Judgmental forecasting and value analysis of promotional events

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Thesis of 30 ECTS credits
Master of Science in Engineering Management
May 2015

CONFIDENTIAL UNTIL 2020

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Thesis of 30 ECTS credits submitted to the School of Science and Engineering
at Reykjavík University in partial fulfillment
of the requirements for the degree of
Master of Science in Engineering Management

May 2015

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ABSTRACT

Accurate sale forecasts can help companies improve the operation of their entire supply chain. Although it is possible to create good forecasts with statistical forecasting methods, a judgmental forecasting is often needed. Forecaster has to have his/her own estimation of events that cannot be included in the statistical model. One of the things that need special attention is sales promotions. To develop software that can help the user define future promotions and make a forecast for the promotion effective is a significant step towards creating a more accurate forecast. To estimate future promotions, it is good to have the option of viewing and valuing past promotions. This thesis offers a method to classify promotions and a model to calculate the value of past promotions. It can be used for future promotions to estimate their value and their effect on the sale of the affected products. The model for calculating the value of promotion was tested on real data. Three promotions were analysed, statistical forecast was calculated to create a baseline sale, and an additional sale was then used to calculate the value of the promotions. This model can then be employed in the analysing tool AGR event analyser. This model will be easy to implement and will use easily accessible data. It is believed that it would improve overall forecasting, by viewing past promotions and use them to forecast for future promotions.

Keywords; Forecasting support systems, Judgemental forecasting, Supply chain, Promotional analysis, Promotional value analysis.

ÚRDRÁTTUR

Góðar söluáætlanir geta bætt skilvirkni aðfangakeðjunnar hjá fyrirtækjum. Tölfræðilegar aðferðir duga oft til að gera góðan grunn að spá, en oft er nauðsynlegt að bæta gæði spánna. Það má til dæmis gera með því að notast við huglægar aðferðir og fá þá sem vinna söluáætlanirnar til að bæta við viðbótarupplýsingum. Eitt af því sem er algengt að þurfi sérstaka meðhöndlun eru söluherferðir. Hönnun á hugbúnaði sem hjálpar notendum að skilgreina framtíðar söluherferðir og búa til spár fyrir söluherferðir er mikilvægt umbótaskref að nákvæmari söluáætlunum. Til að hægt sé að spá fyrir um framtíðar söluherferðir er gott að geta skoðað og metið fyrri söluherferðir. Í þessari ritgerð er sett fram aðferð sem flokkar söluherferðir og líkan sem metur virði söluherferða. Líkanið var sannreynt á raungögnum úr íslensku fyrirtæki. Þrjár söluherferðir voru greindar, gerð var tölfræðileg spá sem notuð var sem grunn sala og viðbótar sala síðan notuð til að meta virði söluherferðarinnar. Líkanið verður svo hægt að nota inn í hugbúnaðinn AGR söluherferðir, til að greina og meta söluherferðir. Líkanið er einfalt í uppsetningu og byggir á aðgengilegum gögnum. Líkan sem þetta á að geta bætt gæði söluspáa með því að meta eldri söluherferðir og nýta til að meta söluherferðir í framtíðinni.

Lykilorð; Spáhugbúnaður, huglægar spáaðferðir, Aðfangakeðja, Greining söluherferða, Virði söluherferða.

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1. INTRODUCTION

1.1 PROJECT BACKGROUND

The project is done in cooperation with two Icelandic companies, AGR, which is a supply chain planning specialist offering inventory planning and optimisation software solution, and an Icelandic food and beverage producer and wholesaler. The master's project is part of a larger project, a development of promotion planning software - AGR Event Analyser. It would fit with the current AGR planning and inventory optimising software. The project is funded by sponsorship from the Icelandic technology development fund for three years.

