löytää tuloslaskelmaerien ennustamiseen sopivia ennustemenetelmiä sekä mahdollisia ajureita. Tutkielman tavoite on myös tarkastella case-yrityksen tuloksen ennustamisprosessin toimivuutta ja löytää tapoja parantaa sen ennustetarkkuutta.

Lähdeaineisto

Empiirisessä osassa tarkastellaan case-yrityksen tuloksen ennustamistarkkuutta eri tilastollisilla menetelmillä. Aineistona on käytetty yrityksen antamia lukuja tuloslaskelman erille (myynti, kustannukset ja liikevoitto) vuonna 2009. Ajurit tähän työhön valittiin yrityksen markkinoita tarkkailevista ajurilistoista.

Tutkimusmenetelmät

Ennustetarkkuutta tutkittiin käyttämällä eri ennustemenetelmiä, jotka valittiin tilastollisen ennustamisen kirjallisuudesta. Tutkimusmenetelminä käytettiin erilaisia aikasarja menetelmiä jotka parhaiten kuvaavat tuloksen ennustamisen tarkkuutta tällä aineistolla sekä valittujen ajureiden vaikuttavuutta tuloksen ennustamiseen.

Tulokset

Tulokset osoittivat, että ei ole yksiselitteistä määrää ajureita tuloksen ennustamiseen, jotka voisivat parantaa yksinään ennustamisen tarkkuutta. Havaittiin myös, että parempi ennustetarkkuus saavutettiin, kun yhdistetään useampia menetelmiä. Kohdeyrityksen analyysissä paljastui, että valittujen ajureiden määrä tuloksen ennustamisessa on täysin riippuvainen markkinoiden segmenteistä joilla eri divisioonat toimivat.

Avainsanat

Ennustaminen, subjektiiviset ennustusmenetelmät, tilastolliset ennustemenetelmät, ennustevirheen mittarit, ajurit

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To my lovely wife *Minna Aalto-Nikkola*

To Mr. *Ari Salonsaari* from Rautaruukki Oyj

To Professor *Teemu Malmi*

To my fellow student friends *Janne Björklund* and *Olli Bogdanoff*

To my parents

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1 INTRODUCTION

Forecasting is the process of estimation in unknown situation. Risk and uncertainty are central to forecasting and prediction. When people make decisions in their everyday lives, they make assumptions and predictions, in other words forecasts. When a company makes for example a profit forecasts, they use the profit history as a reference in predicting future profits. To do that, the companies need to have different drivers to produce most specific profit forecasts. Therefore, accurate profit forecasts are extremely important for making future decisions concerning about the company profits. Accurate forecasting has become a challenge for companies operating in today's business environment, characterized by high uncertainty and short response times. (Sanders, Ritzman 2004) A profit and loss account is designed to show the financial performance of a business over a given period (usually monthly or annually) and to indicate whether it is making or losing money.

Nahmias (2009) has divided forecasts into five different characteristics. First, *they are usually wrong*. This is probably most ignored and most significant property of almost all forecast methods. Second, *a good forecast is more than a single number*. A good forecast also includes some measures of anticipated forecast error. Third, *aggregate forecasts are more accurate*. On a percentage basis, the error made in forecasting e.g. sales for an entire product line is generally less than the error made in forecasting sales for individual item. Fourth, *the longer the forecast horizon, the less accurate the forecast will be*. For example, one can predict tomorrow's value of the OMXH Industrial Average more accurate than next year's value. Finally, *forecasts should not be based to the exclusion of known information*. A particular technique may result in reasonably accurate forecasts in most circumstances. For example, the company may be planning a special promotional sale for a particular item so that the demand will probably be higher than normal.

In the financial performance decision making there is always a lag time between awareness of an impending need and the future of that event. This lag time is the main reason for forecasting the future events. If this lead-time is close to zero or zero, then there is no need for forecasting or planning. Usually the lead-time is long and therefore the need of forecasting will play an important role of planning the future financial performance.

As Makridakis (1998) puts it “In management and administrative situations the need for planning is great because the lead time for decision making ranges from several years (for the case of capital investments) to a few days or hours (for transportation or production schedules) to a few seconds (for telecommunication routing or electrical utility loading). Forecasting is an important aid in effective and efficient planning.” So in other words to survive as a business companies need to forecast.

Business forecasting

Business forecasts, by themselves, have no function. However, forecasts can be translated into action through the planning process. A forecast is made by considering environmental variables which are either controllable by the company (e.g. products selling price) or are not controllable (e.g. macroeconomic issues). (Shearer 1994) Since forecasting is just a precursor to planning and decision-making, the usefulness of a forecast relates directly to its “added value” in making plans or decisions. This concept conflicts with the commonly held belief that a forecast is only useful if it is within certain tight bounds of the actual outcome. The purpose of forecasting relates to the decision-makers’ needs via the planning process. The aim is to reduce uncertainty and to give as much information as possible to the decision-makers. Forecasting is a pervasive business activity, and often needs to be drawn together by means of central department such as the planning department. We need forecasts to forecast short-term, medium- or long-term projections. Different methods apply to these different cases. (Shearer 1994)

The wanted outcome is the same for forecasts, short- or long-term, they need to be accurate, cheap and meet the decision needs. Usually there is one problem; forecasts can be either made with cost efficiency or they are adequately accurate. The starting point for the forecasts is to choose either cost efficiency or adequately accurate made forecasts. (Harris 1999)

Drivers in profit forecasting

Regular profit and cash flow forecasts are as vital to business owners and managers as the air they breathe. They provide critical information as to the life of business, not only the owners and managers but also for potential providers of finance. Forecasts are about making reasonable estimates of future, for example sales, costs and cash balances.

To reach the goal of successful business forecasting in all areas including sales, costs and cash balance companies need to construct solid base for forecast drivers. (Makridakis, Wheelwright 1989, 19) In many decision-making areas the level of the forecast driver is of less interest than the timing of critical changes to that driver. (Hope 2006) In other words companies should understand the idea behind the drivers, which are used in driver-based forecasting.

Driver based forecasting process should use the top 15 to 20 business drivers to develop a full forecast based on the movements of chosen drivers. Forecasting done this way also becomes less an analysis of financial trends and more a strategic tool. This statement, for 15 to 20 drivers, came from the case company and their new objective to reduce present used drivers to 15 to 20. The company is now using dozens of different drivers to forecast profits.

When companies make a future forecast on profits nothing is certain, because there are so many variables that could convert the forecast to downfall. (Chung, Kim 1994, 707) There is always possibility that something unexpected happens. Even with the best plan to reach the goal there are so many variables that could change the course of forecasts to disaster. All of the variables are usually impossible to take into account and sometimes it’s better just to concentrate on the key drivers of forecasting.

This study will focus on profit drivers as a key input in driving an efficient profit forecasting. The study is made for the Finnish steel company, Rautaruukki Oyj and their need to improve forecasting processes. The research focuses on finding suitable methods how to forecast profit-loss drivers for the case company. This study will be done as a constructive case study. One of the primary criteria for selecting the constructive research is the demonstration of practical usefulness, including relevance, simplicity and ease of operation by the business community. The purpose is to examine profit forecasting and the process of selecting the main profit-loss drivers in general, but also from a single company point of view.

An important issue in profit forecasting, especially for companies with large and diverse product portfolios, is the information of sales aspect of profit forecasting. The importance of sales forecasting will be a key factor in the case company’s objectives to succeed a reliable profit forecasts.

As Makridakis (1987) puts it “Forecasting is not just a technical or statistical area, but the domain of psychology, politics, management science, economics, and other related disciplines.”

1.1 PREVIOUS RESEARCHS AND THE NEED OF FURTHER INVESTIGATION

There seems to be very little or no literature devoted to profit driver based forecasting specifically. Also empirical studies concerning the subject are rare. However, there is an extensive amount of literature about forecasting and especially strategic performance forecasting methods, but the lack of different profit drivers for forecasting are missing. The most common areas of studies are related to cash flows and inventory control. Because of the lack of research in the area of profit driver based forecasting, there is a clear need to study which drivers for profit forecasting methods are suitable for the purpose.

For a long time the forecasting research was concentrated on statistical forecasting alone while judgmental forecasting was popular only in practice. Today the situation has turned a little bit around and now the research concerning judgmental forecast methods has raised its head.

Profit forecasting in a large steel company is also an area where there is a large amount of different products, line of businesses and market information in the organization that cannot be easily turned into reliable forecasting models. Therefore the need for consistent profit driver based forecasting model plays an important role for carefully planned future profit forecasting. Also the consideration about whether judgmental or statistical forecast methods are used is in place.

1.2 PURPOSE OF THE RESEARCH AND THE STRUCTURE OF THE STUDY

The purpose of this study is to examine the possible profit-loss drivers for profit-loss forecasting. The research focuses on investigating different methods how to forecast with profit-loss drivers for the case company. The research goals for the study are based on the agreement with Rautaruukki financial department.

This study is structured in two parts, the theoretical and the empirical part. The theoretical part will be based on the literature of forecasting methods, the profit forecasting processes and also for forecast accuracy and frequency. Forecasts are conducted by reviewing the most commonly used forecasting methods, statistical and judgmental. Furthermore, the profit forecast process is investigated.

Hence, the research question of the study is:

> *Is it possible to improve profit forecasting accuracy by adding drivers to the profit forecasting processes?*

In the empirical part of the study, a case company's profit driver based forecasting process is described, its accuracy is studied and suggestion are made to improve the process of selecting the right number of the drivers.

One part of this study will concentrate to find methods to improve the order to enhance profit forecast accuracy. This is conducted by investigating the performance of the currently used drivers in forecasting profits and by challenging it with alternative drivers. The following questions are investigated: How accurate have the profit forecasts been and what have created the major forecast errors? What would be the best forecast update frequency and forecast method for each division?

In the second chapter, the most commonly used judgmental and statistical forecast methods are reviewed with an emphasis in comparing the performance of statistical and judgmental methods. In the third chapter, profit forecasting process is investigated and also focusing on the forecasts accuracy and update frequency. Chapter four introduces the research methods and data used in the case study. Chapter five introduces the case company and focuses on describing the current profit-loss forecasting process in the case company and the existing complications related to profit forecasting processes. Empirical analysis is analysed in chapter six. Chapter seven summarizes the study with conclusion, short discussion about research findings and recommendations for future actions.

1.3 DEFINITION OF KEY CONCEPTS

The following definitions will be used in various stages throughout this study:

Judgmental method: A judgmental forecasting method, as known subjective forecasting method, is based on human judgment. The methods in judgmental vary according to the number of judges involved.

Statistical method: A statistical forecasting method, as know objective forecasting method, is based on existing data. Objective forecasting methods include time series and causal methods.

Profit forecasting: Profit forecast is the amount of profit a company expects to make at the end of period. The profit forecast will consist of sales and costs difference.

Sales forecasting: Sales forecasting is a key factor in any company's success. Accurate sales forecasting allows a company to effectively control different operations in the company functions.

Forecast error: The difference between actual (ACT) and forecast (FCT) outcomes for a bucket of time.

2 FORECAST METHODS: JUDGMENTAL VS. STATISTICAL

In this chapter, first, the most common judgmental and statistical forecasting methods are presented. Secondly, the different levels of judgment in forecasting are reviewed. Thirdly, some possible ways of improving forecasts with judgmental adjustments are introduced. Finally, comparing the advantages and disadvantages of both methods are examined.

2.1 JUDGMENTAL METHODS

A judgmental forecasting method, as known subjective forecasting method, is based on human judgment. Human judgment permeates forecasting processes. In economic forecasting, judgment may be used in identifying the endogenous and exogenous variables, building structural equations, correcting for omitted variables, specifying expectations for economic indicators, and adjusting the model predictions in light of new information, official announcements, or "street" talk. Studies with economic forecasters indicate that judgment is given more weight than the modelling techniques in constructing predictions. (Batchelor, Dua 1990) In fact, judgment is "the primary factor that the economist uses in converting mere statistical and theoretical techniques into a usable forecast". (Clements, Hendry 2002)

Judgmental methods are the most widely used in forecasting. Any predictive judgment made upon a future event, based on the information one has access to, can be counted as a judgmental forecast. The methods in judgmental vary according to the number of judges involved, the amount of interaction judges are allowed to have with each other and the amount of interaction that the forecasters has with the judges. Judgmental methods are associated with qualitative forecasting techniques and qualitative methods combines experience, intuition and judgmental to make forecasts. (Barron, Targett 1985) The information that is used in qualitative methods can be slippery because there are many situations where objective forecast model couldn't be used or is not reliable. For example, if there is upcoming new product, when no historical data is available or when a significant change is about to occur are examples of such situations. Unless it is handled carefully the forecasts will be little more than wild guesses. (Barron, Targett 1985)

Qualitative forecasting uses a different approach from that of quantitative forecasting. The former is more concerned with defining the boundaries or directions in which the future will lie; the latter is concerned with making estimates of the future values of variables. In case of qualitative techniques might predict the most profitable product areas and countries of operation for an organization, whereas quantitative techniques would try to forecast the actual levels of profit. (Barron, Targett 1985, 17)

In consequence, one may assume that judgmental methods are commonly less accurate than objective forecasts. Most interesting reason for this is that human decision-making has considerable biases and limitations. There are number of methods that can help in forecasting on the subjective level. The purpose of these methods is to reduce the impact of bias and increase the objectivity.

Barron and Targett (1985) outline the common qualitative forecasting methods to the title of used techniques. Here are some of the methods presented. (Barron, Targett 1985, 17 - 29)

Visionary forecasting

Involves a purely subjective estimates made by only one person’s guesses or hunches. In *panel consensus forecasting*, is probably the most common method used in business because there is a group of people participates to a meeting and produce a forecast as a result of discussion and argument. However, the results that are made in a meeting may be greatly affected by the strong dominations by one-person status of the group or group pressure.

Brainstorming

This meeting based method can be very helpful way to generate forecasts. This technique is perhaps better known for producing ideas rather than generating forecasts. Using this technique, a group meeting is organized to first gather all the possible elements that might have an effect on the variable being forecast. The idea of brainstorming is to hear all the ideas that come up in the meeting without turning down any of them. When all the elements affecting the forecast variable have been collected, it is decided what the forecast will be.

Delphi forecasting

The Delphi method is based on the panel consensus method but tries to overcome the side effects of group pressure. The difference between these two methods is that the Delphi method doesn't allow the members of the group to communicate with each other. The group has a chairman who controls the process. First, the chairman asks each member of the group to make a forecast and all the major factors affecting the variable, are written down and passed to the chairman. Second, chairman collects the submissions of all members of the group and summarizes them.

Third, the summary is distributed back to the group members and the participants are requested to reconsider their forecasts. The participants of the meeting have an opportunity once again to revise their forecast. The process is repeated until the group has reached a consensus or until the participants are no longer prepared to adjust their forecast further. After this, the final result is the Delphi forecast.

Advantages of Delphi method are that individuals' opinions are not affected by the group pressure or rank of other people. Disadvantage is that the method is highly sensitive to the care in the formulation of the questionnaire. Other downside is that the group might never find consensus. (Armstrong 1985, 117 - 119, Nahmias 2009, 57)

Scenario writing

This approach method is not concerned with single estimates of the future. It is several alternative scenarios of the future are formed each scenario having a separate sets of assumptions. The basic idea is rather than creating one forecast, to cover the whole range of different possibilities that could be realistic to expect.

Cross-impact matrix

The method does not directly produce forecasts. However, they are a means of providing estimates of the likelihood or probabilities of future events, which they can then be used as part of the planning process.

A cross-impact matrix produces a special emphasis on cross influences between different events, by considering how the occurrence of one event might affect the probability of another. First, make an extensive list of all the factors that might affect the plans to be made. Secondly, the probabilities of the development of these factors are estimated. Thirdly, form a matrix with each row representing one of the developments and each column also representing a development. Each cell of the matrix then gives the conditional probability of the development in that column given that the development in that row occurs. The overall likelihood of different developments can be calculated by involving different simulations.

Analogies

Can be used when forecasting a variable that has no record of data from the past provided that there is a second similar variable whose histories records are completely know. Analogy method assumed that the data pattern of the first variable would follow the pattern of the second variable.

Catastrophe theory

Method deals with the possibility that a variable may change from one level to another. It does not refer to catastrophe in the sense of disaster but in the sense of a sudden alteration in behaviour. Catastrophe theory does not calculate the expected size of variable changes, but it answers and characteristics to look for indicating the nature of the situation that is investigated.

Relevance tree

Method starts from the present situation and then put out “feelers” to see what the future might look like. This technique is described as *normative*. Basic idea is that depicted the future should ideally look like then working back to determine what is necessary to happen for this ideal future to take place. This method starts from determined a broad objective which is then broken down to several sub-objectives which further broken down to sub-objectives until clear technical developments are found. These objectives and sub-objectives then form a relevance tree whose branches are given relevance weights. As the result, a list of most important developments that are needed to reach the highest level of objective is created.

Combined forecasts

Several studies have concluded that combining judgment methods is at least as accurate as the average judge, almost always more accurate than the average judge and sometimes more accurate than the best individual method. One advantage is that by combining judgments, the biases of the judges can be compensated. The use of combined forecast is expected to be valuable when the level of uncertainty is high. (Armstrong 1985, 132 - 136)

2.2 STATISTICAL METHODS

A statistical forecasting method, as know objective forecasting method, is based on existing data. Objective forecasting methods include time series and causal methods. A time series method uses only past values of the variable being forecast whereas causal methods use data from sources than the series being predicted; that is, there may be other variables with values that are linked in some way to what is forecasted. (Nahmias 2009)

There are three requirements that have to be fulfilled in order to use statistical forecast models:

1. Information of the past is available
2. This information can be quantified in the form of numerical data
3. It can be assumed that some aspects of the past pattern continue in the future. (Makridakis, Wheelwright et al. 1998, 9)

Table 1 show the key operational steps in the forecasting process with time series models and causal forecasting models, which are used in statistical forecasting methods. In addition, Table 1 shows if the methods are costly and necessary. These models that have been presented in the table 1 are examined in the next chapters.

Table 1. Forecasting Models

Method	Description	Applications	Computer Cost	Computer Necessary?
Causal Forecasting Models				
Regression analysis	Explanatory forecasting; assumes a cause-and-effect relationship between input to a system and its output	Short- and medium-range forecasting of existing products and services; marketing strategies, production, personnel hiring and facility planning	Low to medium	Usually
Multiple regression	Explanatory forecasting; assumes a cause-and-effect relationship between more than one input to a system and its output	Same as above	Low to medium	Yes
Time series Forecasting Models				
Moving averages	Used to eliminate randomness in a time series; forecast is based on projection from time series data smoothed by a moving averages	Short- and medium-range forecasting for operations such as inventory, scheduling, control, pricing and timing of special promotions; used to compute both the seasonal and the cyclical components for the short-term decomposition method	Low	No
Exponential smoothing	Similar to moving averages, but values are weighted exponentially, giving more weight to the most recent data	Short-range forecasting for operations such as inventory, scheduling, control, pricing and timing of special promotions	Low	Yes

Source: (Hanke, Wichern 2009, 505 - 506, modified)

The following chapter presents the most common statistical methods that can be categorized into these two categories, time series and causal methods.

2.2.1 Time series methods

Time series methods are often called naïve methods, as they require no information other than the past values of the variable being predicted. The components of a time series include level, trend, seasonality, cycles and randomness. A level indicates the scale of time series. A trend can be either linear or nonlinear (e.g. exponential) and it refers to a pattern of growth or decline. A seasonal pattern repeats at fixed intervals. A cycle variation is similar to seasonality except that the length of a cycle is longer than the length of season. A random series has no recognizable pattern of data. So random series remain after the other components of a time series have been removed. (Nahmias 2009, 58)

Next, time series forecasting methods are presented with different types of underlying time series e.g. level and trend, trend and seasonality.

The naïve forecast is estimating technique in which the last time series actual are used for future forecast periods, without adjusting them or attempting to establish causal variables. This method is usually used as a benchmark for the other methods.

$$f_t = x_{t-1} \tag{1}$$

where

x_{t-1} = observed value in period t

Simple moving average (SMA), an arithmetic average of *n* the most recent observations is calculated. The one-step-ahead forecast made in period t-1 for period t is given by:

$$f_t = S_t = \frac{1}{n}(y_t + y_{t-1} + ... + y_{t+n}) \tag{2}$$

where

S_t = smoothed value at time t

n = number of past observations

Since a level model is assumed, the multiple-periods-ahead forecast is the same as the one-step-ahead forecast. The SMA is at its best when used to forecast stationary series. (Nahmias 2009, 65)

Weighted moving average is a variation of the SMA. To apply the weighted moving average method to a time series, the data should follow a fairly linear trend and have a definite rhythmic pattern of fluctuations. (Mason, Lind et al. 1999, 649)

The forecast for period t in period t-1 is calculated as a weighted average of the *n* past observations:

$$f_t = w_1 x_{t-1} + w_2 x_{t-2} + \ldots w_n x_{t-n} \qquad (3)$$

where w_i (i = 1, 2, …, n) are constants used as the weights.

Simple exponential smoothing is called the constant-level model because it assumes that the variable to be forecast follows a level model. The current forecast is the weighted average of the last forecast and the current value of demand:

$$e_t = x_t - f_{t-1}\ (1) \qquad (4)$$

$$S_t = S_{t-1} + \alpha_1 e_t \qquad (5)$$

$$f_t(m) = S_t \qquad (6)$$

where

$f_t(m)$ = forecast made in the end of period t for m periods ahead

e_t = forecast error in period t

x_t = observed value in period t

α_1 = smoothing constant for the level, $0 < \alpha_1 < 1$

S_t = level of series at the end of period t

(Gardner 1987, 178 – 181)

Hence, exponential smoothing applies a decliner set of weights to all past data. This model assumes that the series being forecast has no trend; the m-step-ahead forecast is equal to the one-step-ahead forecast. The constant-level model behaves much like an automatic pilot or thermostat. As each data point in the time series is observed, one can compute the forecast error.

If the forecast is positive (the last forecast was too low), one should increase the forecast. The more instability there is in the mean of the series, the higher the smoothing constant should be in order for the forecast to keep pace with the changes. (Gardner 1987, 178 -181)

The linear-trend models, as the double exponential smoothing with linear trend, assume a linear trend. Adding a trend component to the constant-level model does the forecast. The following equations (7) – (10) shows how the level, trend and forecast are being calculated:

$e_t = x_t - f_{t-1}(1)$ (7)

$S_t = S_{t-1} + T_{t-1} + \alpha_1 e_t$ (8)

$T_t = T_{t-1} + \alpha_2 e_t$ (9)

$f_t(m) = S_t + mT_t$ (10)

where

$f_t(m)$ = forecast made in the end of period t for m periods ahead

e_t = forecast error in period t

x_t = observed value in period t

α_1 = smoothing constant for the level, $0 < \alpha_1 < 1$

α_2 = smoothing constant for the trend, $0 < \alpha_2 < 1$

S_t = level of the series at the end of period t

T_t = trend of the series at the end of period t

(Gardner 1987, 181 – 184)

With the constant-level model, caution is required in initializing the linear-trend. The recommended procedure to obtain the starting level and trend is to perform a linear regression with time as the independent variable. The values of the exponential smoothing parameters can be found by using a grid search to find the values that result for the smallest mean squared error. In this linear-trend model, the multiple-period-ahead forecast is diverse from the one-period-ahead forecast as the trend component in the forecast equation is multiplied by the number of periods ahead the forecast is done. (Gardner 1987, 181 – 184)

The nonlinear-trend models, as double exponential smoothing with nonlinear trend, the linear-trend model can be modified also to nonlinear trends by adding a new parameter ϕ to control the rate of growth/decline in the forecasts. The ϕ is called trend-modification parameter.

If ϕ is greater than 1, we have an exponential trend and the amount of growth in the forecasts increases each period. If ϕ is less than 1, then the trend is damped and the amount of growth in the forecasts decreases each period.

$e_t = x_t - f_{t-1}(1)$ (11)

$S_t = S_{t-1} + \phi T_{t-1} + \alpha_1 e_1$ (12)

$T_t = \phi T_{t-1} + \alpha_2 e_t$ (13)

$f_t(m) = S_t + \sum_{i=1}^{m} \phi^i T_t$ (14)

where

$f_t(m)$ = forecast made in the end of period t for m periods ahead

e_t = forecast error in period t

x_t = observed value in period t

α_1 = smoothing constant for the level, $0 < \alpha_1 < 1$

α_2 = smoothing constant for the level, $0 < \alpha_2 < 1$

S_t = level of the series at the end of period t

T_t = trend of the series at the end of period t

ϕ = trend modification parameter

(Gardner 1987, 184 – 188)

Thus the double exponential smoothing model for nonlinear trend can be used to approximate the forecasts for any non-seasonal time series of the previous exponential smoothing models:

$\phi \approx 0$, a constant level

$\phi < 1$, a damped trend

$\phi \approx 1$, a linear trend

$\phi > 1$, an exponential trend

(Gardner 1987, 188)

It may be surprising that the nonlinear model often produces forecasts that are approximately the same as those produced by either the linear model or the constant-level. The following examples will explain the forecast similarity. If the trend in a set of data is actually linear, the search for ϕ will yield a value near 1 and the forecasts will approximate the linear model. If the nonlinear model is applied to set of data in which there is no trend, a grid search for ϕ will yield a value near zero and the forecasts will approximate the constant-level model.