1.2 STATEMENT OF THE PROBLEM

Most companies are driven by demand, either service related or production related. It is important for businesses to create a plan for this demand in some way. Most companies generate some sort of forecast to plan for the upcoming season. It can be a forecast created through formal methods, with clear workflow and documentation or informal methods with no formal workflow or documentation. Forecasts are often classified by statistical forecast or judgmental forecast. The statistical forecast uses past sale history or other data to create a forecast while the judgmental forecast is carried out by humans who use their insight and additional information to create a prediction. A combination of both is feasible where the base forecast is obtained with statistical predictions and improved with judgmental forecasting.

Forecasts of demand play a vital role for all supply chain companies. Decisions relating to purchasing, manufacturing, staffing, financial planning and logistics are all dependent on such forecasts. A good forecast can save substantial time, money and effort in all the supply chain if it is accurate. An example of this would be purchasing department possibility to get better deals on the purchase by a more accurate long time forecast delivered to the supplier or by accepting longer lead time on orders. The transportations can be much cheaper if the forecast is close to actual sales volume since better deals can be obtained by accepting slower delivery instead of needing hasty delivery by flight. The manufacturer can schedule their production to more accuracy if the forecast is good, and consequently get more efficiency from the production line and better utility from the staff. The financial department is informed when inventory level is at the highest peak and can make some precautions in advance. Also, the top management will be better informed about what is ahead for the next weeks/months and can, therefore, be on top of things. If the forecast is bad it can also be very damaging to companies. In addition to higher costs in the supply chain there are other more serious matters that might occur. There might be a risk of stock-out which often results in lost sales, unsatisfied customers or overstock, all very expensive consequences. The company might even have to hold products that will be impossible to sell, as in the case of shelf life products or fashion items. A good forecast can play a vital role in the company struggle to survive.
It is possible to produce quite a sophisticated forecast by using statistical forecasting methods. However, there is still need for judgmental adjustment by a forecaster to include elements that are not accounted for in the statistical forecasts. Elements, for example, like promotions, new

product launches and other cases where historical data does not give good indication of the future. It is, therefore, important to design and implement a forecast support system that can handle promotion in a sufficient way.

The development of a software that helps the user to define and forecast for future promotions and other events can potentially be a significant step for companies to deliver a more accurate forecast. A forecast that again gains lower cost in the supply chain and delivers more profit to the company. One of the things that are essential to define future promotions is to view and value past promotions. However, when looking into literature on how past promotions are evaluated, incredibly little can be found. It is, therefore, a worthy challenge to define some basic methods to estimate the effect and value of promotions. Information on the value of promotions can be useful when deciding future promotions.

1.3 OBJECTIVES AND AIM

The aim of this project is to find a suitable method to estimate the value of sales promotions and other events that have an impact on sales. Although much literature exists on promotion, most of it is from the marketing perspective however effect on the supply chain is usually neglected. On the other hand much has been published about advanced planning and supply chain although mostly from the logistic perspective, not from the marketing view. Increased knowledge on the value of past promotions will provide a valuable input for marketing departments when scheduling future promotions. Given improved knowledge on the value and effect of promotions, logistic departments could also have better sales forecast to optimise the supply chain. In this project, a method for analysing promotion and estimating its value has been constructed. That information can be used both in promotional reviews where the value of different promotions are compared and for planning future promotions to increase accuracy. The promotional activity is one factor that is vital to adjust forecast since statistical forecasting method lacks that extra input.

In this thesis, some of the related literature will be reviewed. Most of the literature is related to forecasting support systems since some new and interesting publications have been published in recent years. Less has been written about the value analysis of promotion due to lack of literature on the subject. Then a basic model of how to estimate promotion and value cost of promotion will be represented. It was deliberately kept as simple as possible. One of the prerequisites was that the model would be easy to implement and explain for future users. The model was then tested on real data from a company, which is presented in the case study. All numbers from the promotion have been scaled to protect classified information. The company and the promotion planning process is described and the technic for the case study explained. Three promotions were analysed, information about each promotion and the sale history of the promoted products and potential shadow products. In the following chapter the data from the case study is analysed further, by applying the model described earlier. The baseline forecast and forecasting error are calculated and the value analysis of the promotion is presented. At last discussion about the results of the case study are discussed and it is validated on how it fits with the model set up in the beginning. How the result can fit in with the promotional planning tool being designed is also discussed.

2. THEORETICAL FRAMEWORK

This literature review chapter is an overview of the background and previous studies in this field. Literature on forecasting support system and behaviour in judgemental forecasting includes some highly interesting recent publications. This chapter will also cover some basic knowledge in sales forecasting, statistical forecasting, promotion and an overview of what was found when searching for value analysis of promotion.

2.1 SALES FORECASTING

Forecasts of demand play a vital role for all supply chain companies. Sales forecasting is the task of estimating the demand for a certain product in the future. It is usually carried out on stock keeping unit level (SKU) and sometimes forecast for location is needed as well (SKUL). Producing accurate sales forecast is a crucial and challenging task. It can have high effects on the whole supply chain, in procurement, manufacturing and logistics. Despite the importance of forecasting in companies, it is still a task that is often carried out poorly, not with enough focus from top management and contains little integration between different departments [1]. The level of forecasting in companies' culture can differ greatly. It can range from having almost no forecasting at all, up to having very sophisticated methods of forecasting. In the work of Moon, Mentzer and Smith [1]16 organizations were examined and four stages of forecasting culture were defined, where stage 1 is very naïve forecasting and stage 4 is a state the art. The forecasting management framework they use is quite similar to what others have suggested in other literature like Fildes and Hastings [2], and Mentzer et al [3].

Forecasting can be made by using statistical methods or by relying on human experience to predict the future. A classical setup for companies would be to have some statistical forecasting baseline and then make adjustments to the forecast with a group of experts. These manually made adjustments are often referred to as judgemental forecasts. In most companies this task is carried out by middle management, often marketing directors, production directors and forecast executives [4] [5]. They often have to review hundreds or even thousands of time series of past sales history, so reviewing takes away valuable time from important and often overloaded workforce. It has been shown that forecast adjustments are not always useful and are in fact only useful when the forecaster has some additional information like an upcoming promotion [6]. A forecaster also tends to adjust forecast excessively [7] [8] wasting valuable time with the result of increasing forecasting error. It is, therefore, a major challenge to develop a system that minimises the error in forecasting as well as minimise the time spent on forecasting by middle management.

2.2 FORECASTING SUPPORT SYSTEMS

Systems that combine statistical methods with judgemental forecasting are usually referred to as forecasting support system (FSS). The need for such a support system is growing since the task of sales forecasting is becoming increasingly complex. This is due to a more competitive consumer market, shortened product life cycles and more aggressive marketing [5].

Given the vitality of a good forecast and the complexity of this task it is important to have advanced tools to execute the task of forecasting. This would be a tool that takes the best from

both statistical methods and expert knowledge that cannot be formed into a model. Forecasting support system is one type of decision support system where interest has been growing. In the recent years several articles have been published about forecasting support systems (FSS), but not as many as one would expect given the importance of such a tool in the industry [1]. A recent publication in the international journal of forecasting "Forecasting support system: What we know, what we need to know" by Fildes and Goodwin [9] stated that the term forecasting support system induced 15 papers between 1993 and 2002 and 38 papers between 2003 to 2012. Currently, there appears to be some awakening in this research field even though this can be considered as relatively little research output. There is still much to be done in this area of research. For example, there are very few papers on the relationship between judgment and promotion in forecasting performance [5].

The industry has been investing heavily in forecasting support systems with software giants like SAP, SAS, Microsoft and J.D. Edwards all issuing FSS systems. The software industry is not however responding to the needs of small to midsize companies and the software packages available are very limited in this area. It seems that in the solutions available the software is either focusing on producing a good statistical forecast or a good method to make judgmental forecasting but lacks the ability to obtain the best of both methods.