2.2.2 Causal methods

The purpose of causal methods is to link the variable being forecast to the causes that historically have influenced it and to use variables established relationship to forecast. There are five different methods to use in causal based forecasting. (Makridakis, Wheelwright 1987a) This study will only focused on the two main methods, which are single equation regression, as known simple regression, and multiple regressions.

In *Single Equation Regression*, dependent variable Y_t is thought of as determined number of causes as well as past values of the dependent variable itself. The relationships between Y and its causes are identified by examining past data.

The regression equation in simple regression is of the following form:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon \qquad (15)$$

where

y is a dependent variable to forecast, x an independent variable used to forecast y and β_0 and β_1 are the constants. The ε is a regression residual. To estimate the y we have to use the following model where β_0 and β_1 have been selected to minimize the sum squares of residuals:

$$y_t = E(y|x) = \beta_0 + \beta_1 x \qquad (16)$$

The mean or expected value of y for given value x is denoted by the symbol $E\ (y|x)$. The principle of least squares estimates of the regression coefficients in single equation regression can be stated as follows: choose as the best-fitting line that minimizes the sum of squares of the deviations of the observed values of y from those predicted. This can be calculated from the following equations:

$$\beta_0 = y - \beta_1 x \qquad (17)$$

$$\beta_1 = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sum(x-\bar{x})^2} \qquad (18)$$

(Mendenhall, Reinmuth et al. 1993, 500 - 505)

In *Multiple Regression*, there is more than one independent variable to estimate the values of a dependent variable.

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_k x_{kt} + \varepsilon$$

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_k x_{kt} \qquad (19)$$

In the equation the error term ε has an expected value of zero and a constant variance. The independent variables $x_1, x_2, \ldots, x_k$ are known constants and it's recommended that as few variables as possible are added to the model and new variable is added to the model only if its regression coefficient is statistically significant. It depends on the researcher knowledge and judgment of the relationship of the variables when he/she is selecting the variables to the model.

Regressions can be linear in variables. If regression equation is nonlinear in variables, it can be transformed into a linear one just redefining the variables. The following equations will demonstrate this transform from nonlinear to linear regression by writing the $z_t = 1/x_t$. Then y is regressed on z.

$$y_t = \beta_0 + \frac{\beta_1}{x_t} \qquad (20)$$

$$y_t = \beta_0 + \beta_1 z_t \qquad (21)$$

(Dougherty 2002, 153 - 163)

Regressions can be transformed also from nonlinear in variables to linear equation by taking logarithms. This will happen just by taking logarithms of both sides of the equation as in equation (23).

$$y_t = \beta_0 x_t^{\beta 1} \qquad (22)$$

$$\log y_t = \log \beta_0 + \beta_1 \log x_t \qquad (23)$$

(Dougherty 2002, 153 - 163)

Another common functional form of regression is presented in equation (24). In the equation the β_1 should be interpreted as the proportional change in y_t per unit change in x_t. This equation can be changed into a model where there is linear in parameters by taking logarithms of both sides. The new equation model (25) is logarithmic in variables only from the left side, and for this reason the new model is described as semi-logarithmic.

$$y_t = \beta_0 e^{\beta_1 x_t} \qquad (24)$$

$$\log y_t = \log \beta_0 + \beta_1 e^t \qquad (25)$$

(Dougherty 2002, 153 - 163)

There is possibility that nonlinear regression equation cannot be transformed into a linear model, the sum of squares of the residuals is minimized by trying out different combinations of the regression parameters until such parameter values that would reduce the residual sum of squares can no longer be found. (Dougherty 2002)

2.3 THE JUDGEMENTS ROLE IN FORECASTING

Surveys of corporate forecasting practices show that most important forecasts focus on judgment. (Bunn, Wright 1991) There are several possible roles for judgment in forecasting depending on the information that is available for the forecasters. One major focused area of judgmental forecasting is on time series. On judgmental time series forecasting the focus area is on the data of the past values of the variable to be forecast and used to produce an assessment of the future values. (Goodwin, Wright 1993) There are three roles for judgment that have been reported in the literature. First, the forecasters may only have time series data available in which case forecasters have tried to anticipate the future from the patterns of the past data. Second, judgmental forecasters may be in the role of adjusting a statistical forecast judgmentally, possibly with some light of the contextual information. Third, forecasters have to produce a judgmental forecast by incorporating both time series data and contextual information. In some cases, judgmental forecasts are made without having time series data available (e.g. new products). (Goodwin, Wright 1993)

2.3.1 Model building

The formulation of a statistical forecast requires the input of many aspects of judgment. (Bunn, Wright 1991) A human judge is required in the first instance to select a forecasting model and judgment is important in building models.

According to Bunn and Wright (1991), they have indentified four areas where judgment may play a role in statistical model building: selecting the variables included in the model, specifying the model, estimating the parameters and for data analysis. As the result of the model building, a statistical model used in producing the forecast is constructed. (Webby, O Connor 1996)

Variable selection

In the statistical and econometric literature proposes that the selection of variables should be essentially judgmental with insightful use of diagnostic statistics as against automated selection. The judgmental challenge is to creatively use one of eliciting key variables from experts. (Bunn, Wright 1991) Model specification and parameter estimation can be automated using techniques such as multiple regressions or “bootstrapping”, but judgment is still required to identify the variables. (Webby, O Connor 1996, 99 - 101)

Model specification

If causal information is quantitative, it can be incorporated fairly easily into formal model or through building an econometric model. Specifying the model, the researcher structures his/her outlook of the data-generating mechanism after which the researcher uses his/her experience and conception of the data-generating mechanism. In the literature there appears to be two main ways of incorporating. First, it is determined how the forecast variable depends upon the forecasts state. The researcher’s understanding of this equation describes the forecast variable and it determines the structural of the equation. Second, an appropriate estimation technique is selected to define specific values for the model parameters. This resulting equation is called a structure. (Belsley 1988, 441 - 442)

With econometric model, judgmental information can be subjectively coded into the model by using quantitative variables. One possible option for incorporating extra-model information to the model is to run the model intervention where the influence of broken-leg implication is determined within the modelling process. (Webby, O Connor 1996, 101)

Parameter estimation

Parameter estimation can be interpreted as series of events to define whether there exists a structure, i.e. a set of parameter values, for the model (structural equation) that is consistent enough with the set of data used in the estimation. The starting point for a structure is to give the best fit with some measure of fit to the structure. The researcher should always compare whether the set of parameter values is consistent with his/her primary understanding of the data-generating mechanism. If the set of parameters found and the researcher observation do not match, the researcher should investigate whether the data is erroneous. If there is no match then the researcher should reconsider the model. (Belsley 1988)

Data analysis

In data analysis, judgment plays an important role. The forecasters must to choose, how many historical data item of the series to include in the model building. It will require for an estimation of whether there has been structural instabilities in the data series. To forecast unusual events outside the model requires judgmentally forecasting the events and excluding forecast affect from history of the time series. These specific events may include e.g. discontinuities, outlier and influential observations. (Bunn, Wright 1991, 511)

2.3.2 Combining forecast

To combine different forecasts, judgment is needed to select the forecasting models, which could include statistical and/or judgmental methods. This will be a very challenging task to find out an effective way to combine different models. Judgmental forecast can be combined either subjectively or objectively. (Goodwin 2000)

There is a lot of research indicating that combining independent forecast leads to improved accuracy. (See Clemen, Armstrong 1989)

Based on Makridakis et al. (1982) survey, they found out that there was a better accuracy of combined forecasts than a single forecasting method. Makridakis et al. (1982) study was made with statistical methods.

According to Sanders and Ritzman (1994), they had a different point of view. They showed that combining the subjective with objective forecasts is most effective when there is contextual information available and that when contextual information is available, combining judgmental forecast with statistical forecasts gives more accurate results than combining only statistical forecasts.

Combining forecast methods there is good reason to believe that some forecast are more accurate than others and the forecasts from more accurate forecasters should be given more weight than those from less accurate. (Makridakis, Wheelwright 1987a) The methods that can be used are presented next.

Simple average is an average of all the individual forecast methods, which are calculated by giving each method an equal weight. This method has an advantage of being easy to use and it treats the forecasts symmetrically. (Makridakis, Wheelwright 1987a) There has been empirical study that the simple average tends to outperform many more complicated procedures. (See e.g. Makridakis, Andersen et al. 1982, 111 - 153)

Outperformance can be investigated through the Bayesian model. In Bayesian model priori probabilities are estimated for the forecast methods being combined. In the model the weights of a forecast method represents the probability that the respective forecast method outperforms all the other methods. Thus the Bayesian model comparison does not depend on the parameters used by each model. Instead, it considers the probability of the model considering all possible parameter values. (Bunn 1975)

When using the weighted average to combine forecasts it permits to take the relative accuracy of the individual methods into account, as well as, the possible dependency among the forecast methods. Then the optimal weights should be such that it would minimize the error variance of the combined method. Therefore, knowing the covariance matrix would permit the use of the optimal weighting but in practice the covariance matrix is not known. (Winkler, Clemen 1992, 609 - 610)

In *Regression,* where constant is included and the weights of the individual forecasts (regression coefficients) are not restricted in any way. Granger and Ramanathan (1984) showed that this approach has the advantage that even though the individual forecast methods would be biased the combined forecast is still unbiased.

In *Regression with restricted weights*, the constant term is used in least squares regression but in sum of the regression coefficients is restricted to one. (Granger, Ramanathan 1984, 197 - 204, de Menezes, W. Bunn et al. 2000, 3 - 4)

There have been some suggestions to extend the regression based forecast combination techniques. (See Diebold, Pauly 1987) Based on Diebold and Pauly (1987), they have proposed techniques with the rolling weighted least squares and time-varying parameter. Reeves (1982) have introduced a method based on multiple objective linear programming, which allows multiple objectives to be used on forecasting combination.

2.4 EFFECTIVE FORECASTING WITH JUDGMENTAL ADJUSTMENTS

There is substantial evidence from economic forecasting literature that statistical forecast can be made even more accurate when experts judgmentally adjust them to take into account the effects of special events and changes that were not incorporated into the statistical model. (Fildes, Goodwin et al. 2009) The economic forecasting literature (See Fildes, Goodwin et al. 2009, Eroglu, Croxton 2010) has showed that judgmental adjustments tend to improve accuracy, though sometimes only marginally, but that they may also introduce bias. Therefore judgmental adjustments of statistical forecasts are widely used for improving forecast accuracy.

Despite the overall effectiveness of this method, it may allow forecasters to introduce biases in statistical forecasts when they judgmentally adjust them. This indicates that a forecaster's personality and motivational orientation have significant effects on forecasting biases, whereas work focus of control has no effect on forecasting biases. Analysis of researchers indicates that experience, work focus of control and motivational orientation drive a forecaster's willingness to judgmentally adjust a statistical forecast. (Eroglu, Croxton 2010)

Experimental argument on the same question generally suggests that forecasters often make unnecessary judgmental adjustments to statistical forecasts. (Lawrence, Goodwin et al. 2006) In particular, forecasters make adjustments even when they do not possess additional information about special events.

This could be due to the widely observed illusion of control effect from the forecasters, where forecasters who make adjustments exhibit greater confidence in their forecasts. Based on Lim and O'Connor (1996) survey, they found that a tendency by forecasters to make damaging adjustments persisted, despite a computer display showing that they were reducing the accuracy.

However, experimental evidence also suggests that when an adjustment is made on the basis of events not reflected in the statistical forecast, it is likely to improve accuracy, as long as the information about the event is reliable. (Lim, O Connor 1996) Importantly, organizations employ substantial recourses in the forecast adjustment activity, and economic rationality argues that forecasters must view it as valuable. Fildes and Goodwin et al. (2009) made four different hypotheses and they have tested these in their research. The idea was to find if these hypotheses could improve effective forecasting and judgmental adjustments.

First hypothesis, which was tested where *judgmental forecast* adjustments could improve, *forecast accuracy*. Managers are able to select the most inadequate system forecasts and then to adjust them in the correct direction. In addition, that larger judgmental adjustment is more effective in improving forecast accuracy than smaller ones.

Second, *the forecasts selected for adjustment are those in need of improvement and when adjustments are made*, the sizes of the judgmental adjustments are positively associated with improvement in accuracy.

Most importantly, the relationship between the volatility of the time series (as measured by the coefficient of variation of the raw data) and the relative accuracy of judgmental and statistical forecasts should be examined very carefully.

According to Sanders and Ritzman (1992) study concluded that when series has low coefficients of variation, statistical time series methods outperformed judgmental forecasters who had expertise relating to the variables to be forecast.

Moreover, the experts increasingly outperformed statistical time series methods as the volatility of series increased. (Fildes, Goodwin et al. 2009) There is also a downside when volatility in a series reflects noise or unanticipated discontinuities; there is evidence that judgmental forecasters will perform poorly relative to statistical methods as the volatility increases. (O'Connor, Remus et al. 1993)

Third, *judgmental forecast adjustments improve the forecast accuracy more under high volatility than low volatility conditions*. While accuracy is the most important property for a forecast, two further properties are also important: bias and efficiency. Mean bias is a systematic tendency for the forecast to be either less or greater than the actual. Regression bias is the extent to which the forecasts systematically fail to track the actual observations. (Fildes, Goodwin et al. 2009) Good example is that forecasters may tend to be too high when outcomes are low and too low when outcomes are high.

Finally, *the judgmentally adjusted forecasts are biased*. When forecasts are based on management judgment there is a tendency to be inefficient; that is, where the forecasts could be improved by modifying them to take into account information available to the forecaster at the time. Moreover, when estimating effects, forecasters may over-rely on the recall of single analogies from the past, and they may anchor too closely to these recalled effects. (Lee, Goodwin et al. 2007)

These hypotheses are theoretical interest, more excitingly they also open up the prospect of improving the accuracy of companies' forecasting processes by exterminate any consistent biases, inefficiencies and size effects. (Fildes, Goodwin et al. 2009)

2.5 ADVANTAGES AND DISADVANTAGES OF JUDGMENTAL AND STATISTICAL METHODS

The forecasting literature has historically been divided on the relative value of judgmental versus quantitative forecasting methods. (Sanders, Ritzman 2004) At present, most researchers agree that both judgmental and statistical forecasting methods have their unique strengths and weaknesses.

In consequence, one may assume that quantitative forecasting methods have the advantage of being objective, consistent, capable of processing large amounts of data, and considering relationships between numerous variables. Quantitative methods produce forecasts quickly and the compilers of forecast do not get bored with repetitive tasks. However, quantitative models are only as good as the data upon which they are based and they are always based on the assumption that past patterns or relationships are going to continue in the future.

When changes occur in the data that are not incorporated in the model, the generated forecasts cannot be accurate. (Sanders, Ritzman 2004) Therefore quantitative methods for forecasting need to incorporate their judgments to the forecasts. Judgment plays a role in every type of forecasting method, its role is more important in one set of methods than in another. (Jain 1985, 27) Judgmental forecast of practitioners often have up to date knowledge of changes and events occurring in their environment that can affect forecasts. (Sanders, Ritzman 2004)

The aspects of judgmental biases for forecasting are critical to viewed, because of their direct affects to forecasts. A human bias with serious negative consequences refers to changing our minds (or decisions) when there is no need to do so. People are often unable or unwilling to apply the same criteria or procedures when making similar decisions. (Makridakis, Wheelwright et al. 1998)

Table 2 presents few commonly reviewed biases in human judgment, which also apply to judgmental forecasting.

Table 2. Sources of bias

TYPES OF BIAS	DESCRPITION OF BIAS
Inconsistency	Incapable to apply the same decision criteria in similar situations.
Conservatism	Failure to change (or changing slowly) one's own mind in light of new information/evidence.
Regency	The most recent events dominate those in the less recent past, which are downgraded or ignored.
Availability	Reliance upon specific events easily recalled from memory, to exclusion of other pertinent information.
Anchoring	Being unduly influenced by initial information, which is given more weight in the forecasting process.
Illusory correlations	Belief that patterns are evident and/or two variables are causally related when they are not.
Regression effects	Persistent increases (or decreases) might be due to chance rather than a genuine trend.
Attribution of success and failure	Success is attributed to one's skills while failure to bad luck, or someone else's error. This inhibits learning, as it does not allow recognition of one's mistakes.
Optimism, wishful thinking	People's preferences for future outcomes affect their forecasts or such outcomes.
Group pressures	Social pressures, for example, of a group cause people to distort their judgment.
Underestimating uncertainty	Excessive optimism, illusory correlation, and the need to reduce anxiety result in underestimating future uncertainty.
Selective perception	People tend to see problems in terms of their own background and experience. People seek information consistent with their own views/hypotheses and downplay/disregard conflicting evidence.

Source: (Makridakis, Wheelwright et al. 1998, 500 - 501)

Important factors that give credibility to judgment methods are domain knowledge and contextual information. Domain knowledge has also been shown to be important in the judgmental adjustment of quantitatively derived forecast. (Sanders, Ritzman 2004)

The biases inherent in judgmental methods can generate large and volatile swings of forecast errors, which can have serious implications to company’s forecasting. Experimental evidence generally suggests that forecasters often make unnecessary judgmental adjustments to statistical forecast. (Lawrence, Goodwin et al. 2006)

An ideal forecasting methodology is one that incorporates the advantages of both judgmental and quantitative forecasting approaches. (Sanders, Ritzman 2004)

Makridakis et al. (1982) showed that mathematically combining quantitative forecasts reduces forecast errors. Numerous other studies have supported the finding that combining independent forecasts improves accuracy. (E.g. Lobo, Nair 1990)

The overall conclusion from these studies is that gains from combining are greatest when methods combined differ substantially and are based on different sources of information. Also, the constituent forecast should be absent of bias or has biases that cancel each other out. (Sanders, Ritzman 2004)

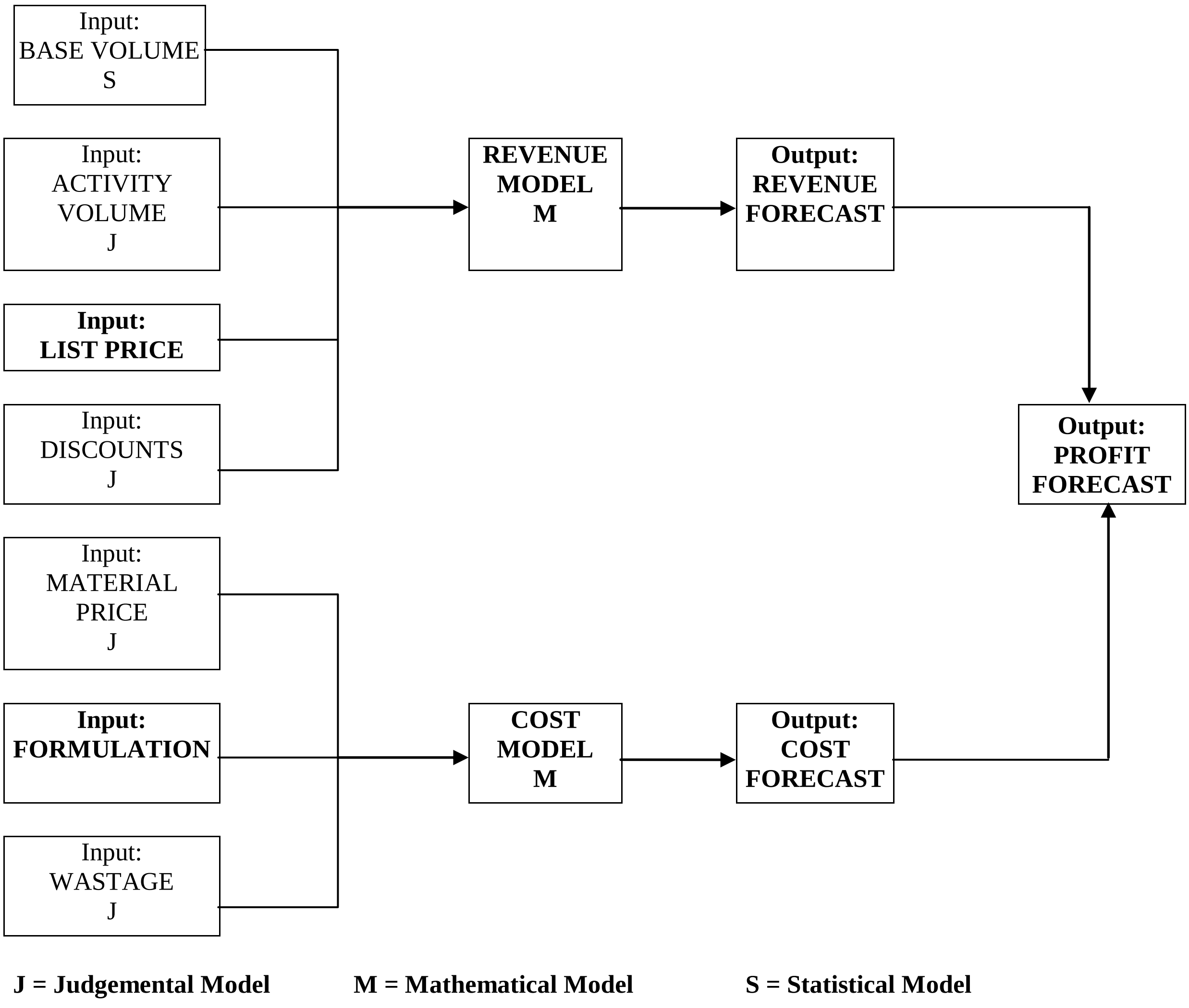
Finally, combining is the most effective when correlation between forecast errors on constituent forecast is low, meaning that each forecast brings different information to the integration process.(Goodwin 2000, 261)

3 PROFIT FORECASTING PROCESS

In this chapter, first, sales forecasting process will be presented as a key driver to successful profit forecasting. Secondly, the cost of sales estimation processes are reviewed as a basic driver that mediates to the profits. These two chapters will provide basic knowledge how to conduct profit forecasts because the profit forecast consists of sales and costs of sales difference.

Figure 1 presents a profit forecasting system, showing how, in practice, judgemental, mathematical, and statistical models are used in combination. Many forecasting authorities advocate one particular approach. Morlidge and Player (2010) illustrated their view about the most simple forecast processes will required all three kinds of models in combination.

Figure 1. A profit forecasting system



Source: (Morlidge, Player 2010, 120)

3.1 SALES FORECASTING

A company considering the development of sales forecasts will need to answer a diversity of questions before it can design a sales forecasting method to meet its needs. There are a several different questions about sales forecasting. The following questions are examples of optional questions. Who need a sales forecast? What should we forecast? What are the main determinants of sales? Which direction do we forecast? How do we evaluate a forecast? (Hughes, Singler 1983) Improving the sales forecasting process and its performance have long been a concern of managers and a focus of forecasting research. (Davis, Mentzer 2007, Mahmoud, Rice et al. 1988, Wright 1988)

Researchers have been developed and disseminated increasingly sophisticated sales forecasting techniques, which believed to more accurately, model the complexities of different marketplace conditions. (Fildes, Hastings 1994) However, these improvements in forecasting techniques are useful only if applied to an organisation's decision making and planning processes. (Winklhofer, Diamantopoulos et al. 1996, 194) Sales forecasts are estimated judgmentally (Sanders, Manrodt 1994) in an environment where much new information will become available just before the event time.