It has been shown that by combining both statistical forecast and judgmental forecast a more accurate forecast is obtainable. It has even been shown that by taking a simple average of the two methods a better forecast can be obtained [10].

2.3 STATISTICAL FORECAST

The interest of using statistical methods for forecasting dates back to over a century. It is also referred to as objective forecasting method as opposite to subjective forecasting method. Objective forecasting method can be split into time series methods and regression. In both cases forecasts are based on past history where time series uses only the past history of the series to be forecasted while regression models often incorporate the past history of other series. In time series forecasting, the goal is to find predictable, repeatable patterns in past data. Based on the identified pattern, different methods are appropriate [11]. Time series methods have the advantage of easily being incorporated into a computer program for automatic forecasting and updating. Making it very popular in forecasting sales volume for companies that handle numerous SKUs and forecast must, therefore, be made semi-automatically.

Common methods are moving average, the family of exponentially smoothing (exponentially smoothing, Holt method and Holt-Winter method) and some more advanced technics like Box-Jenkins and Filtering theory,(e.g. Wiener and Kalman filters). Although advanced methods have been developed it does not always give more accurate sales forecast. In fact, a research by Armstrong from 1984 on 39 case studies [12] showed that in 20 out of 39 cases the forecast delivered with advanced technique resulted in same or similar error as naïve forecast (exponential smoothing), performing better in 11 cases but worse in 7 cases. More recent studies are consistent with these findings like the work of Green and Armstrong from 2015, where 97 comparisons were reviewed in 32 papers, comparing simple and complex

forecasting methods. None of the papers provided evidence that complexity improved forecasting accuracy [13]. Simple methods are quite acceptable when forecasting sales volume and in this thesis the main focus will be on them.

Moving average is a simple but popular forecasting method that takes the average of a few of the most recent observations. Exponential smoothing is also simple and popular. The current forecast is the weighted average of the last forecast and the current value of demand. One can choose the factors by how sensitive the model is to changes. The Holt method is a double exponential smoothing designed to track time series with linear trend, and the Holt-Winter method is a triple exponential smoothing designed to track time series with linear trends and seasonality. It uses three smoothing factors, one for last forecast; the second one for linear trend and the third for seasonal factors

These methods are excellent in identifying patterns, trends and seasonal effects and have a good ability to ignore white noise or irregularity in the data which should not be forecasted for. However, all of these methods have a significant weakness, as they are not able to include additional potentially relevant information, such as promotions that are designed for affecting sale quantities. Since they are only taking past time series into consideration and identifying a pattern in these data, they are incapable of identifying actions that are intended to change customer demand like promotional campaigns [5]. It is, therefore, important for sales forecasts to have some base from statistical forecast and then use judgmental forecasting to add the parts that are still missing in order to make a good forecast.

2.4 JUDGMENTAL FORECASTING

Judgmental forecasting is an active research area that has gained a growing interest over the last 25 years. The topic of managerial adjustments in the context of supply chain demand forecasting has been neglected until recently [7]. It has been shown that human judgment is valuable in terms of improving forecasting accuracy, but it has also been shown that it can be damaging and contains several biases [14].

There have been some studies on what sort of judgmental adjustments to statistical forecast are useful and which have a negative impact on the overall forecasting error. It was found that negative judgmental adjustments are based on more reliable information and consequently lead to less forecasting errors than positive judgmental adjustment [7]. It has also been recognised that larger adjustments tend to decrease forecasting errors where smaller adjustment seems to increase forecasting errors [7].

It should be noted that a recent publication points out that this might be due to how error is calculated and that traditional forecasting error calculations (MAD, MSE, MAPE) might not be a good measuring tool when handling sales forecasting errors [15], [16]. That will, however, be a subject for others to discuss.

There seems to be a tendency with forecasters to over-adjust forecasts. Since statistical forecast can handle trend, seasonal effects and normal sale quite well, the only real input needed from the forecaster is when additional information is available. In fact, research indicates that forecast accuracy tends to be reduced when forecasters judgmentally adjust

statistical forecasts if they are not in possession of important new information about exceptional events [17].

Many studies have shown that people often prefer judgmental methods rather than statistical approaches when forecasting time series [18] even though statistical forecast is often more accurate than judgmental [19]. There are several explanations on why judgemental adjustments seem to be not as efficient as they could be or why forecasters tend to over-adjust forecasts. The reason for this could be that people mistakenly identify noise as systematic patterns like trend or seasonal effects [20]. It could also be for controlling reasons they feel in control and have ownership of the forecast [21]. Some might see this as a way of showing that they have looked at the forecast and made some adjustments or to please senior manager.

Researchers have been working on useful methods on how it is possible to make forecast support systems in such a way that the statistical forecast will cover forecasts that are possible to predict but experts would then add judgmental forecast for those products needed. If this were possible the forecasting error and the time experts spend on forecasting tasks would reduce [5].

Recent research neither shows restrictiveness nor guidance in the support system led to improved accuracy [22]. When the forecasting support system was restrictive to minimising small adjustments in the forecast, users tended to make the adjustment even larger in order to be able to change the forecast and also led to the fact that necessary adjustments were not carried out. When the support system provided some guidance the advice was often ignored resulting in poorer result than would be expected.

The role of the forecaster has also been studied. A study by Önkal, Lawrence and Sayim showed that different results came from participants with different roles. In the study, each one got the role of marketing director, production director or forecast executive without being told how to act or behave during the forecasting process. The study showed that the marketing was optimistic, production was pessimistic while the forecaster was closest to reality [4]. Other researchers have studied the impact of a group taking part in the forecasting process instead of an individual, showing that the group forecast was overall better than the average of an individual forecast [23].

It still remains a question how to get the best of both statistical and judgemental forecasts since judgemental adjustments would mostly likely be at their highest efficiency if only applied where additional information is available. In an article from 2013 Trapero et al. suggest [5]:

> *One possible way to reduce the number of judgemental adjustment made by forecasters is to use the available information more efficiently. Thus, if we are looking for a reduction in the number of adjustments, a potential solution would be to model the effects of promotion on sales forecast, for those promotions where past information is available. The forecast would then be adjusted to take into account any factors which are excluded from this enhanced model.*

Some systems have been designed for this purpose of a promotion support system. However, a good and general commercial solutions software has yet to be published.

2.5 PROMOTION SUPPORT SYSTEM

Trade promotion is the single largest category in the market mix budget of U.S. consumer packaged goods companies and estimations show that promotion accounts for 70% of the total marketing budget [24], [25]. Many businesses use relatively simple methods for promotional planning. Cooper et al states that in interviews with a number of executive personnel in large grocery chains in the U.S, the most sophisticated practice was to order the same amount of product for upcoming promotion as was ordered for the "last like" promotion [26]. In an Icelandic research [27] only a few companies and their methods of handling promotion into forecast were examined and none had a promotional support system.

To handle the complexity of promotional features (price discounts, types of display, types of advertising etc.) it is possible to approach the problem of promotional forecast by using multivariate statistical model with information from past promotion [28].With this aim, several promotional support systems (PSS) have been developed with promising result; see SCAN*PRO [29], PromoCast [26] and CHAN4CAST [30]. They all, however, only emphasize sales volume and the effect of promotions but do not cover the subject of estimating the value of promotion.

It was quite a struggle to find literature to estimate the value of promotion. Although many articles were studied about this and similar subjects, the result was quite poor. Even though the search was extended to marketing literature it did not give any further results and no article was found on how to estimate the value of promotion. Many articles, however, subjected the result of the promotion as to what has the most effect on the customer. One quote was found in Silva-Risso et al. publication [24]:

> Calendar profits are the net result of the contribution from incremental sales minus the opportunity cost from giving away discounts to non-incremental sales and the fixed cost associated with implementing promotional events (e.g. retagging, features, displays).