Numerous surveys of sales forecasting process (See McCarthy, Davis et al. 2006, Mentzer, Cox 1984, Mentzer, Kahn 1995, Sparkes, McHugh 1984) have consistently shown that qualitative methods, such as executive opinion and customer expectations, are more widely used than quantitative forecasting techniques, even though there is an extensive body of research supporting the superiority of quantitative forecasting methods in sales forecasting. Sales forecasting serves a critical linking function between internal decision-making and uncontrollable, external variables that have the potential to affect the demand for a firm's products. (Mentzer, Moon 2005)

The strategic corporate planning operates in an environment of uncertainty. Sales forecasts attempts to reduce some of this uncertainty by predicting *what* will be sold *to whom* and *when*. The gained information regarding *what* (products and services), *to whom* (market segments), and *when* (time patterns), is necessary input for planning in all functional areas of the company. It is useful to classify these needs as long run and short-run needs for sales forecasting. (Makridakis, Wheelwright 1987b)

Sales forecasting over a sufficient long future time horizon is an important prerequisite for efficient production planning and a solid base for firm policy decisions. A medium- to long-run forecasting horizon can be seen as 4 – 13 months. (Kotsialos, Papageorgiou et al. 2005) The long run forecasting is needed for organizational changes such as divisional decentralization and changing the sales force organization. For the sales forecasting as long-run forecasts are needed when companies are adding new products, extending product lines, dropping out old product and also in capital budgeting process and changes in the production facilities will require a long-run sales forecasting. (Hughes, Singler 1983)

Short-run forecasting for sales management is often complicated by the need to deal with many thousands of items simultaneously. (Bunn, Vassilopoulos 1993) According to Fildes and Beard (1992) they indentified this as an important research issue and observe that, although most organisations group products into a hierarchy of product lines, markets and classes, the conventional forecasting approach is to extrapolate each item's data series individually. A short-run forecasting horizon can be seen as daily, weekly or monthly base. Short-run sales forecasts are used in predicting the annual sales. This requires an extensive knowledge from several different strategy elements such as product planning, price changes, advertising etc. (Hughes, Singler 1983)

3.1.1 Sales forecasting process

Sales forecasting is a key factor in any company's success. Accurate sales forecasting allows a company to effectively control inventory, production facilities, labour, inventory levels and logistics, and is the base of which most all other operations within the company function. (Moon, Mentzer et al. 2003)

The process of sales forecasting is undertaken to predict demand at different stages. It's a complex managerial function and hence needed to be undertaken by a scientific way. Continuous improvement in sales forecasting process is a worthy goal for any organization. (Moon, Mentzer et al. 2003) The sales forecasting function includes process of forecasting, administration, hardware, software, users and developers of forecast. Historically sales forecasting has been considered as a side activity by most of the companies. Very few companies have seen sales forecasting by a scientific management point of view.

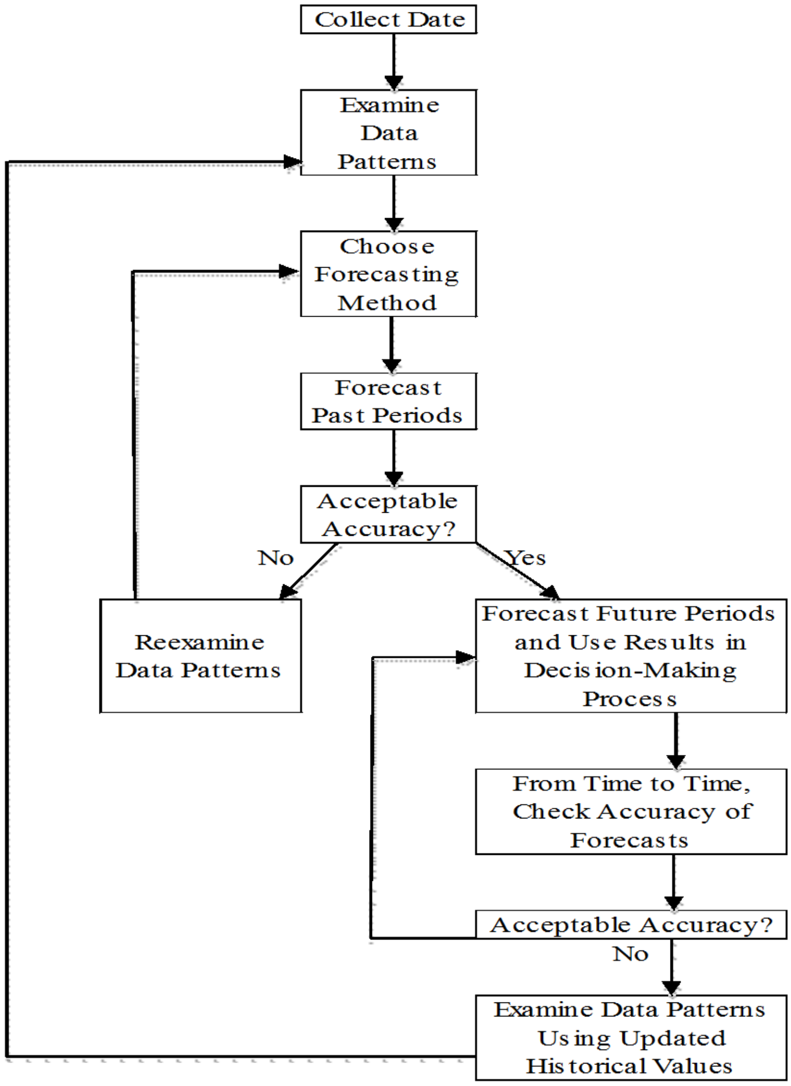
Less research has been reported in sales forecasting in comparison to other managerial functions. Planning based on sales forecasting; may be part of a selected strategy for growth and profitability. Sales forecasts are important for understanding market share and the competition, future prediction needs, and the determinants of sales, including e.g. pricing. (Frees, Miller 2004) Unfortunately, companies in many industries have found that their sales forecasting processes and systems have not kept pace with rapid technological advances; and the failure to update new data has inhibited companies' ability to achieve new business advantages.

On the other hand, those who have kept the pace with new technology are experiencing the benefits of improved marketing intelligence, increased sales forecasting accuracy, lower finished goods inventories, and higher customer satisfaction. (Chase 1996) To improve sales forecasting process, companies increasingly take advantage of computer and information system technologies. For example, *Point of Sale* (POS) data collection is gathering near-real-time sales movement at a *Stock Keeping Unit by Location* (SKUL) level of detail. (Moon, Mentzer et al. 2003, Smart 1995)

Sales forecasting process is inherently a company intelligence management process. By failing to equate sales forecasting to a process of intelligence management, companies inadvertently fail to capture key forecasting intelligence. Personal experience, learning from mouth-to-mouth business activities, sales leads, and customer-specific history, are all key elements that could facilitate the sales forecasting process effort, are often not tracked nor collected in many companies. (Kahn 2000)

Figure 2 shows the key operational steps in the forecasting process, which can be used in sales forecasting process.

Figure 2. The Operational Phase of the Forecasting Process



Source: (Hanke, Wichern 2009, 507)

A Multiple Indicators and Multiple Causes (MIMIC) Model

A *Multiple Indicators and Multiple Causes* (MIMIC) model is developed in which managerial evaluations of forecasting effectiveness are modelled as a function of different forecast performance criteria, namely, accuracy, bias, timeliness and cost. (Winklhofer, Diamantopoulos 2002) Accuracy and bias relate respectively to the magnitude and direction of the forecast errors, the difference between actual and forecast sales.

The MIMIC model specification is described by the following equations:

$$y = \Lambda\eta + \varepsilon \tag{26}$$

$$\eta = \Gamma x + \zeta \tag{27}$$

(Winklhofer, Diamantopoulos 2002, 153)

where,

y = indicators of η

x = the antecedents of η

ε = errors in measurement

Λ = reflect the loadings of the y-variables on the latent construct (η*)*

Γ = indicates the impact of the x-variables on η

ζ = random disturbance term

The MIMIC model implies that manager's evaluations of forecasting effectiveness are determined by the performance of the forecast in terms of accuracy, bias, timeliness and cost. The model has four different variables (accuracy, bias, timeliness & cost) to be taken under consideration and these four variables have four different hypotheses depending of performance criterion. The first hypothesis considers the accuracy; forecast accuracy will be positively related to managerial evaluations of forecasting effectiveness. The second hypothesis is for biases; lack of bias will be positively related to managerial evaluations of forecasting effectiveness. The third hypothesis is for the timeliness; timeliness will be positively related to managerial evaluations of forecasting effectiveness. The final hypothesis is for the cost; costs will be negatively related to managerial evaluations of forecasting effectiveness. (Winklhofer, Diamantopoulos 2002) The MIMIC model then should be seen as a starting point in modelling sales forecasting process effectiveness.

3.1.2 Sales Forecasting Management (SFM) framework

Over the three decades, significant advances have been made in developing sales forecasting techniques that more accurately reflect macroeconomic conditions. (Davis, Mentzer 2007) One of these developing techniques is *Sales Forecasting Management* (SFM) framework.

This framework offers to the managers to facilitate the exploration of the effects of organizational factors in sales forecasting. Davis and Mentzer (2007) proposed that a company’s sales forecasting climate influences its sales forecasting capability, which in turn determines performance outcomes. The measurement of performance will provide a feedback loops that monitor and control the company’s sales forecasting capability and sales forecasting climate.

The SFM framework concentrates on four different components: (1) sales forecasting climate, (2) sales forecasting capability, (3) performance outcomes and (4) performance measurement. The sales forecasting climate component is interesting part of this SFM because there are lots of debates going on about the similarities and differences between organizational climate and organisational culture. (Denison 1996) Davis and Mentzer (2007), defined the sales forecasting climate as the sheared perceptions, held by the employee, (1) leadership support for sales forecasting, (2) the credibility of sales forecasting and (3) the reward alignment in support of improved performance. The sales forecasting capability component includes information technology, information process, cross-functional communication and cross-functional ownership. To build a distinctive sales forecasting capability requires a focused commitment of resources and continuous learning. (Day 1994)

The sales forecasting accuracy, defined as the extent to which the sales forecast actually predicted the future demand (Makridakis 1993), is widely accepted as an appropriate standard for evaluating sales forecasting performance. Researchers suggests that sales forecasting performance should be judged on the extent to which sales forecasting supports improved business performance that affects the bottom line, such as inventory costs, profitability, supply chain costs and customer service levels. (Moon, Mentzer et al. 2003, Mahmoud, DeRoeck et al. 1992, Mentzer 1999) The performance measurement component defines the periodic measurement of progress toward time-based targets, establishes a baseline for evaluating the efficacy of organizational learning routines and gauging their impact on performance outcomes. (Prahalad, Hamel 1990, Sinkula 1994) The usefulness of performance measurement is positively related to improvement in the firm’s sales forecasting capability.

The SFM framework is a quite straightforward process model and therefore does not address potentially important moderators of the proposed relationships. For example, firm characteristics such as strategy orientation, the level of centralization or functional power differences could have an impact on the proposed relationships among constructs. (Davis, Mentzer 2007, 492) Also the external factors such as environmental contingencies and industry factors might affect the significance or strength of conceptual linkages. For example, the level of forecasting risk facing the firm may moderate the linkage between sales forecasting climate and sales forecasting capability. (Winklhofer, Diamantopoulos 2003)

3.1.3 Cost of sales forecasting

Companies' management is concerned not only with costs from past operations but also estimates, forecasts, of future costs. Cost estimation of future costs are determined by relating activity volumes with associated costs. Cost estimation is concerned with separating total costs into fixed and variable cost components with respect to the activity base. To know the company's historical cost behaviour can support decisions involving cost control, product pricing, budgeting and operational planning. (Reeve, Warren 1994)

Cost estimations are the determination of quantity and the predicting or forecasting, within a defined scope, of the costs required to construct and equip a facility, to manufacture goods, or to furnish a service. Using past data and calculating and forecasting the cost of methods and management, within scheduled time frame, determine costs. Cost estimation provides the basis for project management, business planning, budget preparation, and cost and schedule control. (Uppal 2001)

Uppal (2001) compiled the process of cost estimation as following; the first step is established the project's scope of work and the format for providing information for factual business decisions. Secondly, some sort of estimates must be prepared such as order-of-magnitude estimates can be considered as the benchmark estimates and are continually modified and improved as the project is better defined. Once the definitive scope of work has been agreed to all participants the process of cost estimating can begin.

3.2 MEASURING FORECAST ACCURACY

Inaccuracies in sales forecasting can mean excess inventories or lost sales, so it’s no surprise that researchers have reported surveys that show accuracy as the most important criterion in selecting a sales forecasting strategy. (Dalrymple 1987, Lawrence, O'Connor et al. 2000) Implicit to the equation where “lower errors = better forecast performance” is assumption that managers base their assessments of the effectiveness of a sales forecast primarily on an evaluation of forecast accuracy. (Winklhofer, Diamantopoulos 2002)

When conducting sales forecasts, first assumption is the one that states that forecasts will always be in error and there can be no 100-percentage guarantee of accuracy. When the forecast accuracy is analyzed, the attention should be given to the variability of forecast error distribution and to the location of the distribution. The ideal forecast error distribution would have a mean of zero and be peaked i.e. have a small variance.

In forecasting literature, several of forecasting error measures has been presented. Most of these measures involve averaging some function of difference between an actual value and its observed value. The differences between observed values and forecast values are often referred to as residuals. Then the residual is the difference between an actual observed value and its forecast. (Hanke, Wichern 2009, 82)

Forecast error (or residual):

$$e_t = f_t - \hat{f}_t \qquad (28)$$

where f_t is the actual value of the forecast variable in period t and $\hat{f}_t$ is the forecast for variable x in period t.

The forecast error can be divided into two categories: One, resulting from under-forecasting and the other from over-forecasting. Each one has a different impact on the company’s cost and sale, and consequently, profit margin. (Jain 2003)

In this study only three techniques to calculate forecast errors are presented; *Mean Squared Error* (MSE), *Mean Percentage Error* (MPE) and *Mean Absolute Percentage Error* (MAPE).

In *mean squared error* (MSE), each error or residual is squared and then summed and divided by the number of observations. The MSE is given by equation (29):

$$MSE = \frac{1}{n}\sum_{n=1}^{n}(Y_t - \hat{Y}_t)^2 = \frac{\sum e_t^2}{n} \qquad (29)$$

(E.g. Nahmias 2009, 63, Hanke, Wichern 2009, 121)

This approach penalizes the large forecasting errors, because the errors are squared. In other words the technique "prefers" a smooth error pattern. It's important because a technique that produces moderate errors may well be preferable to one that usually has small errors but occasionally yields extremely large ones. MSE is directly linked to the estimate of the standard deviation of forecast errors (σ) over a review interval of forecasts. When computing MSE with spreadsheet program it's quite easy and parameter optimization for e.g. smoothing methods is based on minimizing MSE. (Hanke, Wichern 2009, 121, Silver, Pyke et al. 1998, 109)

Controlling the biased forecast (estimate constantly too low or high) it's important to take corrective actions as soon as possible. *Mean percentage error* (MPE) is used in these cases. MPE proportions the forecasts errors to the actual values and assumes the linear loss function.

$$MPE = \frac{1}{n}\sum_{t=1}^{n}\frac{(Y_t - \hat{Y}_t)}{Y_t} \qquad (30)$$

(Hanke, Wichern 2009, 83)

When using MPE one can check the possible bias of forecast very easily. If the forecasting approach is unbiased, the MPE will produce a number that is close to zero. This means that forecast errors are on average evenly distributed on both sides of actual values (over- and underestimates).

Mean absolute percentage error (MAPE) is not affected by the magnitude of the values because it's expressed as percentages. Finding the absolute error for each period and dividing it by the actual value observed and then averaging these absolute percentage errors compute MAPE.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|Y_t - \hat{Y}_t\right|}{Y_t} \qquad (31)$$

(Hanke, Wichern 2009, 83)

The MAPE is especially useful when measuring how large the forecast error is compared to actual values (Y_t). Notice that MAPE cannot be calculated if any of the Y_t are zero. (Hanke, Wichern 2009)

3.3 FORECAST FREQUENCY UPDATE

Morlidge and Player (2010) suggested that forecasts update frequency should be investigated more short-term than longer term. But in order to make good design choices for forecast frequency it should be more specific. The more rapidly an important forecast variables changes, the more frequently forecasters should refresh the forecasts. The criterion of importance is the likelihood of a change in the variable concerned affecting the "steering decisions". On the other hand, in a traditional "budgeting" style process all variables are automatically reforecast, the approach to forecast Morlidge and Player advocated differentiates between "critical variables" which are frequently refreshed and "non-critical variables" which are refreshed infrequently. (Morlidge, Player 2010, 69)

To adopting a more discriminating approach to forecast frequency speeds up the process and reduces the effort involved in forecasting but there is another important benefit. It is impossible to eliminate random variation from any process. Therefore, if forecasters reforecast unnecessarily it is likely that one will inject noise into the process, which in turn could generate spurious analysis and, worse, unnecessary actions.

The length of the forecast frequency horizon needed is determined by decision-making lead times – and it will vary between and within business. The logical consequence is that the forecast frequency horizon should be related to the longest lead-time in the business. Therefore, if the longest lead time is the 12 months then the forecast horizon should be at least 12 months. (Morlidge, Player 2010, 62)

From a theoretical point of view, if the “longest lead time” is 12 months forecasters need, at all times, a 12-month horizon. This is also called the “rolling forecast”: a forecast where the horizon rolls forward such that there is always a consistent level of visibility. When using rolling forecast and 12-month horizon, the forecast update can be made either every quarter or even every month. This can increase visibility by a factor of three over one with fixed annual horizon when forecast update is quarterly.

It is frequently the case that sales forecasts are available at the detailed product level for only a relatively short time horizon. For the rest of the forecast horizon, only aggregate sales forecasts at the product family level are available. The problem is how to fit a forecast simulation model to a history of these aggregate and disaggregate forecasts. (Zhou, Jackson et al. 2007, 831)

Updating forecasts too often can be as fruitless as forecasting too infrequently. One benefit of increasing frequency might be that forecasts become more accurate, because updates that are more frequent pick up "real" changes in demand much faster. Therefore, one might suspect that industry forecasters believe that forecasting more often is better, or at least that monthly forecasting is better than quarterly (or longer) forecasting. One should probably consider that do not forecast too often, yet not too infrequently either. (Lapide 2007, 18)

SUMMARY OF THE LITERATURE REVIEW

Literature review describes the forecasting models, processes, as well as forecasting accuracy and update frequencies. These parts were essential for the study to understand the forecasting models, processes and key factors before conducting the empirical part.

First, there were two main forecasting methods under investigation, judgmental and statistical. To produce forecasts the statistical method was divided into two different approaches, time series and causal methods.

Judgmental methods are the most widely used in forecasting. Therefore, judgmental methods were examined closely to understand their elicit advantages. In the end of chapter two, the advantages and disadvantages of both methods were investigated.

Second, part three examined the sales and the cost of sales in forecasting processes, as a part of the profit forecasting. The section also studies the forecasts accuracy and update frequency. Previous researches show that forecasting accuracy is the most important criteria when choosing the process for profit forecasting.

Based on the theoretical review, the profit forecasting process consists from different variables, methods, time horizons and human judgments. Theoretical information provides the basis and different analysis between different methods and variables used in empirical research. One interesting aspect that the theory provides is the *judgmental methods* for forecasting. Judgment can be used in identifying the endogenous and exogenous variables, building structural equations, correcting for omitted variables and specifying expectations for economic indicators. Theory shows that human judgement should be valued more in profit forecasting processes. Furthermore, the theory gives an idea of why and how the forecasting process has been studied before, and how this knowledge should be utilized in the future researches.

4 RESEARCH METHODS

This chapter introduces the research methods used to examine the profit forecasting processes in the empirical analysis.

The case company provides the data for this study. The data used is from year 2009. The data consists of actual figures from January to December and forecast figures from February to December. The data will be examined starting from business unit level, to division level and the concern level. The forecast data was available from several years but the decision to use year 2009, came from the case company. The main reason to use year 2009 was the extremely hard conditions in steel markets, which were also influenced by the financial crisis at the end of the year 2008. This will give interesting perspective for the study.

Interviews are used as part of the empirical research. Five key persons related to forecasting process in Rautaruukki Oyj are interviewed. The interviews will give inside look on how the forecasts are made in steel industry company and a preview to the existing complications in forecasting processes. Interviews were conducted by using theme interviews. The subjects that discussed in interviews were; the current forecast process for sales and cost of sales, the interviewees' own opinion on how the forecasting processes should be, the worst problems in current forecast process and the forecasting frequency. The results of these interviews are presented in chapter five.

4.1 FORECAST METHODS

This study presents the two most common approaches of forecasting methods, judgemental and statistical. These two methods by themselves could not be used to investigate forecasts, because a forecast process requires both of the methods in different combinations. Therefore judgemental and statistical methods are both used in the empirical part when investigating the profit forecasts and accuracy.

The use of statistical methods, time series and causal, is to identify historical patterns of behaviour and then use these to extrapolate the future figures. This method has obvious benefits for decision-making purposes, since different elements of variables represent different levers that can be pulled to affect future outcomes.

Without statistical methods one could not investigate properly the data and the different outcomes on different variables. These methods are used as a benchmarking against each other. Therefore, it was investigated which statistical method gives the most importance to the decision-making, when assessing the profit forecast accuracy. When examining the statistical methods and its outcomes, one should remember that before making any assumptions about the forecasting figures, there should be correlation between different variables.

The use of judgemental method is unavoidable because judgment is the most straightforward approach to forecasting in many situations. It is also the only way to estimate the impact of novelty. Even the straightforward mathematical models are fed by assumptions, which are an output of a judgmental process. One should remember, that judgmental methods are the most commonly used in business forecasting. (Morlidge, Player 2010) Most of the business forecasts (e.g. sales and cost budgets) are based on the judgmental of an individual or a group of individuals. Therefore, this method and its models have great impact of producing the statistical forecasting methods. Therefore, it was investigated how much judgmental method will influence to the statistical forecasting methods.

4.2 FORECAST ERROR MEASURES

When forecast accuracy is analysed and the scale of the forecast series differ to a great scope, a suitable forecast error measure should be independent of scale. In other words, the forecast errors should not be too sensitive to observations. The importance of the items included in the forecasting process diverse. The measure should be able to weight the items according to their significance.

The theoretical part introduced three different techniques to measure forecasting errors; *MSE, MPE & MAPE.* When measures of variability are compared, MSE treat items differently depending on the items scale, whereas MAPE and MPE are dealing with percentage errors.

In other words, MSE penalizes the large forecasting errors and the technique prefers *only* a smooth error patterns. The MPE allows positive and negative percentage errors to cancel one another and therefore this technique can be affected by the magnitude of the values. The MAPE is very useful when measuring the size of forecast errors, which are compared to actual values. One can compare the error of fitted time series that differs in any level. Therefore, MAPE was selected for the measure of forecast errors in this study. It is also easier to interpret than MSE or MPE.

When it comes to measuring the forecast bias, the mean absolute percentage error is independent of scale. In this context, bias refers to persistent forecast error. When the percentage errors are weighted by actual profit forecast items, each item receives a weight that signals its importance for the forecast accuracy.

4.3 FORECAST METHOD SELECTION

The present forecasting methods used in the case company were questioned. The idea was to study, if a better method or methods could be found by simulating profit forecasting with different methods. The accuracy of the different methods simulated, then compared to the accuracy of the case company's methods. The gained results of the test simulation were tested for statistical meaningfulness.

When selecting an appropriate forecasting method(s) there are certain things that must be considered. The following list will give perspective to the factors that should be considered when forecasts are made.

- The quality and quantity of data available
- The purpose of the forecast. Accuracy vs. explanatory
- The inside information possessed by forecasters
- Expected changes
- Forecast frequency

For selecting the forecasting methods for the case company the following things had to be considered. In the case company the forecasts are made 1 – 13 periods ahead, and then the selected method(s) have to be suitable for several forecast periods ahead.

Because the resources for making forecasts are limited, and because the persons who are making the forecasts might have little or no training in the field of statistics, the method should be relative simple to use and should not need complex calculations. Furthermore, the profit forecasting requires a high rate of accuracy in the case company. Therefore the selected method should be easy to calculate with any information systems. Also the selected method(s) should be easy to explain so that the method(s) would get management's support and acceptance.

The forecasting methods that were used in the empirical part are listed below:

- Naïve forecast methods
  - Simple moving average
  - Weighted moving average
  - Simple exponential smoothing

I will test these three methods to see how these methods indicate the changes in forecasted figures against actual figures. The reason why I selected these methods was simple; the data for this study was quite small only values from the year 2009 and this ruled out the causal methods such as simple regression and multiple regression models.

5 CASE STUDY: RAUTARUUKKI OYJ

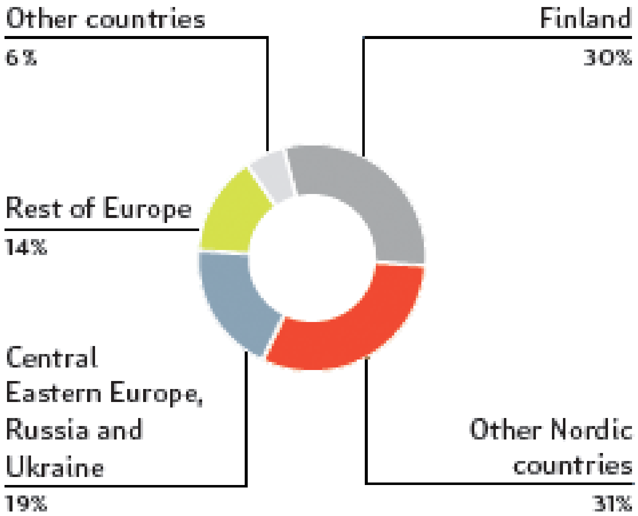
This chapter starts the second part of this study, where the theories introduced in the first part of the study will be applied to assess the practices of the case company. In this chapter, the case company in general will be briefly introduced, brief description of how the profit forecasting is produced at the steel industry company and the existing complication of profit forecasting in the case company will be reviewed.

5.1 CASE COMPANY INTRODUCTION

This study has been executed as an assignment for the case company, which operates in the field of metal industry. Rautaruukki was established in 1960. The Finnish government to ensure the availability of raw materials for the Finnish shipbuilding and other metal industries originally founded the company. Rautaruukki Oyj became a listed company in 1989 and the Finnish government abdicated Rautaruukki’s majority of shares in 1997.

Rautaruukki supplies metal-based components, systems and integrated systems to construction and the engineering industry. The company has a wide range of metal products and services. Rautaruukki’s net sales in 2009 were approximately EUR 2.0 billion and reported negative operating profit was EUR -332 million. The company’s weak performance in year 2009 was due mainly to lower sales volumes and selling prices. Rautaruukki has operations in 27 countries and employs 11,700 people. Rautaruukki's market area is Europe. The company has a strong position in the Nordic countries. Long-term focus of growth is in Central Eastern Europe, Russia and Ukraine. The company's share is quoted on NASDAQ OMX Helsinki (Rautaruukki Oyj: RTRKS). In 2004 all the different companies in Rautaruukki Corporation started using the marketing name *Ruukki*. Ruukki’s operations are structured into three business areas: *Ruukki Construction*, *Ruukki Engineering* and *Ruukki Metals*. (Rautaruukki Oyj 2009)

Figure 3. The breakdown of Ruukki net sales 2009 (%)



Source: (Rautaruukki Oyj 2009)

Ruukki Construction

Ruukki's construction business, *Ruukki Construction* (RC), supplies more efficient, timesaving steel construction solutions for commercial and industrial construction, as well as for infrastructure construction and transport infrastructure projects and residential roofing products. Ruukki Construction net sales in 2009 were EUR 589 million (30 % share of consolidated net sales). Ruukki's aim is to be the industry leader in steel construction in Europe. The strategic focus areas are commercial & industrial construction, residential construction and infrastructure construction. The main products and services are; building frames, wall and roofing products, integrated systems for single- and multi-storey construction, bridges, traffic noise barriers and highway guard rails for infrastructure construction, piles, retaining wall structures and foundations for harbour construction and roofing products. Ruukki Construction's main market areas are Nordic countries, Baltic States, Central Eastern Europe, Russia and Ukraine. (Rautaruukki Oyj 2009)

Ruukki Engineering

Ruukki's engineering business, *Ruukki Engineering* (RE), supplies components and fully assembled systems to the engineering industry. Ruukki Engineering net sales in 2009 were EUR 312 million (16 % share of consolidated net sales).

Customers are globally operating OEM companies of heavy machinery in the lifting, handling and transportation equipment industry, the energy, offshore, marine and paper industries. Ruukki supplies customers in the lifting, handling and transportation equipment industry with systems such as fully assembled cabins and booms for mobile machines, as well as medium and heavy welded structures such as frames. The company delivers nacelle components, flange profiles and windmill tower plates to equipment manufacturers in the energy industry. Ruukki also manufactures oil sumps and common base frames for diesel engines. Ruukki Engineering serves globally operating European countries. (Rautaruukki Oyj 2009)

Ruukki Metals

Ruukki's steel business, *Ruukki Metals* (RM), has a broad product offering including hot- and cold-rolled products, colour- and metal-coated products, as well as tubes, bars, beams and profiles. In addition, stainless steel and aluminium are sold as trading products and processed in service centres for customers. Ruukki also provides prefabrication, parts processing, storage and logistics services together with technical support and consultation. Ruukki Metals is responsible for the company's steel production and steel service centres. Ruukki Metals net sales in 2009 were EUR 1.050 million (54 % share of consolidated net sales). The main customer segments are the heavy and light engineering industry and the construction industry. Ruukki Metals main market areas are Nordic countries, Baltic States, and Russia and selected customers for special steel products in Western Europe. (Rautaruukki Oyj 2009)

5.2 PROFIT FORECASTING IN THE STEEL INDUSTRY COMPANY

The following chapter will give inside information how the profit forecasting process is conducted in the case company. The starting point is to look how the sales forecasts are made and then move to the costs of sales forecasts, to get the idea how the profit forecast is conducted. The chapter is divided into two parts, sales and costs of sales forecasting process. The Sales, General and Administration (SGA) costs were ignored from this study when conducting profit forecasts. The information is gathered by interviewing the key persons who are responsible for the forecasting processes for divisions' point of view and the information is completed by the corporate point of view.

Forecasting scenarios

In *Ruukki*, before any forecasts are made, there will be set of three different scenarios; base, worst and best case. These three cases form the basis for the forecasts. Forecasts are straddled in different scenarios before execution. The cases, best and worst, are valued with percentages of changes against the base case, which are the zero variables. For example, in financial planning the case will be worst-case scenario because of the changes in financial outcomes need sensitive adjustments. The forecasts for sales are made with best-case scenario and cost of sales is made with base-case scenario.

5.2.1 SALES FORECASTING PROCESS

The sales forecasting process in Ruukki's three divisions vary quite a lot, because all the three divisions operate in different market segments. Therefore, every division is reviewed separately.

Ruukki Construction

Predicting the sales for RC division is very complicated because the division and its units operate in different kind of construction segments. For example, the division provides enormous bridge components, which are very difficult to predict in advance, residential construction and infrastructure, and also smaller construction components for basic construction (e.g. steel beams, roof elements and traffic noise barriers). The process for sales forecasting will start from the key persons who are responsible for each segment. Before making any decisions about future opportunities they will revise the information about the sizes of different markets. After this, they will check the historical data on divisions "hit rates" on biddings. Continuing the process, the key sale persons prepare different prospects for the division management and these are preliminary ideas about the market opportunities that are available on the markets. One key element is to follow different developments of permits in different countries. These permits are building licences, mining licences and different construction licences (e.g. bridges and industrial construction). After this, divisions' management and units' directors will decide which opportunities they will try to get involved by participating in competitive bidding against other rivals. After these biddings the management will have knowledge about the possibilities of future sales. (RC, Vice President)

The next step on sales forecasting process is to evaluate the order books and order intakes. This will give basis for the forecasting process to be continued. Also the historical data about the divisions' product portfolio, which includes all the possibilities what the division can provide to its customer, is reviewed. This is done because the information about the product portfolio will give historical information on different products sales. This information will help to evaluate the future prospects of sales for the division. (RC, Vice President)

Overall the process of sales forecasting in RC includes several steps (e.g. planning, initialization and bidding) before any sales forecasts can be made and also different kind of information (past and present) about markets, products and permits. The key idea in sales forecasting for RC is the collaboration with different persons.

Ruukki Engineering

Forecasting the sales for *Ruukki Engineering* is totally different process compared to the *Ruukki Construction*. *Ruukki Engineering* operates in engineering business segments, which include booms, frames, energy, offshore and marine business solutions. The process of sales forecasting starts from the key sales persons whom enter theirs sale forecasts into information system. This forecast is the preliminary forecast. The second stage is that the controllers will enter their own predictions of net sales into the other information system by adjusting the forecasts with the historical data. This is very rough prediction and it will be compared with the sales person's forecasts. The outcome ultimately becomes the sales forecast. The main function for the controllers is to keep the sales forecast data valid, which the key sales persons have entered. Basically the sales forecast process is divided into two different prognoses, to the economic forecasts and to the key sales person's forecasts. (RE, Business controllers A)

Ruukki Metals

The forecasting process for sales in *Ruukki Metals* is done by every month as rolling forecasts. The process starts from sales organization about two weeks before deadline, where main customer forecasters update their sales forecasts into information system. This is called as Demand Plan. After the sales organization has downloaded their information about customers' sales forecasts, the demand planners collect the demand plan data from the information system to Excel for review of possible manual adjustments to the file if needed.

After the manual adjustments, the data will be forwarded to business unit controllers and business unit managers whom will review the data with Demand Planners to adjust the data for business unit level. To adjust the data for business unit level it requires financial accounting tool for adjustments. When the adjustments have been approved for business unit level the process will continue to Vice President of Sales who will review the data with business unit managers and controllers. If the Vice President of Sales approves the sales forecast it will continue to division level consolidation for reporting.

In consolidation the forecast data will be adjusted once again before the data will be send to Vice President of Finance. The Vice President of Finance will review and adjust the data for division level admin items. After this the sales forecast is presented to division president who will review the data with Vice President of Finance. When the sales forecast is approved it will go to the *Ruukki Metals* executive group for review. When the executive group and division president gives the approval for the sales forecast, the sales forecast of *Metals* will be published for Corporate. If there isn't any requirements for adjusting the *Metals* sales forecast behalf of the Corporate Finance team, then the Chief Financial Officer (CFO) will approve the sales forecast and then the process of sales forecasting is ended.

5.2.2 COST OF SALES FORECASTING PROCESS

The cost of sales forecasting process in *Ruukki* is based largely on the production of steel from which *Ruukki Metals* is responsible and therefore the cost of sales process starts with the amount of steel needed in every division. This chapter will provide the short summary of all the three divisions and after that the overall idea of cost of sales forecasting process.

In *Ruukki Construction,* the cost of sales forecasting process starts with the calculations of gross margin of sales and after this, the cost of materials is created by the *Ruukki Metals*' forecasts for the development of raw steel prices. The output now gives an indication of how the cost of sales will be reform. This sum is the whole cost of sales for *Ruukki Construction* and therefore it has to be allocated to different product portfolios. This will be done with information systems. One thing that could impact hugely to the amount of cost of sales forecasts is action plans. (RC, Vice President)

In *Ruukki Engineering,* the formation of cost of sales forecasts starts by the cost pool controllers whom will enter the estimates to the information systems based on the historical data. Then the business controllers will download the figures from the inputted systems and make some adjustments to the figures before downloading the valid figures (cost reports) to the main system. Now the allocations of costs for different products can be made. (RE, Business controller B)

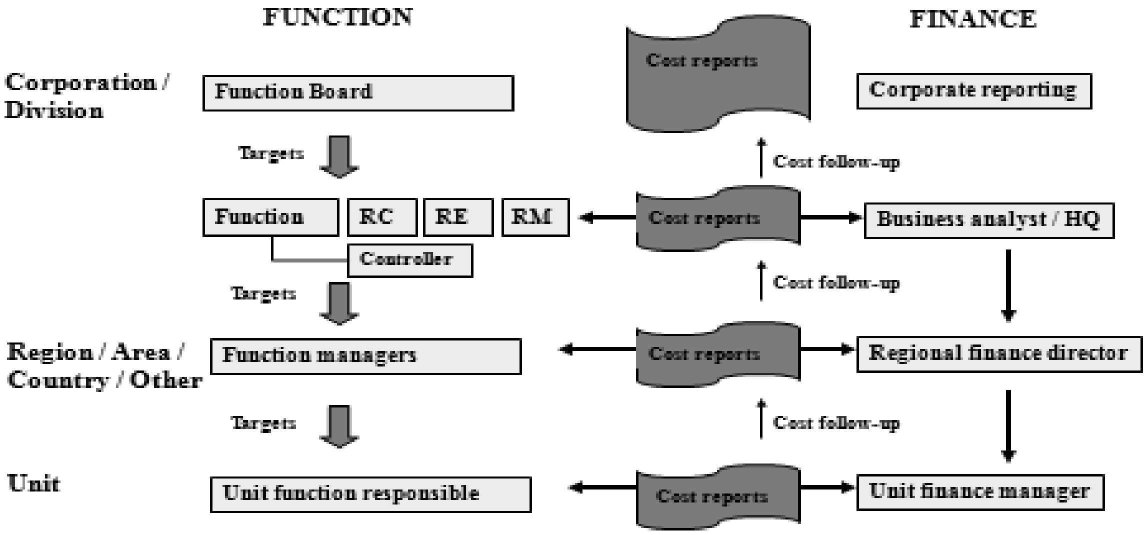
In *Ruukki Metals*, the cost of sales forecasting starts from the standard cost of goods sold forecasts from the main product groups. The basic idea is that the standard cost of goods sold estimates are made for one month ahead and if the standard cost estimate will differ from the baseline, the forecast for cost of goods sold will be adjusted for the amount of the change in standard. These adjustments are made in business unit level and the business unit controllers are responsible for these estimate changes. (RM, Vice President)

The purpose of cost of sales forecasting task in steel industry company is to ensure systematic proactive cost planning and control that the target budgets are realized and/or deviations are recognized and reported on time. All purchases are planned to meet the budgets before making subcontracts and task plans are made before starting forecasts. The aim is to report on real time the status and the forecast of the cost budget, by means of budget monitoring, so that any cost overrun can be dealt with immediately. Preceding actions was to ensure that an internal target has been created in the information system.

The actions after the first preliminary step were focusing on monitoring the budgets, actual historical costs, instalment milestones and other income sources. If the cost forecasts exceed the budgeted costs, the reasons for this have to investigated and evaluated as well as the corrective actions have to agreed upon and taken immediately.

Figure four will demonstrate the cost of sales management and reporting stages through the company.

Figure 4. Cost of sales management and reporting process



5.3 THE EXISTING COMPLICATIONS IN PROFIT FORECASTING PROCESS

Ruukki Construction

The complications that *Ruukki Construction* encounters in the process of profit forecasting are the validation of data, maintenance of inventories, sales commissions and the number of different indicators used in the forecasts. (RC, Vice President) For this study the main interesting complications are data validation and the number of different indicators (drivers) used in forecasts.

The data validation is one of the existing complications and the problem here is which data is relevant or not. Before the data is implemented to the several information systems it should go under the strict validation process, which data the division can be used and which data are relevant for making the profit forecasts. The problem here is the different amount of different data, which will be inputted to the systems. The key items are the data for net sales and cost of sales.

The data validation, if it's done proper or not, will have an effect on forecast accuracy. The right data is very important factor in the outcome of profit forecasting. (RC, Vice President) The second existing complication is the number of different indicators used in profit forecasting process. There are so many different drivers to be considered when conducting profit forecasts, including the drivers needed to forecast sales and cost of sales, but in the same time too many drivers used will confuse the focus of outcomes. (RC, Vice President)

Ruukki Engineering

The complications that *Ruukki Engineering* encounters in the process of profit forecasting vary largely. Furthermore, the problems are interrelated to each other. For this study all the complications that are reviewed below, are interesting factors for the profit forecasting process.

One complication that creates especially big problems in profit forecasting process is forecasting with information systems because they are not on a strict schedule, which leads to the forecasts varies largely in different units. Also the number of information systems used in the process, which causes differences in the forecasts, due to difference in information systems. Furthermore, the number of forecasters has been also one problem because, of the judgmental point of view, the forecasters opinions varies largely on the profit forecasting processes. This relates to the next problem, which is the communication between salesperson, units directors and controllers. The controllers prepare a proposal of forecasts for the unit directors and salespersons, which lead to the problem that the proposal will not be discussed by the key persons on the contrary the forecast proposal is considered only as given. (RE, Business controller B)

The forecasts frequency is seen as one of the complications. This is due to the fact that some salespersons update their forecasts on a weekly basis and some may update their forecasts on monthly basis. At the moment the forecasting process chain is too heavy due to the confusions of the forecasting frequency, which leads to the fact that the profit forecast process is too detailed. (RE, Business controller A)

"The big picture has been disappeared along the way." – RE Business controller B

One of the stated problems is the driver(s) used in profit forecasting process because the division operates in engineering business and there are no unambiguous drivers to be used.

Ruukki Metals

The complications that *Ruukki Metals* encounters in the process of profit forecasting is the problems with new forecasting process model. The new forecasting model starts creating the profit forecasting process form the administrative units. Where as the old forecasting process model started from the profit forecasting process from customers' sales forecasts. The current challenge is to figure out how the internal chain could operate more efficiently. One reason for this complication is that the division sets all its resources on the external chain. Furthermore, the division problem is based on the lack of internal understanding of the business. (RM, Vice President)

The forecasts accuracy, volumes and their impact to the profit forecast outcomes are seen as one of the problems. This is due to the fact that the forecasting process model has been changed to a new one. The forecasts accuracy has been suffered by the change. The forecast on volumes has been very difficult due to the fact of Financial Crisis in 2009. The process of volume forecasting is too heavy and it ties up lot of resources, which makes the whole process chain too slow to act in rapid movement in the markets. Furthermore, the impact of forecasting volumes is dependant on divisions' industry knowledgement. This has been seen as one of the problems. The industry knowledge is too scattered and it should be more specific. This relates to the main problem which is the driver(s) used in profit forecasting process because the division operates in various businesses and there are no unambiguous drivers to be used. (RM, Vice President)

The current profit forecasting process in the case company have been seen too slow for any rapid changes which is caused by the numerous of different forecasting methods and forecasters. Also the accuracy for profit forecasts has been seen too inadequately. The reasons for this were too complicated methods, numerous of different drivers and forecast update frequencies, which have been too long. The division's chief financial officers are responsible for the profit forecasting process. The forecasts proposals for division's financial officers are made by the group of different regions sales managers' with help of divisions' business controllers and controllers.

6 EMPIRICAL ANALYSIS

Chapter's purpose is to provide an explanation to the research question, which is; *is it possible to improve profit forecasting accuracy by adding drivers to the profit forecasting processes?* I will first demonstrate the effect of different forecasting methods to the profit forecasting processes accuracy without drivers and with different drivers. Then I will evaluate the usage of selected drivers in profit forecasting process and methods in this study. After this I will present the common reasons for forecast errors in the process of making profit forecasts. I will end this chapter with an analysis of the forecast update frequency needed for the case company.

6.1 FORECAST ACCURACY AND ERRORS WITH DIFFERENT METHODS

In this section, the forecast accuracy and errors of forecasts made in year 2009 with different forecasting methods are investigated. The outcomes will be reviewed with the perspective of *Corporate*, *Ruukki Construction*, *Ruukki Engineering* and *Ruukki Metals*.

6.1.1 Simple Moving Average (SMA)

As Figures 17 – Figure 28 in Appendix 1 demonstrates the simple moving averages accuracy average, accuracy median and standard deviation for net sales, cost of goods sold and operating income in periods 2/2009 – 12/2009. This method is tested to show how forecasting accuracy is made without using any drivers and this will give different perspective for the other methods which are using drivers for profit forecasting processes.

The forecast accuracy of net sales has been reasonable good during the whole investigation period. Only *Ruukki Engineering* shows little bit lower values for net sales forecast accuracy and also the standard deviations of forecast accuracy figures are higher than others. The reason for this was the whole engineering businesses delay on figures in year 2009. The impact of the recession, which started in the end of year 2008, shows its face not until the first quarter of 2009. The impact hit hard to the engineering business and the forecast figures that were made in February and March were too optimistic for the rest of the year (See appendix 1, Figure 19).

This is also seen in Figure 5, which demonstrates the error measure of operating income monetary effects for *Ruukki Engineering*. In Figure 5 to Figure 8, the idea is to demonstrate how the profit forecast errors are changing when first, the forecasted figures are compared for each months (e.g. n=2) actual figures and then, to the next months forecasted figures. This will give the error percentages for how much the forecast differs from actual figures. The value of #DIV/0! in the Figures below means, that the forecasted value and actual value were the same. This means that the forecast accuracy was 100 %, but the model calculates the error measures by dividing the forecast figure with the outcome of actual minus forecast. The impact of bad forecasts for net sales has a clear action to the operating income accuracy and error measures.

Figure 5. Engineering error measures for operating profit (2/2009 – 12/2009), SMA

Error measure (MAPE)										
n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
-	-	-	-	-	-	-	-	-	-	-
15.00 %	-	-	-	-	-	-	-	-	-	-
17.00 %	36.23 %	-	-	-	-	-	-	-	-	-
25.00 %	44.44 %	77.08 %	-	-	-	-	-	-	-	-
40.00 %	51.11 %	59.58 %	70.87 %	-	-	-	-	-	-	-
37.50 %	30.56 %	26.04 %	24.83 %	35.97 %	-	-	-	-	-	-
8.33 %	5.56 %	10.42 %	13.67 %	18.80 %	28.36 %	-	-	-	-	-
12.50 %	30.56 %	35.42 %	32.33 %	29.72 %	26.50 %	31.00 %	-	-	-	-
25.00 %	34.44 %	35.83 %	37.47 %	40.11 %	42.14 %	44.68 %	48.85 %	-	-	-
15.00 %	21.11 %	25.83 %	27.07 %	28.67 %	31.10 %	33.15 %	35.64 %	39.48 %	-	-
30.77 %	43.59 %	50.48 %	55.15 %	57.93 %	60.17 %	62.26 %	63.99 %	65.67 %	74.41 %	-

One of the reasons of good forecast accuracy on net sales for *Ruukki Construction* and *Ruukki Metals* based to the fact that these units had a lot's of possible prospects under order already before the year 2009. The accuracy measures can be seen in appendix 1, Figures 18 and Figures 20.

The forecast accuracy of cost of goods sold has been very good throughout the concern, which is seen in appendix 1, Figures 21 – Figures 24. The knowledgement of historical demand data and anticipation of the recession was prepared carefully. For the steel production part, where the whole business starts for every division, *Ruukki Metals* was very accurate on their forecasts for steel production. This helped the other divisions to plan their material costs quite accurately. The result was that the forecast accuracy for cost of goods sold was averaged out of 90 %.

The forecast accuracy of operating income tends to decline when the length of the forecast horizon increases (See appendix 1, Figures 25 – Figures 28) and the error measure percentages varies largely when the forecasts are made with simple moving average method (See Figures 6 – Figures 8). When the forecasts are made in 12 months ahead the error measures varies from 10 % to 80 %. This is too large gap between error measures. When looking the error measures with *Corporate, Construction, Engineering* and *Metals,* there can be seen that shorter periods of forecasts will give better values for accuracy and error measures. It was said that simple moving average is at its best when used forecast stationary series. (Nahmias 2009, 65)

For this point of view the SMA method is not the efficient way to investigate the profit forecasting accuracy because the steel industry is very dynamic business segment and this should require more specific method to generate the forecasts in monthly perspective.

Figure 6. Corporate error measure for operating profit (2/2009 – 12/2009), SMA

Error measure (MAPE)										
n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
-	-	-	-	-	-	-	-	-	-	-
25.44 %	-	-	-	-	-	-	-	-	-	-
4.17 %	9.95 %	-	-	-	-	-	-	-	-	-
15.63 %	14.86 %	11.30 %	-	-	-	-	-	-	-	-
25.86 %	39.46 %	42.53 %	41.75 %	-	-	-	-	-	-	-
25.00 %	39.86 %	52.17 %	57.39 %	58.94 %	-	-	-	-	-	-
1.85 %	5.76 %	11.73 %	18.57 %	22.26 %	23.92 %	-	-	-	-	-
45.36 %	53.65 %	43.12 %	49.20 %	49.73 %	56.59 %	47.14 %	-	-	-	-
79.17 %	69.14 %	36.78 %	28.62 %	27.31 %	24.43 %	28.45 %	28.61 %	-	-	-
33.33 %	28.15 %	21.11 %	20.62 %	24.41 %	30.72 %	38.75 %	45.15 %	49.96 %	-	-
20.83 %	31.79 %	30.79 %	27.96 %	23.92 %	22.54 %	23.89 %	27.20 %	30.04 %	32.22 %	34.17 %

Figure 7. Construction error measure for operating profit (2/2009 – 12/2009), SMA

Error measure (MAPE)										
n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
-	-	-	-	-	-	-	-	-	-	-
47.92 %	-	-	-	-	-	-	-	-	-	-
30.00 %	24.44 %	-	-	-	-	-	-	-	-	-
91.67 %	25.56 %	91.67 %	-	-	-	-	-	-	-	-
67.78 %	28.89 %	64.34 %	37.33 %	-	-	-	-	-	-	-
50.00 %	22.00 %	28.67 %	25.00 %	31.94 %	-	-	-	-	-	-
33.33 %	37.04 %	31.94 %	34.89 %	36.48 %	32.63 %	-	-	-	-	-
#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	-	-	-	-
31.25 %	43.06 %	49.48 %	51.58 %	50.63 %	44.92 %	40.48 %	39.07 %	-	-	-
33.33 %	42.59 %	48.61 %	52.89 %	55.19 %	55.80 %	53.78 %	52.12 %	51.91 %	-	-
29.17 %	43.52 %	50.87 %	56.03 %	59.88 %	62.55 %	64.24 %	64.61 %	64.90 %	72.17 %	74.12 %

Figure 8. Metals error measure for operating profit (2/2009 – 12/2009), SMA

Error measure (MAPE)										
n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
-	-	-	-	-	-	-	-	-	-	-
17.05 %	-	-	-	-	-	-	-	-	-	-
7.32 %	10.57 %	-	-	-	-	-	-	-	-	-
10.71 %	9.05 %	7.32 %	-	-	-	-	-	-	-	-
40.48 %	57.14 %	61.31 %	62.95 %	-	-	-	-	-	-	-
23.68 %	39.18 %	50.77 %	55.77 %	58.90 %	-	-	-	-	-	-
0.00 %	8.33 %	17.50 %	26.00 %	30.83 %	34.39 %	-	-	-	-	-
#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	-	-	-	-
17.50 %	25.86 %	32.24 %	35.60 %	41.52 %	46.20 %	49.72 %	52.66 %	-	-	-
10.00 %	22.22 %	17.04 %	23.82 %	30.37 %	38.07 %	45.81 %	52.08 %	52.57 %	-	-
43.75 %	59.72 %	83.00 %	10.50 %	12.76 %	14.47 %	16.55 %	18.57 %	20.22 %	23.94 %	22.64 %

As said before the SMA doesn't have generally any key drivers for profit forecasting processes. There can be seen couple of drivers that could be used to solve forecast accuracy, but these drivers are too common and one could not have any valuable or specific information to the profit forecasting processes. For example, the gross domestic products (GDP) trend in Finland has so little influence in evaluating the forecast of net sales in *Ruukki*. The year 2009 was exceptional year for evaluating the gross domestic products trend impact for the profit forecasting process because the trend was very unstable and the GDP sank the whole year ending up with the total of minus eight percent. (Tilastokeskus, 15.7.2010)

6.1.2 Weighted Moving Average (WMA)

The Figures 29 – Figure 40 in Appendix 2 demonstrates the weighted moving averages accuracy average, accuracy median and standard deviation for net sales, cost of goods sold and operating income in periods 2/2009 – 12/2009.

The weighted moving average (WMA) is a variation of the SMA method. The first difference to SMA method is that in WMA the t period in period t-1 is calculated as a weighted average of the *n* periods. The second difference to SMA method is that WMA method uses drivers as weights to calculate the forecasting accuracy. The weights (drivers) that are used in the following methods are GDP, inflation, steel price, coal price, industrial production and building permits. The drivers influence to the forecasted values as weights as relative proportion (percentage, %) of net sales, cost of goods sold and operating income for each division.

The forecast accuracy for net sales was little bit less than the SMA method. As seen in appendix 2 Figures 29 – Figures 32 the accuracy average was usually less than 85 %. The one exception unit was *Ruukki Metals*, which achieved the accuracy of 85 % to 90 % throughout the year. There were two reasons for this; first the driver used for net sales was steel price which influenced to the net sales values much more than other divisions. The reason for this was that *Metals* benefited more from higher steel prices than others. Secondly, *Metals* had a lot's of possible prospects under order already before the year 2009. *Ruukki Construction* forecast accuracy was promising in the begging of the year but in the recession kicks in hardly in the second quarter. The reason behind this was the change in construction business and the driver that was used in calculation, building permits in Finland. In Finland the construction permits for commercial and residential infrastructure collapsed hard. This information had the huge influence for *Construction* net sales forecasting, which can be seen in appendix 2 Figure 30. The forecast accuracy drops from 85 % to under 50 %.

Once again *Ruukki Engineering* makes the biggest exception in net sales accuracy. The reason is same as in SMA method but this time the weight influences writ larger to the figures. The accuracy average and median were almost 10 % smaller in every month than in SMA method. Also the standard deviation was higher than in SMA method. This will express dispersion in the original units of measure. Furthermore, a period 6/2009 to 8/2009 (See appendix 2, Figure 31) shows that the deviation is higher than normally. The reason for this could be the fact that the forecasters called for an economic recovery too early and the adjustments against GDP that was made in second quarter was too optimistic.

From the *Corporate* point of view the forecast accuracy for net sales varies more than in SMA method. This was resulting from the *Engineering* and *Constructions'* deviations in forecast accuracy. This deviation was also affected by the drivers used in the WMA model. This indicates a bias to forecast the net sales items too pessimistically. In addition, in all of these four forecasting units, the biggest part of the effect to net sales has come from the long-term forecasts i.e. forecast made for whole year ahead. (See appendix 2, Figure 29) The forecast accuracy drops dramatically from 9/2009 to 11/2009 and the same time the forecast error measure increases when the forecast horizon was long-term. This was due to the fact that the divisions estimated their net sales forecasts too high for the end of the year.

The dramatic changes in world economy had a great influence to the forecast accuracy and error measures because the different business segments where *Ruukki* operates began fading faster than no one could ever imagine.

It can be seen from Figures 33 – Figures 36 (See appendix 2) depicting the overall effects of forecast accuracy to cost of goods sold that the effects of the forecasts made in year 2009 were clearly quite same as in the SMA model. The average forecast accuracy effect to cost of goods sold has not improved noticeably against the SMA model even though there seems to be slight improvement in the longer horizon forecasts. Furthermore, it seems that the WMA model doesn't produce any significant variables to the cost of goods sold forecast accuracy. The driver (coal prices) used in WMA cost of goods sold forecast doesn't improve the forecast accuracy. The biggest variation in cost of goods sold forecasts has the *Engineering* division. The forecast accuracy wasn't stable in any periods in year 2009. The accuracy average changes too much against to the SMA model, which can be seen in the standard deviation values. The standard deviation figures shows that the distributions of figures are more peaked than in the SMA model. (See appendix 2, Figure 35)

With the WMA model the forecast accuracy of operating income tends to decline even more than with the SMA model when the length of the forecast horizon increases (See appendix 2, Figures 37 – Figures 40). Furthermore, operating income weighted MAPE illustrates that there are clear signs of improvement in the forecast errors than in SMA model, especially in the forecast made in 11 periods ahead. (See Figure 9 – Figures 12) This was interesting observation because the forecast accuracy was declining but the MAPE values were improving. On the other hands the operating income forecast accuracy values were more stable than in SMA model and the standard deviation shows less deviation with the values. This indicates that the drivers used in WMA model could produce more stabile forecasts than in SMA model.

If the data follow a fairly linear trend and have a definite rhythmic pattern of fluctuations the WMA model will produce fairly accurate values for profit forecasting. Therefore, this method for steel industry business is risky to apply because the fast changes in economic, as in year 2009, will cut the linear trend and will have a bad impact to the values. Also one important factor is that if there are zero values in the historical data, this method is not the best way to calculate the forecasts.

The reason for this is that the zero values will affect largely to the accuracy averages and error measures, which happened here also. This can be seen in Figures 10 and Figures 12. When there are zero values in the data, the error measures will not have importance to the next values, which can be seen fairy well in Figure 12. In other words, the zero values will delude the forecast error outcome.

Figure 9. Corporate error measure for operating profit (2/2009 – 12/2009), WMA

Error measure (MAPE)										
n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
-	-	-	-	-	-	-	-	-	-	-
21.75 %	-	-	-	-	-	-	-	-	-	-
2.71 %	6.37 %	-	-	-	-	-	-	-	-	-
25.47 %	25.20 %	20.32 %	-	-	-	-	-	-	-	-
37.24 %	52.61 %	54.28 %	53.37 %	-	-	-	-	-	-	-
36.25 %	53.01 %	64.40 %	70.03 %	71.97 %	-	-	-	-	-	-
5.37 %	11.89 %	17.95 %	25.88 %	30.47 %	33.05 %	-	-	-	-	-
30.93 %	41.43 %	48.09 %	54.15 %	60.71 %	65.05 %	67.92 %	-	-	-	-
28.54 %	14.26 %	17.25 %	20.66 %	24.17 %	27.90 %	30.72 %	33.03 %	-	-	-
30.83 %	23.74 %	19.06 %	20.88 %	26.77 %	35.39 %	45.77 %	55.09 %	62.01 %	-	-
16.46 %	27.33 %	26.54 %	23.23 %	20.19 %	21.14 %	24.66 %	30.79 %	35.76 %	39.38 %	40.15 %

Figure 10. Construction error measure for operating profit (2/2009 – 12/2009), WMA

Error measure (MAPE)										
n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
-	-	-	-	-	-	-	-	-	-	-
47.60 %	-	-	-	-	-	-	-	-	-	-
42.00 %	29.56 %	-	-	-	-	-	-	-	-	-
29.20 %	27.50 %	18.79 %	-	-	-	-	-	-	-	-
37.67 %	31.11 %	38.08 %	37.39 %	-	-	-	-	-	-	-
45.58 %	22.89 %	20.28 %	25.25 %	25.84 %	-	-	-	-	-	-
30.83 %	33.52 %	28.26 %	34.29 %	38.15 %	35.78 %	-	-	-	-	-
#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	-	-	-	-
28.44 %	40.07 %	46.85 %	48.84 %	47.53 %	40.86 %	35.94 %	33.67 %	-	-	-
30.83 %	39.63 %	45.97 %	50.30 %	52.53 %	52.89 %	50.32 %	47.90 %	47.31 %	-	-
26.04 %	40.51 %	48.27 %	53.58 %	57.53 %	60.20 %	61.82 %	61.85 %	61.89 %	62.53 %	63. 48 %

Figure 11. Engineering error measure for operating profit (2/2009 – 12/2009), WMA

Error measure (MAPE)										
n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
-	-	-	-	-	-	-	-	-	-	-
16.50 %	-	-	-	-	-	-	-	-	-	-
#DIV/0!	#DIV/0!	-	-	-	-	-	-	-	-	-
21.25 %	41.39 %	75.73 %	-	-	-	-	-	-	-	-
38.50 %	49.22 %	57.98 %	69.84 %	-	-	-	-	-	-	-
50.63 %	43.19 %	36.93 %	32.26 %	42.04 %	-	-	-	-	-	-
17.08 %	14.72 %	16.35 %	17.24 %	20.94 %	29.97 %	-	-	-	-	-
21.88 %	42.36 %	46.15 %	42.84 %	40.23 %	34.92 %	37.80 %	-	-	-	-
21.25 %	30.39 %	32.04 %	33.54 %	36.14 %	38.01 %	40.51 %	44.81 %	-	-	-
9.75 %	15.39 %	20.79 %	21.95 %	23.45 %	25.78 %	27.70 %	29.96 %	33.95 %	-	-
27.88 %	40.64 %	47.91 %	52.68 %	55.44 %	57.62 %	59.69 %	61.28 %	62.92 %	64.99 %	66. 87 %

Figure 12. Metals error measure for operating profit (2/2009 – 12/2009), WMA

Error measure (MAPE)										
n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
-	-	-	-	-	-	-	-	-	-	-
12.10 %	-	-	-	-	-	-	-	-	-	-
0.91 %	3.54 %	-	-	-	-	-	-	-	-	-
19.82 %	18.64 %	15.79 %	-	-	-	-	-	-	-	-
54.05 %	72.54 %	75.03 %	76.64 %	-	-	-	-	-	-	-
34.74 %	52.22 %	62.87 %	68.26 %	71.93 %	-	-	-	-	-	-
7.50 %	17.50 %	26.19 %	35.51 %	41.08 %	45.62 %	-	-	-	-	-
#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	-	-	-	-
19.37 %	28.16 %	33.42 %	39.03 %	44.49 %	49.75 %	53.80 %	57.72 %	-	-	-
10.75 %	13.61 %	19.19 %	25.42 %	33.31 %	42.08 %	50.97 %	58.75 %	65.40 %	-	-
22.81 %	38.82 %	43.88 %	17.65 %	12.78 %	15.02 %	17.23 %	19.74 %	21.71 %	23.42 %	24.76 %

6.1.3 Simple Exponential Smoothing

The Simple Exponential Smoothing assumes that the series being forecast has no trend and that the variables used to forecast follows a level model. Therefore, when each data point in the time series is observed, one can compute the forecast error quite accurate. The drivers used in this method are calculated as same as in WMA method, but the created value is multiplied with alpha (*α)*. This *α* comes from the proportion of divisions forecasted figures against to the corporation forecasted figures.

The results for net sales forecast accuracy and error measures can be seen in Appendix 3, Figures 41 – Figures 44. With the Simple Exponential Smoothing method, the results for net sales forecast accuracy varies lot more than with SMA or WMA models.

The reason for the forecast accuracy changes were due to the fact this model takes into account the actual (ACT) figures before calculating the forecasts (FCT). To be exact, the model shows the real difference between actual (ACT) and forecast (FCT) figures. In this model, there has been used one key driver for every division, when emphasising the forecasts accuracy and margin of errors. Therefore, the outcome of forecasts accuracy and error changes a lot more than in previous models.

Using this model one can see in Figures 41 – Figures 44 (See appendix 4), that the net sales forecast accuracy varies the most with *Ruukki Engineering*. With this division the actual figures varies too much from the forecasted figures, which influence to the forecast accuracy and Mean Absolute Percentage Errors (MAPE) figures.

The reason for this was the fact that the forecasters called for an economic recovery too optimistic and the judgemental adjustments that were made throughout the year were off balance. The division uses few drivers to estimate the net sales forecasts and the driver that have been used in this model were growth of engineering markets (*Industrial production*). This driver didn't indicate enough to the trend of engineering markets, which causes the forecasts accuracy range too unstable. The forecasters should have checked the forecast figures more often to make adjustment for the forecasts by leaning to the actual figures from last month (t-1).

In *Ruukki Construction* figures (See appendix 3, Figure 42), there can be seen that the division adjusted the figures more carefully and the forecasts accuracy and error measures started to get more stabile after February 2009. There was a too high forecast values for begging of the year, which causes the actual and the forecast figure difference to be under the base case. This was corrected immediately after February with judgemental adjustments to the forecast figures by concentrating to the actual figures after February.

By adjustments, the *Ruukki Construction* lowers the forecast error measures by the end of year 2009 and after this the forecast accuracy improved. The division uses different drivers to estimate the net sales forecasts and the driver that have been selected in this model were *building permits* in Finland. The observation from this driver was that the building permits had the some influence to the net sales forecast figures.

The driver used in this model gives some perspective for the figures more than in previous models because it indicates more with the construction business itself.

In *Ruukki Metals* figures (See appendix 3, Figure 44), the forecast accuracy for net sales was quite stabile and the average net sales forecast accuracy was 97.2 percent. This was due to the fact that this division uses the most of three divisions the adjustments in their figures. The driver that has been used in this model for *Ruukki Metals* was the growth of *steel prices*. The steel prices were quite stabile throughout the year 2009 and this helped the division to control their forecasts to be exact. From the *Corporate* point of view, the forecast accuracy was very stabile and the forecast error measures were under eight percent, which indicates that the corporate financial management were equal to the business trends for the whole steel industry segments. The driver, which was used for Corporate, was the growth of *metal industrial production* in Finland.

It can be said that the *Corporate* made right judgemental adjustments to the forecast figures before announcing the next months forecast figures. The forecast accuracy average of net sales for *Corporate* was 94.7 percent (SMA: 88.2 % and WMA: 83.3 %).

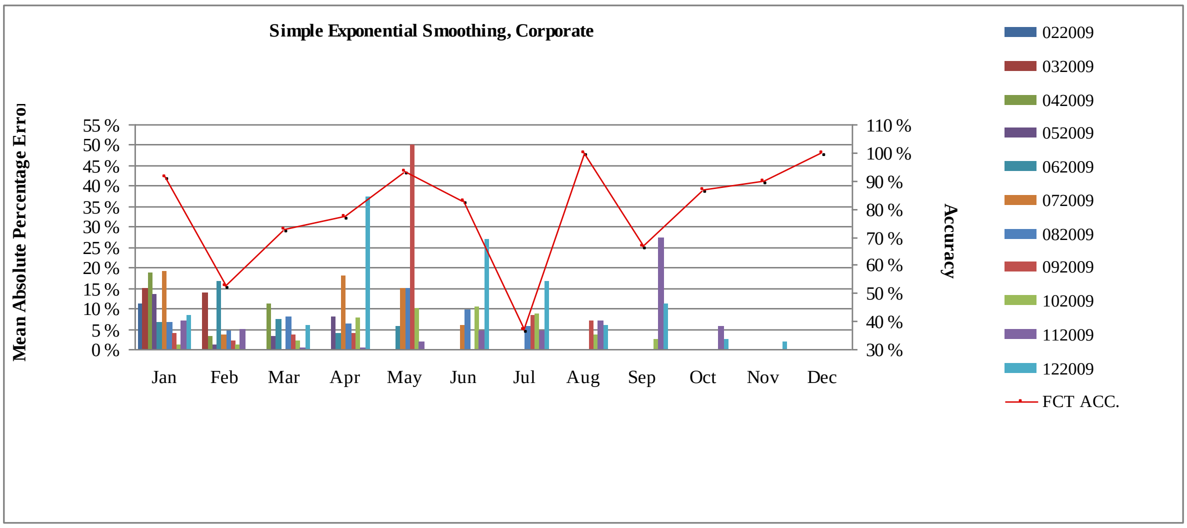
The Figure 13 – Figure 16, shows the operating income values of forecasts accuracy and error measures for *Corporate, Construction, Engineering* and *Metals*. The same drivers were used in estimating the operating income forecast figures that were used in the net sales method. The values changes dramatically and there weren't any stabile trend in the outcomes.

For the *Corporate* (See Figure 13), the forecast accuracy figures were too optimistic for the year when compared to the actual figures. This was due to the fact that every division operating income figures were too high valued against to the actual values. On the other hand, the economic crisis in 2009 was reflecting also to the values of forecast accuracy because of the dramatic changes in the steel industry segments. The driver that was used for *Corporate*, growth of metal industrial production, impact largely to the operating income values because of the dramatic value drops for whole business segments in Finland.

In Figures 13 to 16, the idea is to demonstrate the forecast accuracy and error measures timeline. In the Figures, the left side bulk shows the MAPE percentages and the right side bulk shows the profit forecasts accuracy percentages.

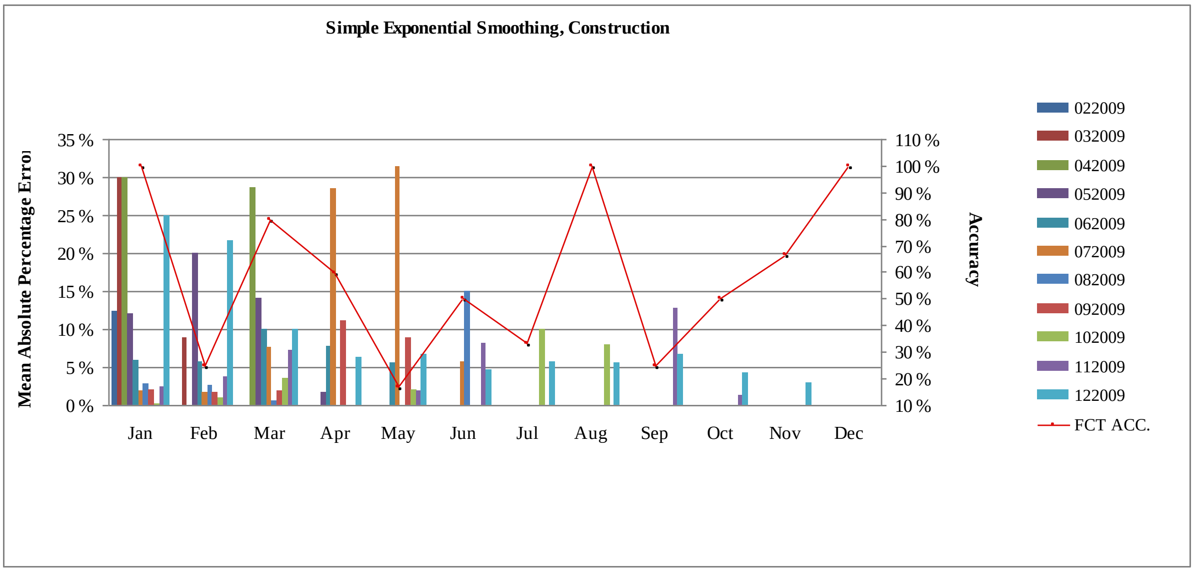
The red line (FCT ACC.) demonstrates how the profit forecasting accuracy is changing for every month. The colour pillars demonstrates months (e.g. 02/2009 = February 2009) and how the profit forecasting error measures are changing when times moves closer to the year end. For example, JAN shows how the profit forecast errors for FEB to DEC would be against actuals if the forecasts are made in January for FEB to DEC etc.

Figure 13. Corporate operating profit forecast accuracy and error measures for periods 2/2009 – 12/2009



The *Construction* operating income values shows (See Figure 14), that the infrastructure in Finland collapsed hard during the economic crises in year 2009. The driver that was used in this model was the *building permits* in Finland, reflects to the values decreasingly. The values for forecast accuracy and error measures indicates that the whole construction business were in unstable condition by measuring it with building permits. There should have been done more indicative judgemental adjustments to the figures after every month's actual values before entering the new forecasts for next months. This could have improved the values of forecast accuracy and error measures for operating income.

Figure 14. Construction operating profit forecast accuracy and error measures for periods 2/2009 – 12/2009



The Figures 15 – Figure 16, shows the forecasts accuracy trends to the *Ruukki Engineering* and *Ruukki Metals*. The same reasons can be seen here also than before. The economic crisis had a huge impact to the operating income values also. The chosen driver for *Ruukki Engineering* shows that the engineering business was starting to collapse and this point the forecasters should have considered the clients forecasts in more detailed, which would have helped to forecast the operating income in more accurately. Therefore, they should have adjusted the clients' forecasts to the market conditions. For *Ruukki Metals*, the same kind of prognoses can be stated than previously. There should have been more adjustments to the operating income forecasts figures after the actual figures from the past month (t-1).

Figure 15. Engineering operating profit forecast accuracy and error measures for periods 2/2009 – 12/2009

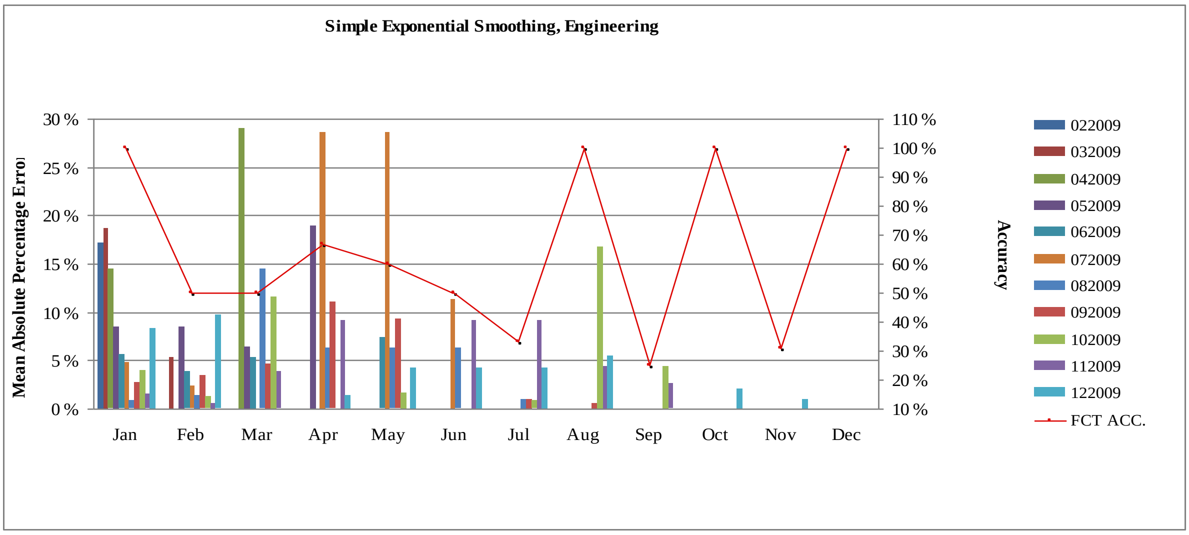
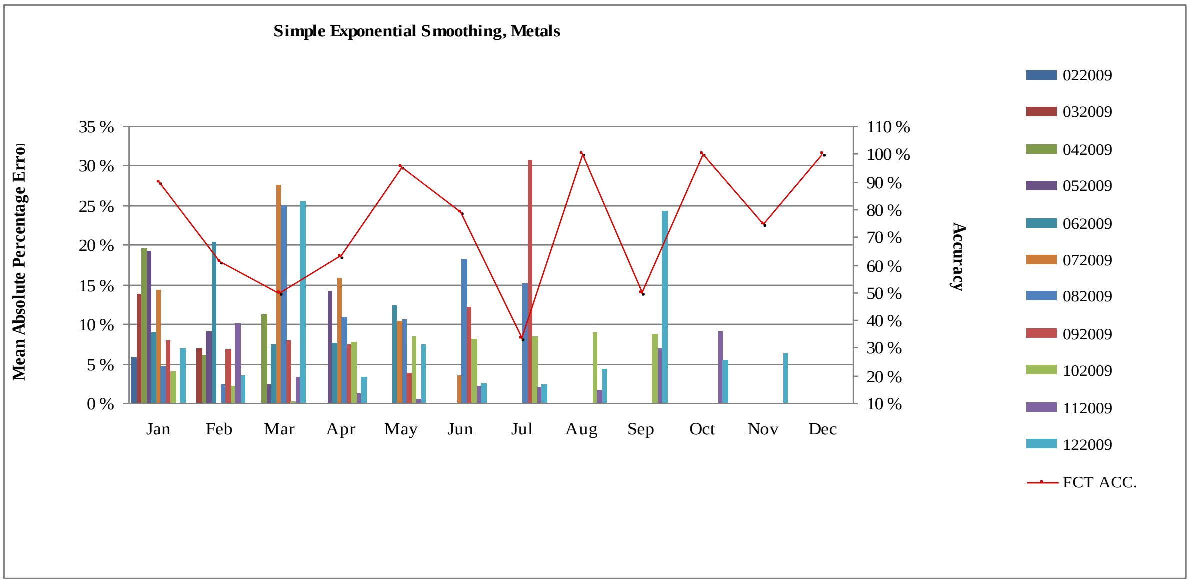


Figure 16. Metals operating profit forecast accuracy and error measures for periods 2/2009 – 12/2009



6.2 DRIVERS FOR PROFIT FORECASTING

Profit drivers are defined as variables that influence profit. The relation between a profit drivers and profit can be described by several characteristics of the relation. A relation's causal-model form specifies how independent variables (profit drivers) causally influence a dependent variable (profit). In this study, the independent variables that have been selected for the study were: *growth of Gross Domestic Product* (GDP), *inflation*, *steel price*, *coal price*, *industrial production* and *building permits in Finland*. The idea for selecting these independent variables was that could these drivers be adequate number for profit forecasting.

Furthermore, could these drivers be efficient number of profit drivers for the case company. Currently the case company handles several dozen profit forecasting drivers to produce profit forecasts, which has been seen really difficult and the process has been really heavy to conduct accurate and reliable profit forecasts.

From the empirical analysis one could stated that these selected independent variables for profit forecasting can give some indications about the usage of these profit drivers. The number of observations for the study was quite small because there were observations only from year 2009 and there could be even more indications about these profit drivers if there would be even longer period of time.

The empirical analysis shows that *growth of oil price, steel price* and *coal price* indicates significantly with profits. This was quite normal finding because the case company operates in steel industry business. Then it can be said that these drivers have impact to the profit forecasting. Interestingly, the growth of *GPD* and *inflation* did not have any impact to the profit forecasting, which is quite odd because the all three divisions uses these two drivers to indicate the sales forecasts which are essential to the profit forecasts. The *building permits in Finland* reflect to the profit forecasting values decreasingly. Forecasters shouldn't ignore this driver because with the Simple Exponential Smoothing-model it gave great signals that the driver is essential to the profit forecasting processes. This driver indicates largely how the changes in steel industry markets are influencing to the profit forecasting values.

When choosing efficient drivers for profit forecasting one should always consider the judgmental point of view. All the drivers that have been used in previously and in this study are closely related to the human judgment about the prospects of different market situations. The examination of the accuracy of the current profit forecasting process implied that the judgmental forecasters have problems in receiving information about the suitable profit drivers to be used. The drivers update frequency determinates the relevant usage of the profit drivers for forecasters. When validating the drivers that are being used, they should also be in the same level as their update frequency. If the update frequencies for profit drivers are once per month then the forecasters should only use drivers in their forecasts methods that are updated every month. This will reduce the misunderstanding of profit forecasting figures.

Some profit drivers have direct effects on profit while other affect profit indirectly by affecting another profit driver that does directly affect profits. These drivers, which are used in the study, will give indicatives of profit forecasting process.

6.3 COMMON REASONS FOR FORECAST ERRORS

In this section, reasons that were found to cause forecast errors are presented. These errors include lack of valid information for information systems, human errors, forecast process related errors and currency exchange rates.

6.3.1 Information systems

The information systems used by the case company offers a wide range of forecast possibilities that can be easily applied to the profit data. The problem here is the number of different information systems used in the profit forecasting process. When there are (maybe) too many different systems used for producing the forecasts the data validation is very difficult. Therefore, there have been problems in spreading the valid data information across the organization. If there are too many information systems used, then it will create the situation where the profit forecasting process turns to be very heavy process chain to handle.

If the information systems are to sophisticate and difficult to use they will lower the usage of these systems and also lowers the relevant information needed on time. The profitability of these systems suffers if they are to complex to produce accurate and on time forecasts.

To avoid this kind of situation there should be a lot of training before using these systems, narrow down the number of systems used and focusing on the data validation before they are inputted to the system. This will help to the data validation for the outputted data.

6.3.2 Human errors

There have been many errors in the profit forecasts that have been caused by human carelessness which partly due to the human error for the vast amount of different variables being forecast.

These errors can be related to the information systems used where some figures has to be calculated manually, which increases the probability of making errors. The possibility of making this type of mistakes can be minimized if more than one person investigates the figures. In other words, forecasters should have better awareness of the forecasted values.

One problem that is caused by the human error is the change in the profit forecast process made judgmentally where there had been given into wrong direction by mistake. The chance of making this kind of errors can be reduced by conducting systematic checks to the forecasts made judgmentally before they are uploaded to the different database when calculating the final forecasts. Therefore, these checks depend to a great extend on the persons who are responsible for calculating and reporting the final profit forecasts.

Finally, forecasters may have sometimes left blank part of the forecasts either accidentally, lacks of communication, or because of lack of information available. The forecasters should be more active in the whole process of profit forecasting to avoid the lack of communication and improve the progression of information. This can be done by enhancing information flow and by building better systematic checks for the forecasts.

6.3.3 Forecast process related errors

The forecasting process is a simplified version of the actual profit calculation process, there may be errors resulting from the profit forecasting process itself. One example of such errors is the fact that some items related to the profit-loss statement are systematically left out from the forecasts because historically these items, related to net sales or cost of goods sold, have been quite small and the forecasts have had a tendency to be too pessimistic.

Another example of a process related error is the drivers used in the profit forecast processes of each division. The current situation is that *Ruukki* uses dozens of different drivers to complete profit forecasts. This complicates the profit forecasting process because there are too many drivers to be taken under consideration, which makes the process too heavy to complete successfully and the forecasts accuracy did not improve although several different drivers were used. If there are too many drivers used in profit forecasting processes, then the drivers will not give the perfect outcome for the forecasts.

On the other hand, the company operates in several business segments and therefore, company needs multiple drivers to forecast their future. The key is to find valid number of drivers for each business segments.

A third example of process related errors are the divisions units' involvement in forecasting processes. The units are usually too passive in the process when forecasts are made. This causes errors in forecast accuracy of sales, cost of sales and profits. Therefore, units should be more actively involved throughout the process of forecasting in order to improve forecast accuracy and decrease the error measures.

6.3.4 Currency exchange rates

For *Ruukki*, there are operations in 27 different countries, which mean that the company currencies for some units are other than Euro. There for forecasts of these other units are converted into Euros by using the currency exchange rate of the period in which the forecast are made. For example, a vast amount of material components are purchased in some other currency for different units. Consequently, their cost of goods sold forecasts are made in the currency in which they are purchased and are then converted by using the currency exchange rate of the period in which the forecast are made for different divisions. One reason for this could be the fact that forecast for most of the different product groups are updated only quarterly, part of the forecasts are made with several periods old currency exchange rates.

The dilemma for net sales conversion from different currency to Euros can be seen in a long-term forecasting. If forecasts are made in quarterly, six months or 12 months ahead the currency exchanges can affect largely to the net sales forecasts because of the economical changes in the business markets.

6.4 FORECAST FREQUENCY UPDATE

The forecast update frequencies have been updated in the case company periodically, quarterly and for 12 months ahead. When the forecasts have been updated periodically with some variables and with the rest of the variables that haven't been updated periodically, this has caused the latest actual figures to be lower than the forecast s for the next 1 – 3 periods and has therefore decreased the credibility of the forecasting process.

Additionally, the current forecast process causes different divisions not to be treated equally. Because of the information that comes from the business markets will come with some delay for other units.

By updating the forecasts every period (month), it is possible to incorporate all the latest available information into the forecasts. Due to the economical changes in the markets, the forecast update frequency has been considered to do every weekly base. This would need lots of resources and it would be very expensive. With weekly forecast update frequency the forecast accuracy could be much better, with the latest data from the markets, but with weekly updates it would bound the forecasters too much and the periodically forecasts would not be in a reliable base due to the fact that the forecasts changes constantly.

Due to the reasons listed above, it has been recommended that forecasts should be updated periodically (monthly base), but not until the actual figures are known. However, it would be very time-consuming and expensive to update the profit forecast items judgmentally every period. Because the work is repetitive in nature, it would also be likely to cause people making the forecasts to get bored with forecasting which, in turn, might reduce the quality of the forecast and create unnecessary errors. Therefore changing the forecast frequency update to periodically for all the items needed in profit forecasting process is not recommendable unless the judgmental forecast process is not reduced.

7 SUMMARY AND CONCLUSIONS

7.1 SUMMARY

The purpose of this study was to find suitable forecasting methods for profit forecasting, and also could it be possible to improve profit forecasting accuracy by adding drivers to the profit forecasting processes. No prior research literature was found from the area of profit driver based forecasting and therefore the subject was justified to be interest.

In the theoretical part of the thesis, a number of judgemental and statistical forecasting methods were presented and the different roles of judgment in forecasting were reviewed. Several strategies to improve judgmental forecasting were summarized. In addition, criteria for selecting forecasting methods, advantages and disadvantages, were investigated, forecasting accuracy being a focus point.

The empirical part of the study focused on investigating the profit forecasting process of a case company and finding the possibility to improve profit forecasting accuracy by adding drivers to the profit forecasting process. The performance of several statistical methods was tested separately for the corporation and each division. Also several forecast error measures for the forecasting methods were calculated and the results were analyzed for testing the forecasts accuracy. The statistical methods showed that using only one forecasting method is not enough to evaluate the forecasts accuracy for profits. The conclusion was that the selected statistical forecast methods should be used as benchmarking each other.

The Simple Exponential Smoothing model was the most suitable method for analyzing the different drivers that could be used in profit driver based forecasting. The result for could it be possible to improve profit forecasting accuracy by adding drivers to the profit forecasting processes, suggested that there is not unambiguous number of drivers in profit forecasting. The analysis of the case company revealed, that in profit driver based forecasting, the number of drivers to be used are dependent on the market segments that the divisions operates. It can be said that the number of drivers used in profit forecasting process should be limited to fewer than 20. Otherwise the profit forecasting process becomes too complex.

The judgemental methods should allow the forecasters to concentrate on the most important variables in profit forecasting, while statistical methods could be used to forecast the less important variables. By this, the quality of profit forecasts would improve, because people would not get so easily bored with repetitive tasks and could concentrate on what is important.

The result of the empirical study cannot be generalized to other context as such. However, the suitability of different forecast methods, forecast error measures and profit drivers to product profit driver based forecasting, as indicated by this examination, may give some hints for the future. The case study may also shed light on important things to consider, when developing a company’s profit forecasting processes.

7.2 DISCUSSION ON THE RESEARCH FINDINGS

The results of the empirical findings show that in this kind of data analyses, judgemental method plays an important role. To combine, the statistical and judgemental methods together, there can be seen that with judgemental adjustments, forecasters can improve forecasts accuracy. Furthermore, combined forecasts methods have better accuracy than single forecasting method. Forecasters who make adjustments to the statistical figures can exhibit a greater confidence in their forecasts. The forecasters work focus on control and motivation will drive forecasters’ willingness to judgmentally adjust the statistical forecasts. These findings support the views of theoretical literature. (See e.g. Eroglu, Croxton 2010, Fildes and Goodwin et al. 2009, Webby, O Connor 1996, Makridakis, Wheelwright 1987a, Makridakis et al. 1982)

The statistical methods that were used in this study shows that only one statistical method is not adequate for profit forecasting processes. For example, the simple exponential smoothing method shows the advantage of being easy to use. It treats the forecasts symmetrically and it gave better forecasting accuracy than SMA or WMA methods. Forecasters may over-rely on the recall of single analogies from past and they may anchor too closely to these recalled effects.

The research could be more informative if it provides analysis of and evidence on alternative relations between profit drivers and profit, beyond the modal relation examined to date. Related, no accounting study provides information on the duration of profit-driver effect or on whether profit driver – profit relations are bidirectional. Motivating and structuring research on profit driver – profit relations based on levels of analysis and other characteristics of relations as in this study have proposed can be provide a broad and valid theoretical and empirical basis to investigate profit drivers and, more generally revenue and cost drivers.

When considering the human judgment about which drivers are needed and which drivers are not, the important factor is to consider very carefully which drivers measures the same thing. By doing this, can be avoided the bidirectional influence. Furthermore, it can be solved which drivers can be left out and which drivers are key elements for profit driver based forecasting.

This study suggest that by adopting a more collaborative and integrated profit forecasting processes, and by structuring the chain of profit forecasting processes in each division to support this approach in order to move towards higher stages in the forecast assessment criteria and valid profit drivers, better forecast accuracy can be achieved. This answers to the research problem of the study.

7.3 SUGGESTION FOR FUTURE RESEARCH

This study concentrated on finding the efficient number of drivers needed when conducting accurate profit forecasting. Within this study, there were also noticed a few problems for future research for the scientific community. One future research could be concentrating on basic level of time series forecasting literature. Usually the time series forecasting literature discusses throughout on quite complex mathematical equations. In particular, information systems concerning forecasting, the task of forecasts to work with better options might be a more general level. However, the source, which would focus on improving the models and the data source to edit aspects of the equations at higher level. In practise, this would mean that the equation parameters used in time series forecasting should influence to the usage of forecasts.

Future research could also include the consensus between financial managements and inputted data. In order to make important decisions, the financial management should be able to trust to the provided information concerning the given forecast results. The financial management don’t usually have the time to familiarize all the statistical theories on the contrary they need (easily) understandable models, which could make it possible to evaluate and understand the results of the model(s) objectively. Throughout only a better understanding and confidence will provide the result of real benefits with various models, when the financial management dare to actually use them in decision making.

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Ruukki Engineering, Business Controller B, 28.10.2010

Ruukki Metals, Vice President, 22.11.2010

APPENDIX 1: FORECAST ACCURACY (Simple Moving Average)

Figure 17. Corporate forecast accuracy for Net Sales (Data for 02/2009 to 11/2009)

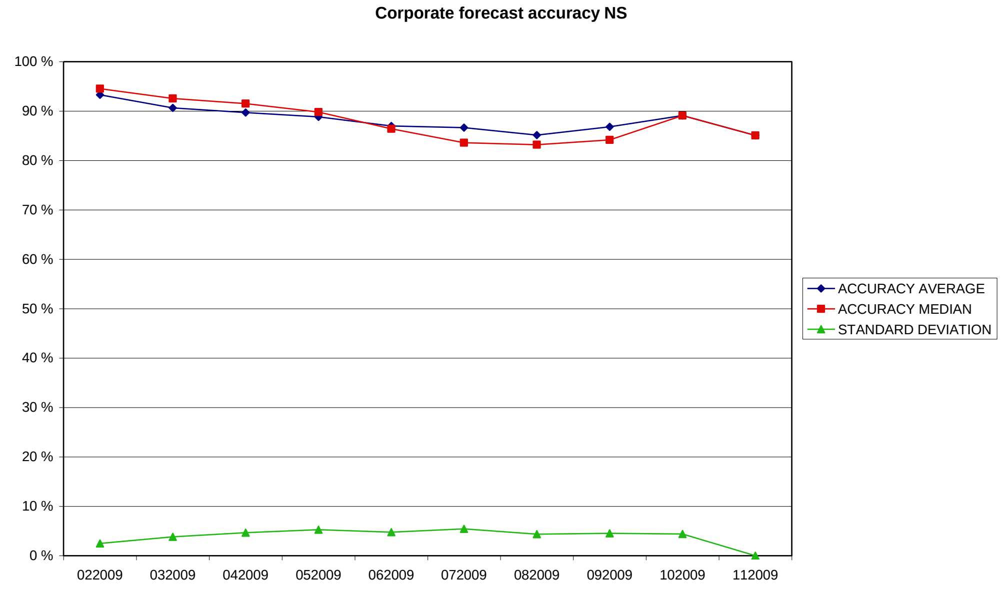


Figure 18. Construction forecast accuracy for Net Sales (Data for 02/2009 to 11/2009)

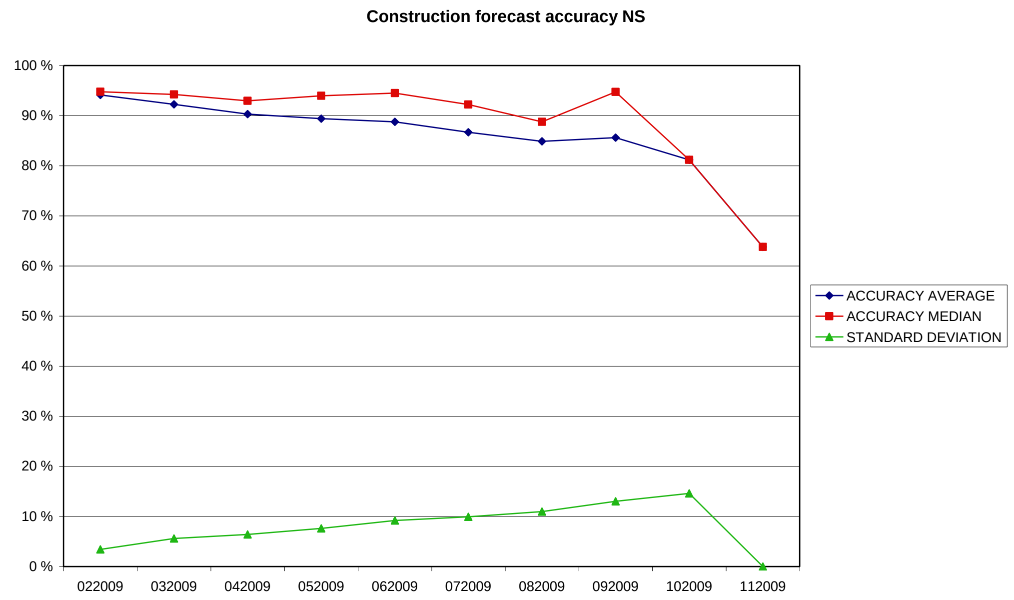


Figure 19. Engineering forecast accuracy for Net Sales (Data for 02/2009 to 11/2009)

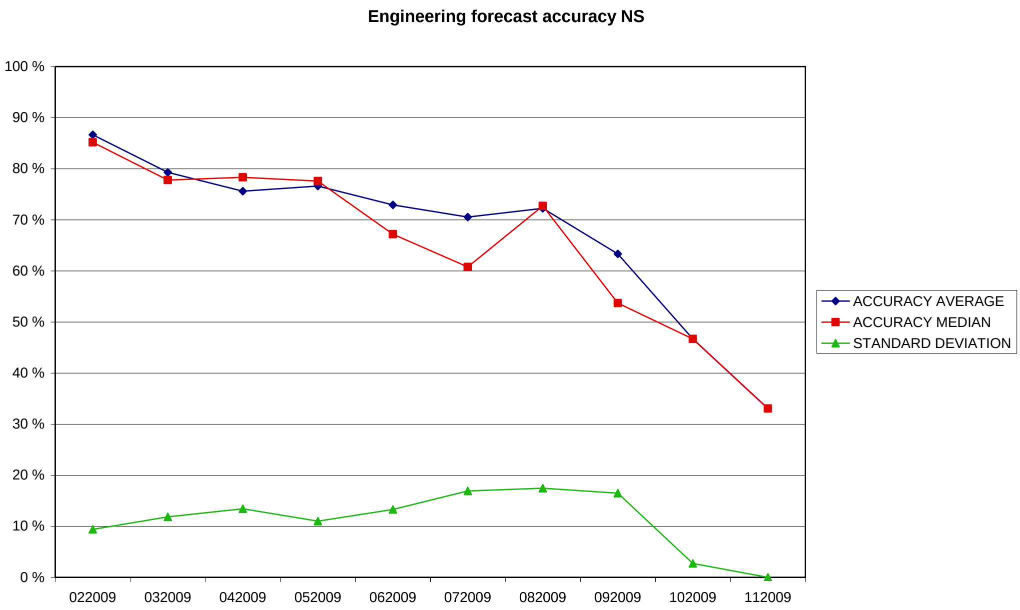


Figure 20. Metals forecast accuracy for Net Sales (Data for 02/2009 to 11/2009)

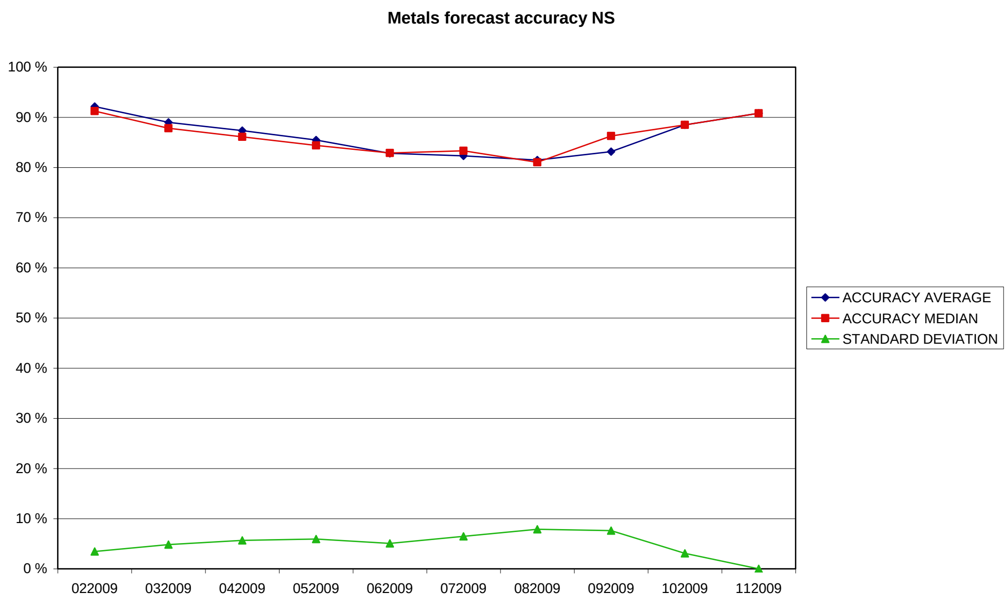


Figure 21. Corporate forecast accuracy for Cost of Goods Sold (Data for 02/2009 to 11/2009)

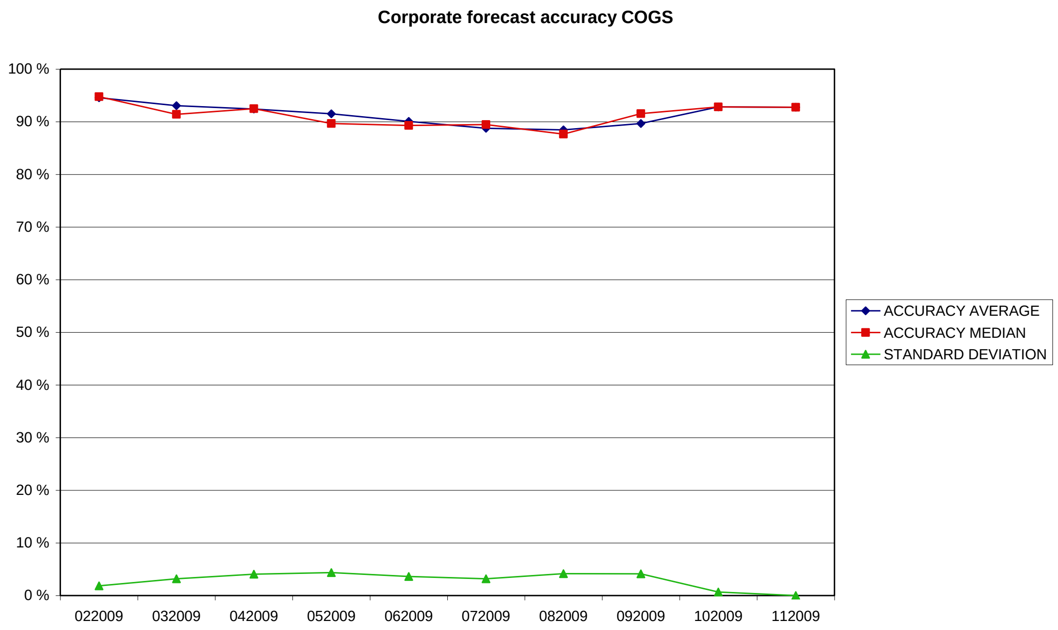


Figure 22. Construction forecast accuracy for Cost of Goods Sold (Data for 02/2009 to 11/2009)

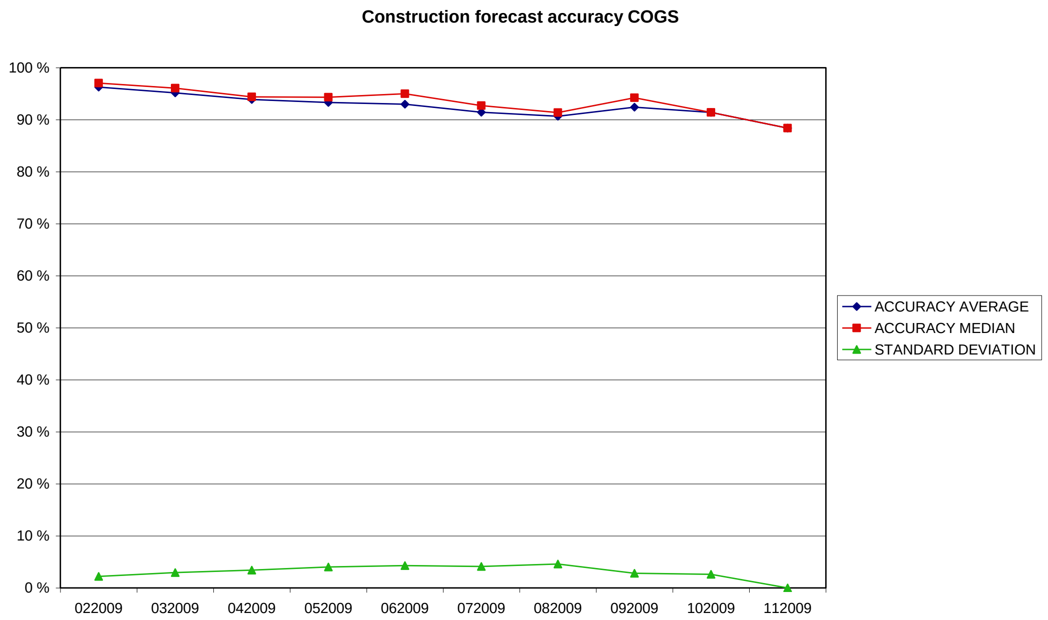


Figure 23. Engineering forecast accuracy for Cost of Goods Sold (Data for 02/2009 to 11/2009)

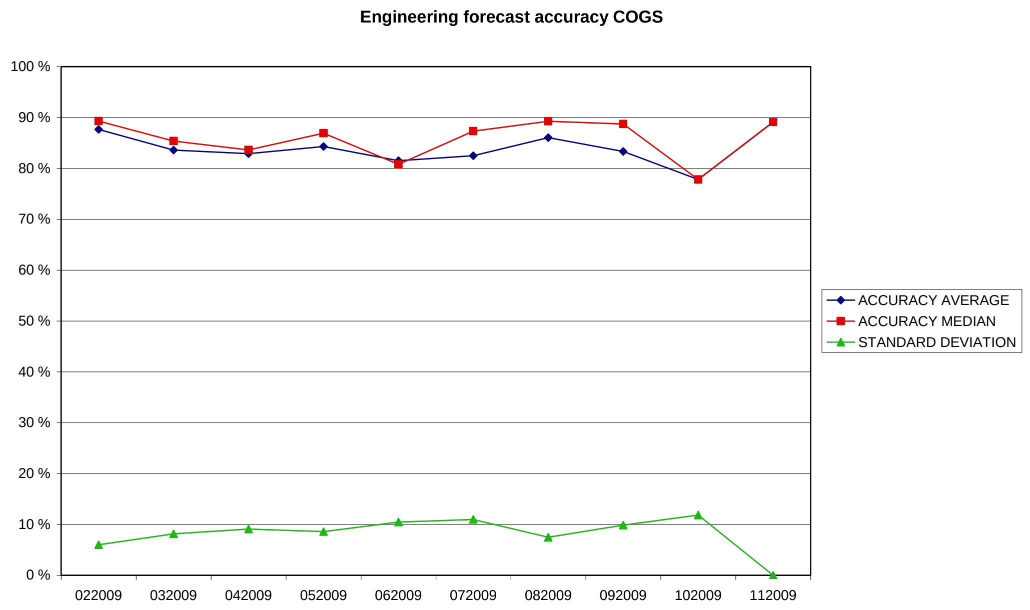


Figure 24. Metals forecast accuracy for Cost of Goods Sold (Data for 02/2009 to 11/2009)

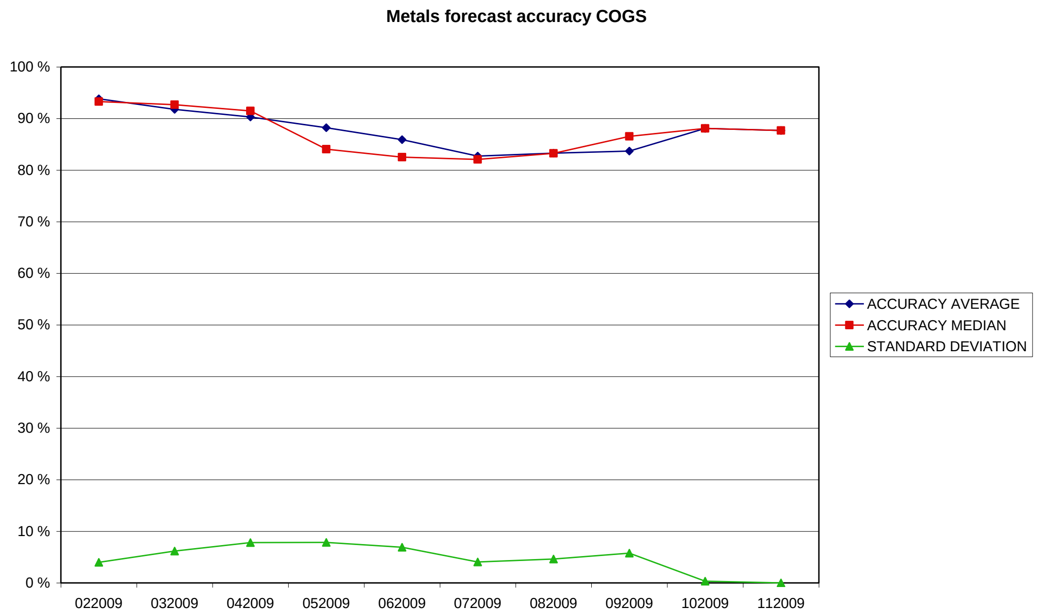


Figure 25. Corporate forecast accuracy for profit (Data for 02/2009 to 11/2009)

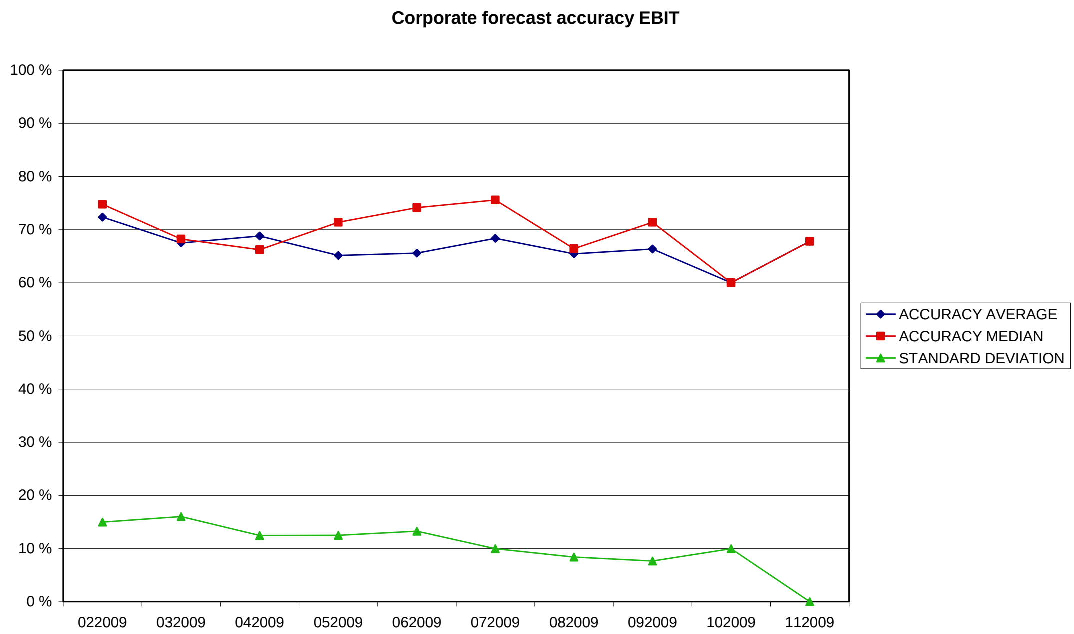


Figure 26. Construction forecast accuracy for profit (Data for 02/2009 to 11/2009)

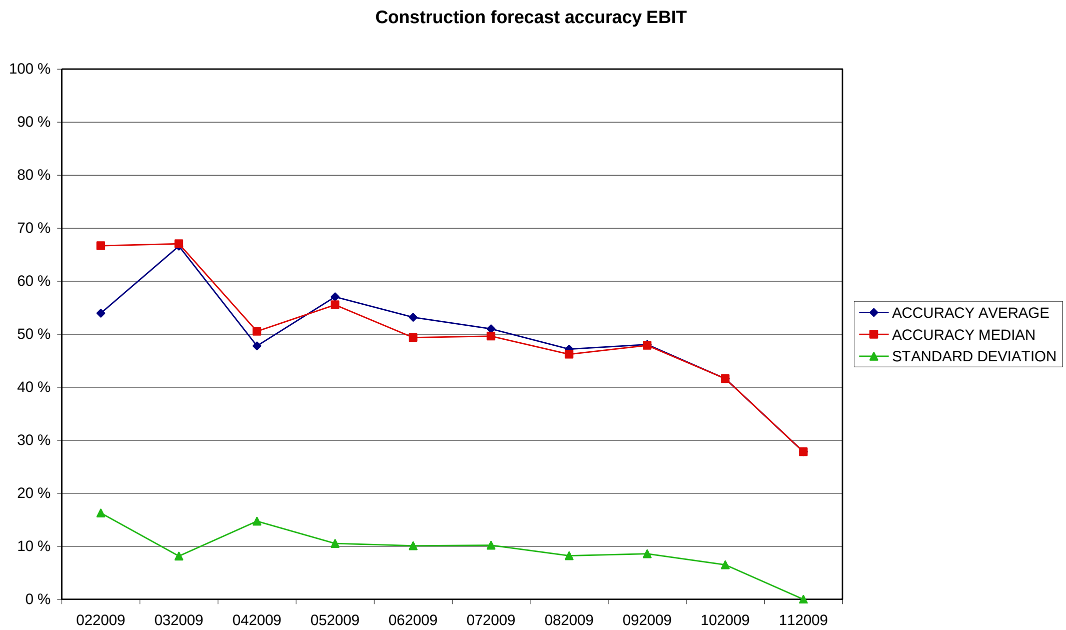


Figure 27. Engineering forecast accuracy for profit (Data for 02/2009 to 11/2009)

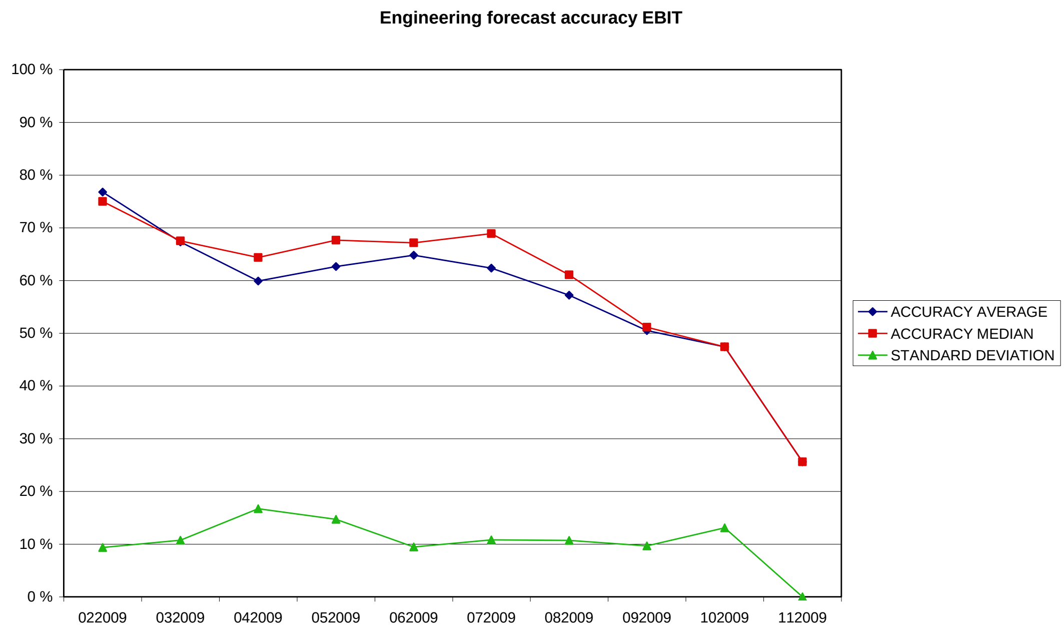
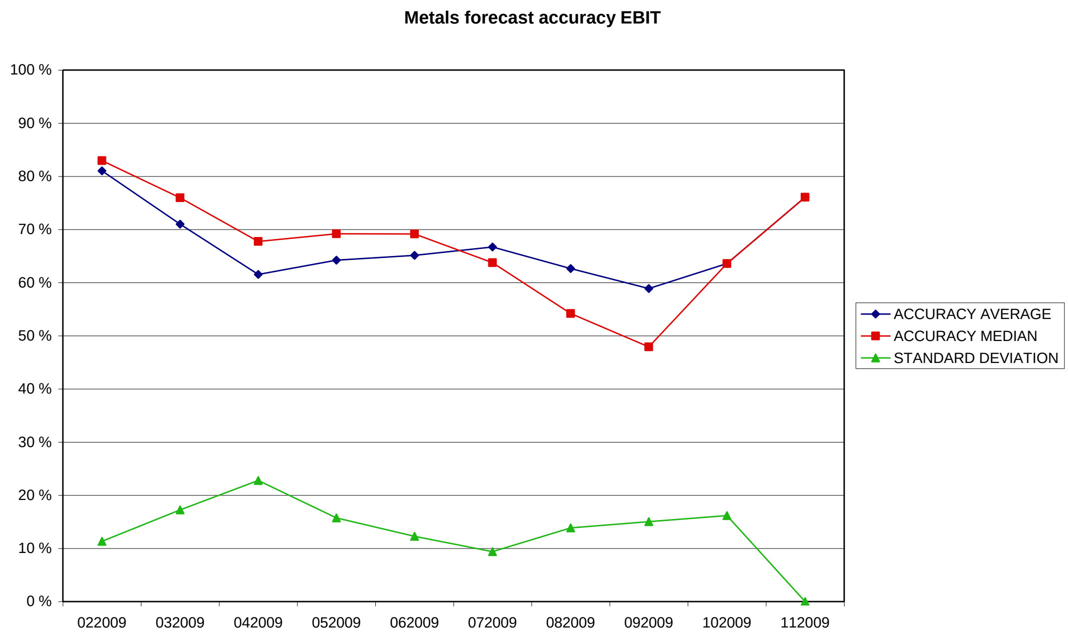


Figure 28. Metals forecast accuracy for profit (Data for 02/2009 to 11/2009)



APPENDIX 2: FORECAST ACCURACY (Weighted Moving Average)

Figure 29. Corporate forecast accuracy for Net Sales (Data for 02/2009 to 11/2009)

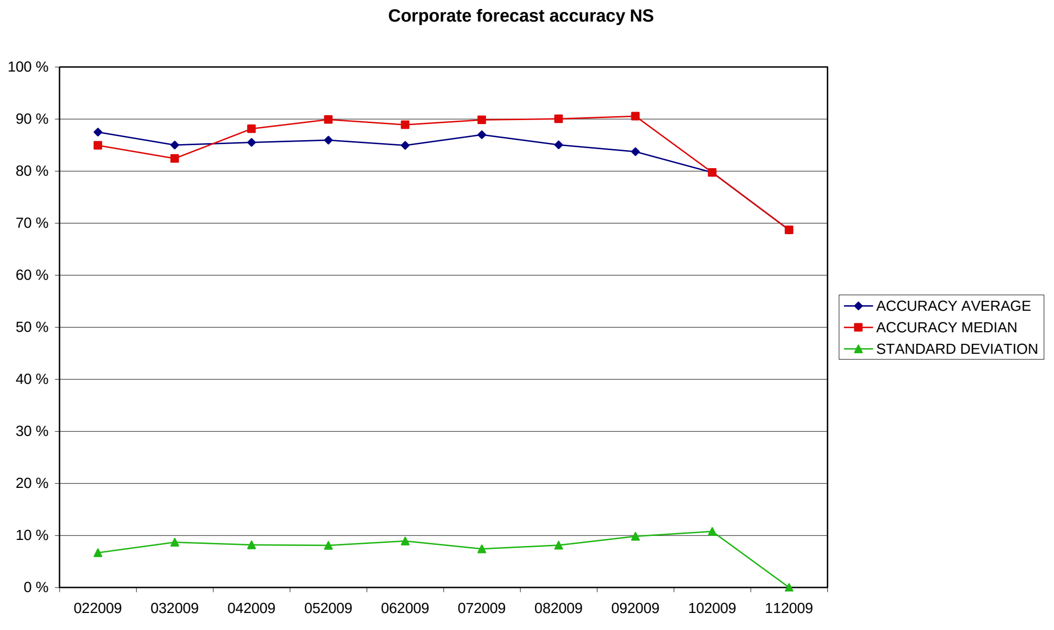


Figure 30. Construction forecast accuracy for Net Sales (Data for 02/2009 to 11/2009)

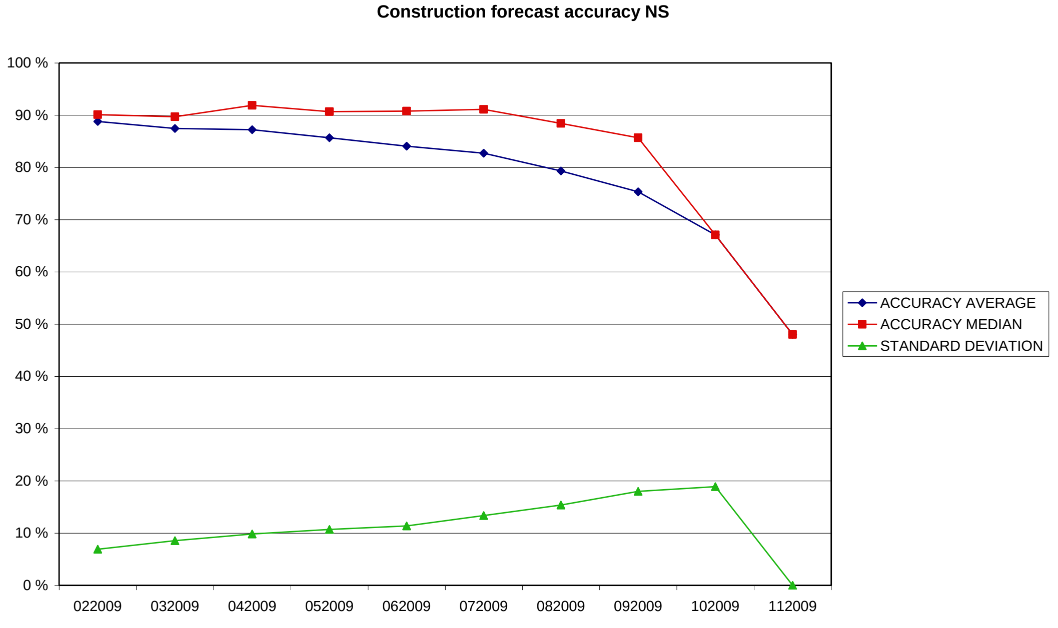


Figure 31. Engineering forecast accuracy for Net Sales (Data for 02/2009 to 11/2009)

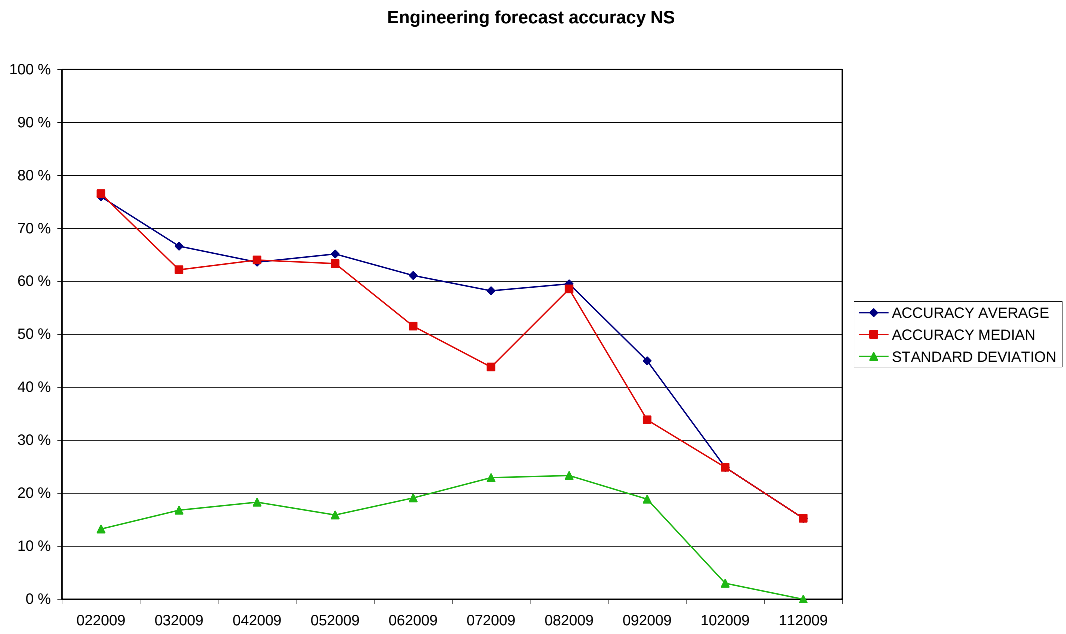


Figure 32. Metals forecast accuracy for Net Sales (Data for 02/2009 to 11/2009)

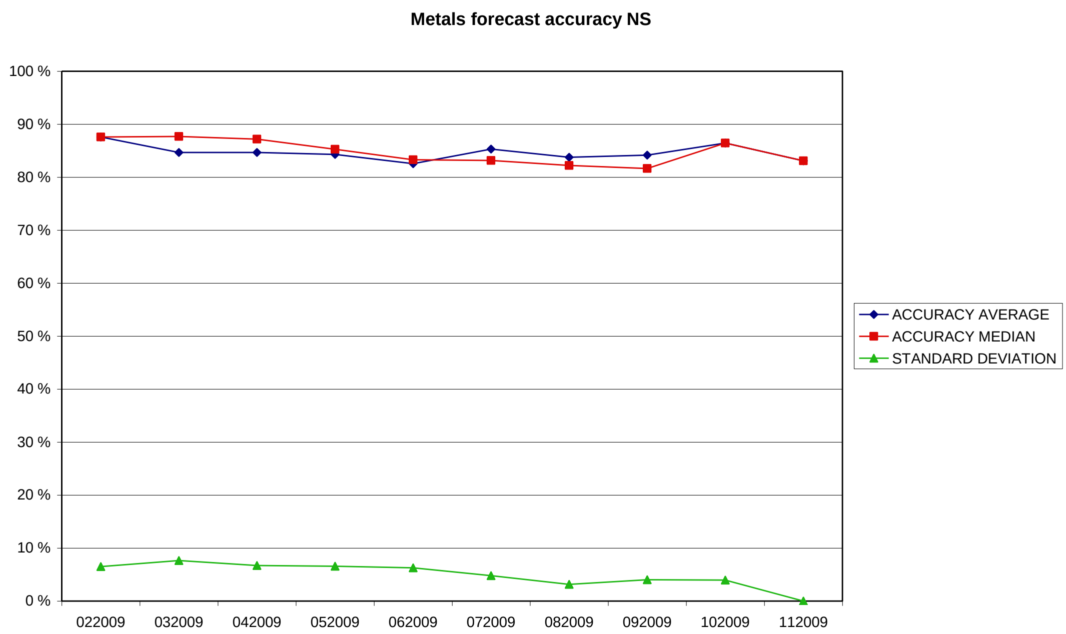


Figure 33. Corporate forecast accuracy for Cost of Goods Sold (Data for 02/2009 to 11/2009)

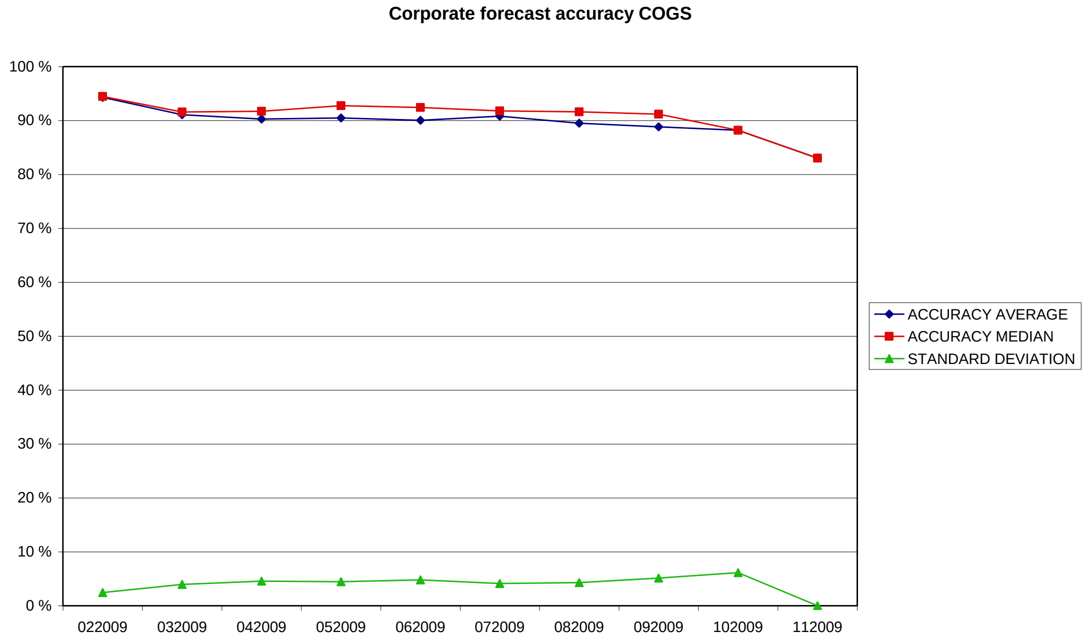


Figure 34. Construction forecast accuracy for Cost of Goods Sold (Data for 02/2009 to 11/2009)

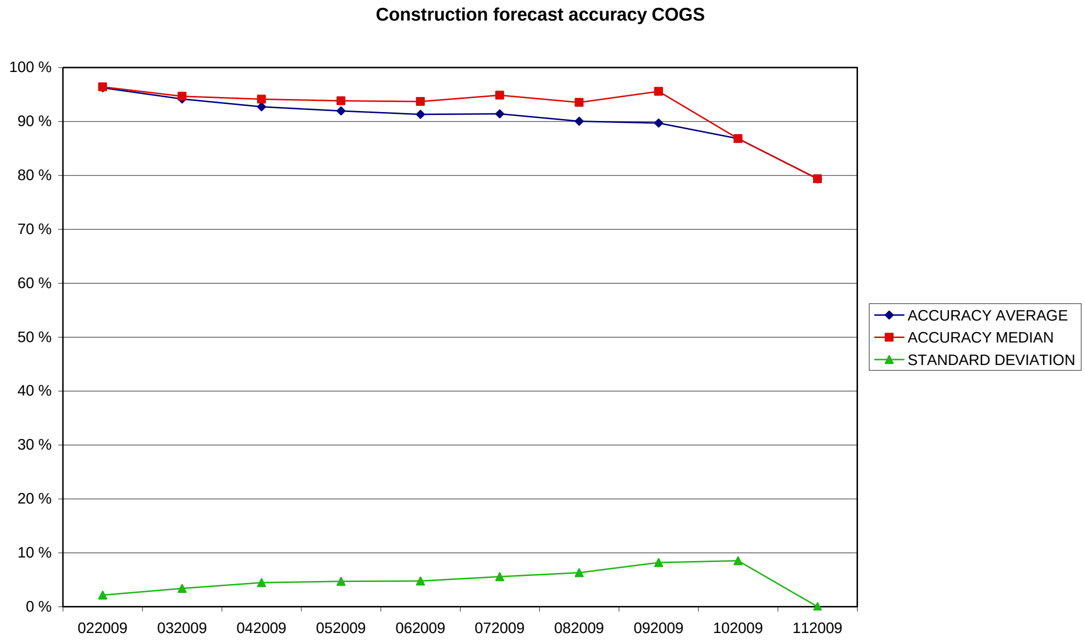


Figure 35. Engineering forecast accuracy for Cost of Goods Sold (Data for 02/2009 to 11/2009)

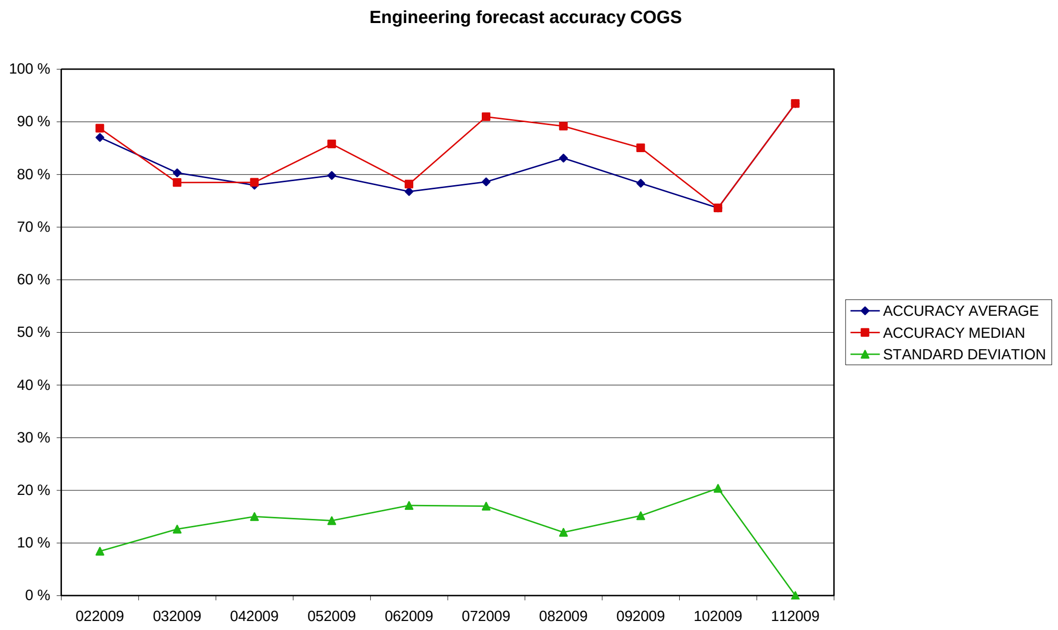


Figure 36. Metals forecast accuracy for Cost of Goods Sold (Data for 02/2009 to 11/2009)

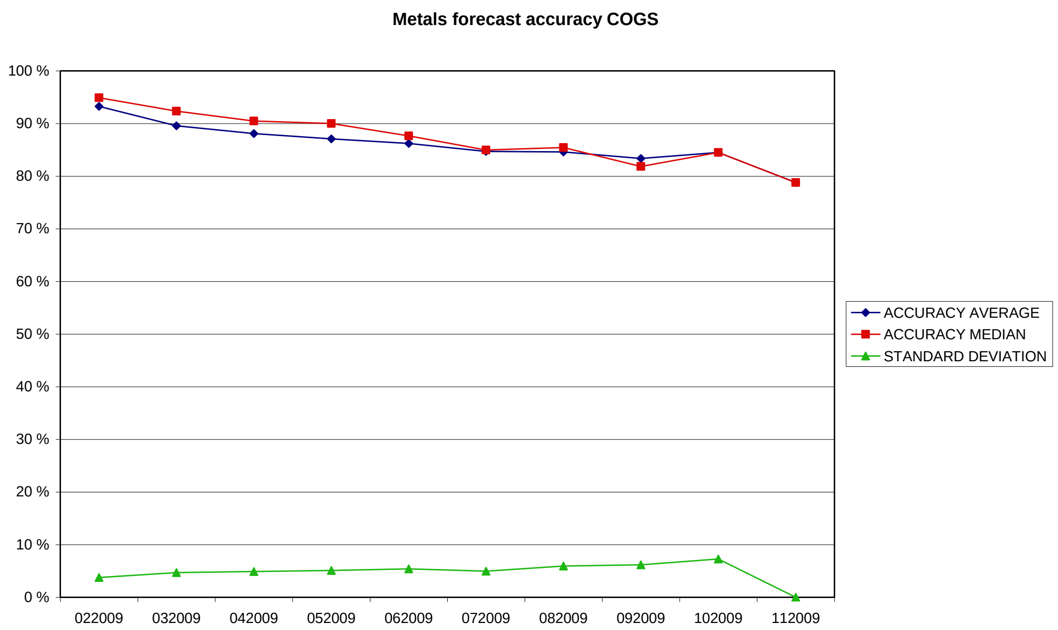


Figure 37. Corporate forecast accuracy for profit (Data for 02/2009 to 11/2009)

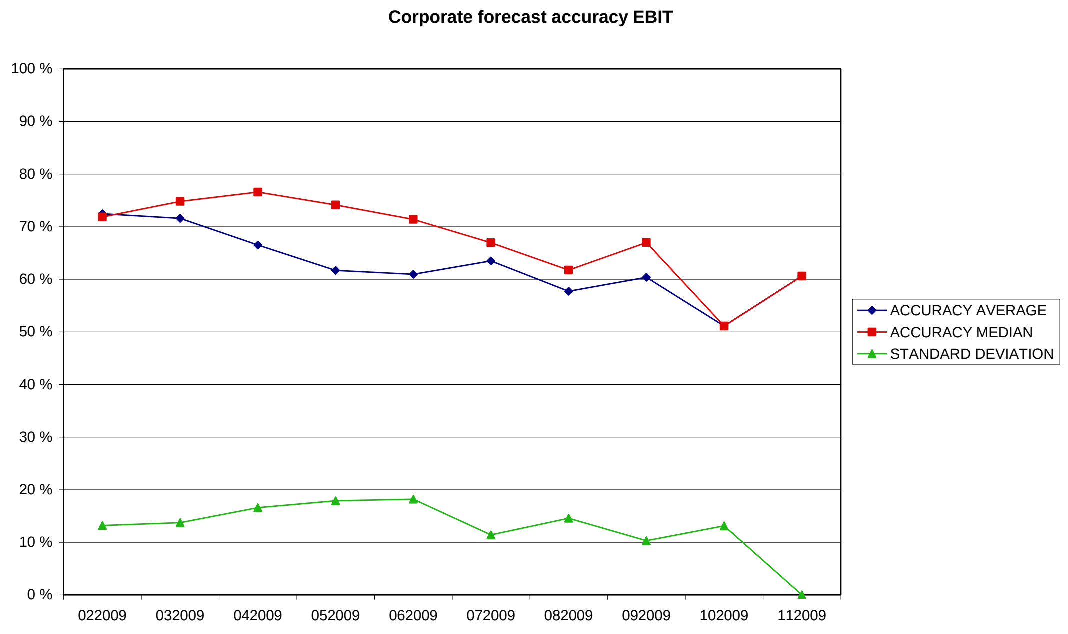


Figure 38. Construction forecast accuracy for profit (Data for 02/2009 to 11/2009)

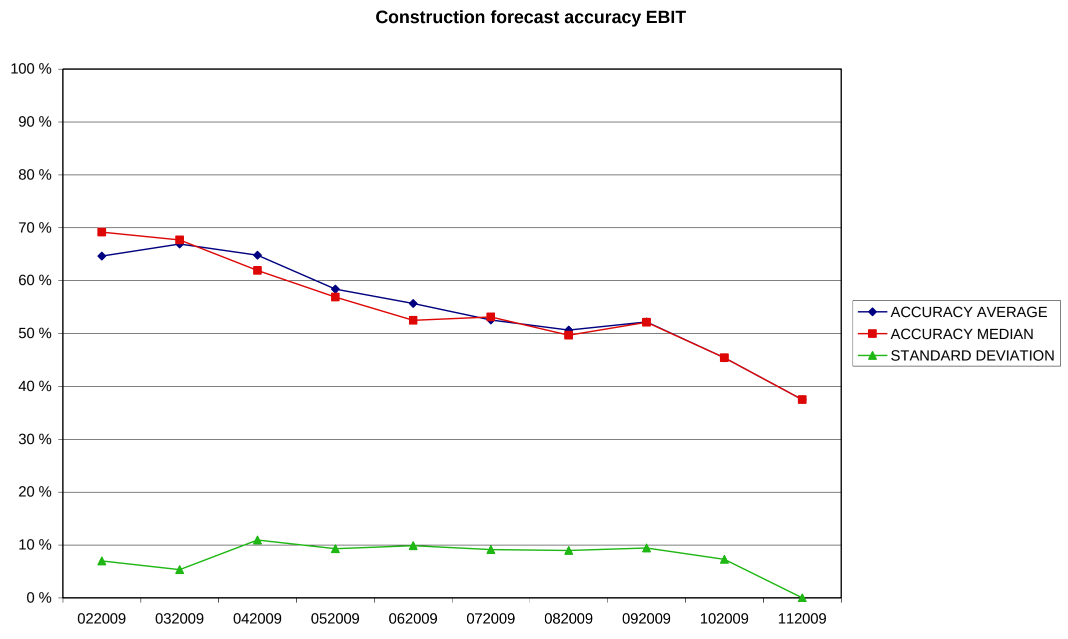


Figure 39. Engineering forecast accuracy for profit (Data for 02/2009 to 11/2009)

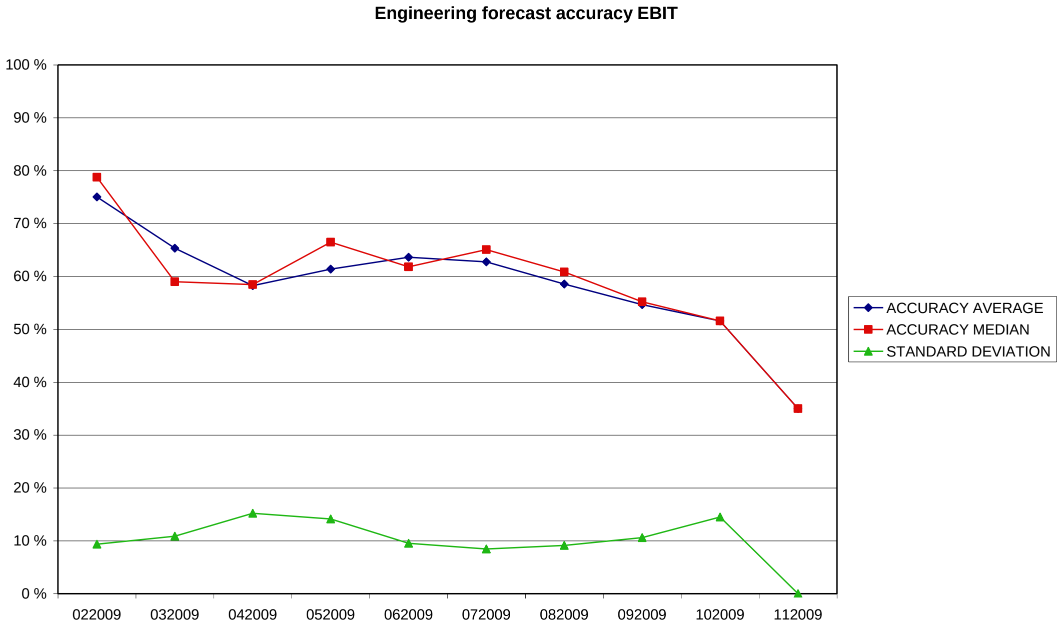
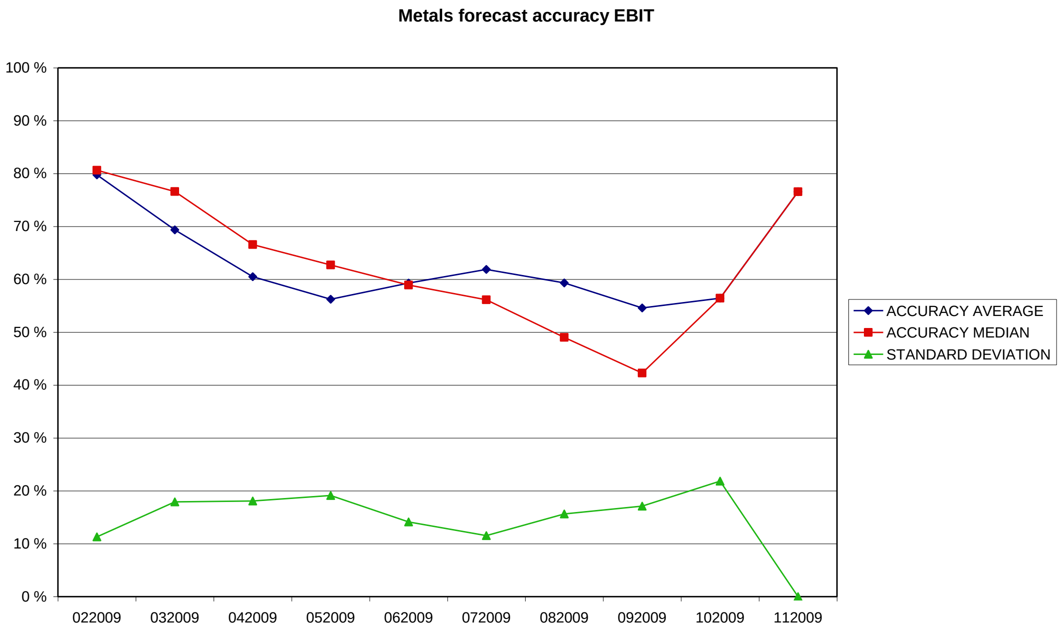


Figure 40. Metals forecast accuracy for profit (Data for 02/2009 to 11/2009)



APPENDIX 3: FORECAST ACCURACY AND ERROR, NET SALES (Simple Exponential Smoothing)

Figure 41. Corporate net sales forecast accuracy and error measures for periods 2/2009 – 12/2009

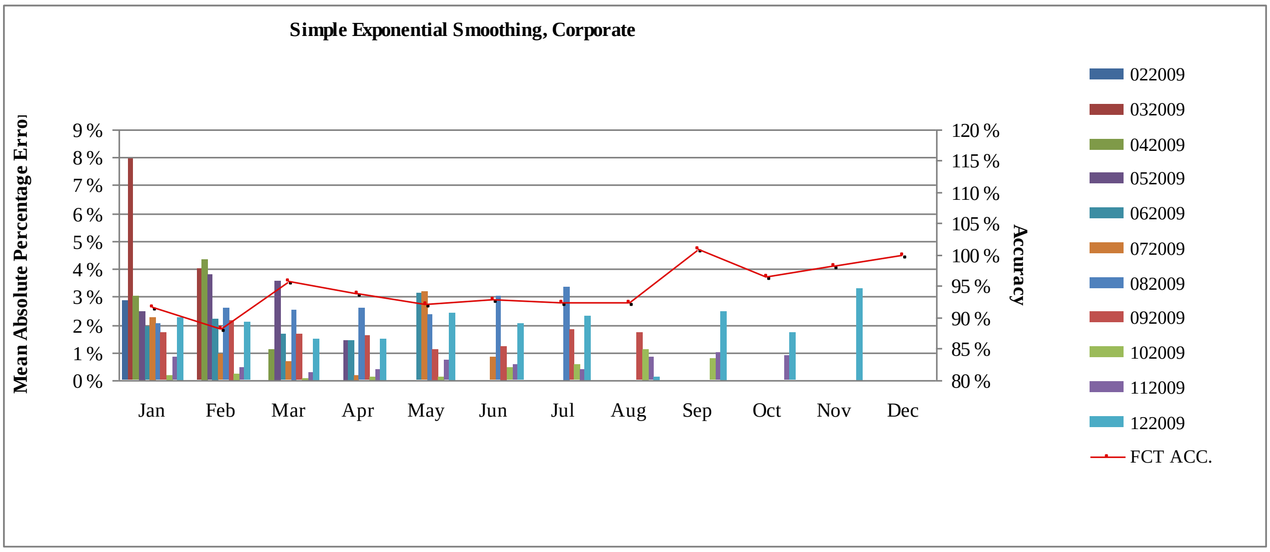


Figure 42. Construction net sales forecast accuracy and error measures for periods 2/2009 – 12/2009

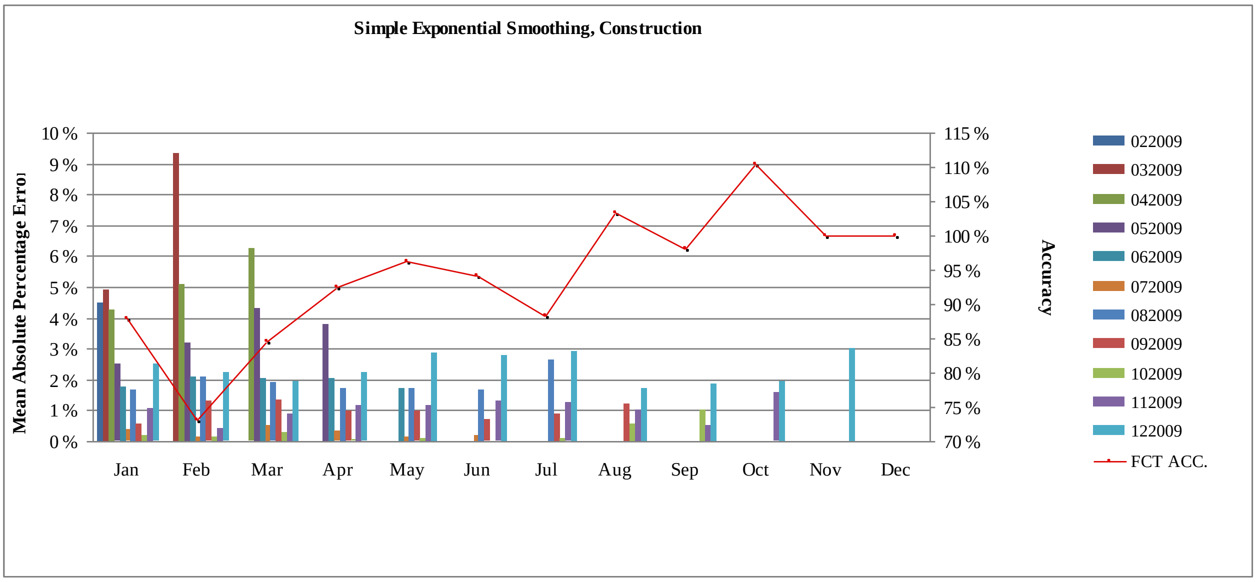


Figure 43. Engineering net sales forecast accuracy and error measures for periods 2/2009 – 12/2009

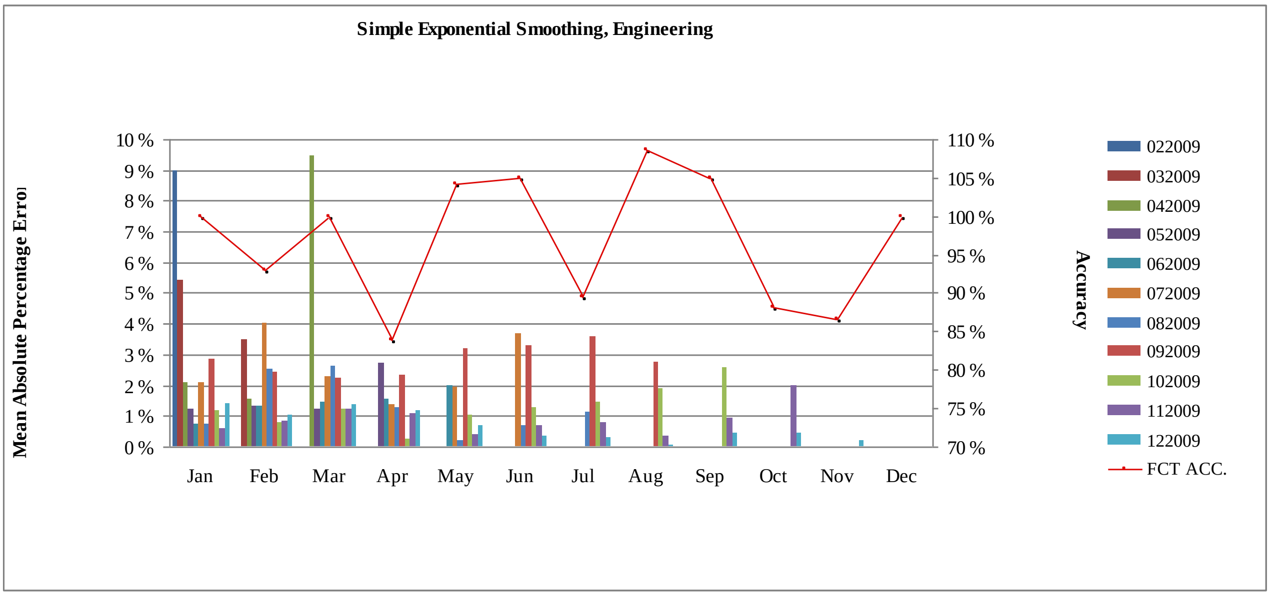


Figure 44. Metals net sales forecast accuracy and error measures for periods 2/2009 – 12/2009