Silva-Risso also suggests an optimization model for calculating promotion calendar that maximizes net incremental contribution. The study, however, focuses mainly on how to schedule promotion in a promotion calendar instead of studying this thesis' main focus, the impact on the supply chain. In Sigurjonsson thesis an optimizing model to identify successful promotions was presented [27]. That model has, however, yet to be validated with real data from promotions.

There might be some interesting aspects on how to interpret these findings. One could assume that marketing departments do not think enough about the total cost of promotions but only the cost of the advertisement itself and neglect the importance of calculating the total cost of the promotion. It could also be that perhaps the forecasting members, who are often located as a function in the logistic department, do not think enough about the cost of promotion since the marketing department is usually accountable for it. Instead, they only consider the extra sales volume that will need to be purchased in order for the promotion to be successful. If this is the case and it is supported by interviews with forecasters and marketing department personnel more research must be done in this area.

3. MODEL DEFINITION

In this method section a definition of the model is listed. The structure of the model is mainly to use in the case study, but with comments or suggestions about how it should be used in the promotion analysis software being designed. The case study is only using a simplified version of the model since only three promotions were analysed. The main focus of this work is to keep the data needed as simple as possible; that will simplify implementation and make the model easier to use. The primary focus is to have the date either entered in by a specialist or directly drawn from an ERP system, mainly focusing on the Microsoft ERP system, Dynamics Axapta and Dynamic Navision.

The study is divided into three groups, classification, impact analysis and value analysis. Classification is made to generate a base to compare promotions, either to focus on their similarities or differentiations. The classification will be different between setups and is primarily used to group sets of promotions together. It will not be used in the case study since it is only for three promotions. Impact analysis determines what impact each promotion has on sales considering several aspects. Sales had to be valued with respect to baseline sales forecast. Duration of the impact also has an effect, that is, how long period should be considered when assessing each promotion. The scope of each impact was also viewed, that is, to what extent other products should be taken into account when estimating the value of promotion. Value analysis determines how each promotion should be valued considering both direct and indirect cost of promotion. The income of the promotion was assessed by the difference between baseline sale and promoted sale and taking into account the affected products. The profit of the promotion could then be calculated. The forecasting method used in the case study is then listed up in section 3.4 followed by the value analyse model in section 3.5.

3.1 CLASSIFICATION

The purpose of classification is to put different promotions into predefined categories so that search and comparison within a group of promotions are more efficient. Groups of similar promotions can then be examined together and that would give a more comprehensive overview than if no classification were made at all.

Promotion can be of many types. When classifying promotions into groups, the common practice in the field was used. The classification was done in two ways. The type of promotions was defined, as was the location of the promotion. It is possible for each dimension to have several groups and subgroups. The aim was to design this classification in a practical way so it would make sense for the user and be of use. This will always be subjected to the data/company involved because every company has its own way of classifying. It is, therefore, recommended that this classification will only be used as a baseline and should be adjusted according to different data/company.

For the software, the method will be as follows. During installation or setup, a structured list of promotion type and location will be set up. It is suggested that grouping will always be from a predefined list for structural and searching purpose. When a promotion is defined, it is given a descriptive name and then an appropriate type. By making predefined groups of promotion types and location the user has the extended possibility to examine and explore similar promotions. For the case study, this classification was simply obtained from the company.

3.1.1 Type of promotion

It is suggested that the top most level will be of classical types of promotions. On the next level, a more detailed category will be available. This will mostly be in the hands of the users for defining appropriate classification but an example of one would be as follows:

- Discounts
  - 5-15%
  - 15-25%
  - More than 25%
- Advertisements
  - Large (Television advertisements and other media)
  - Medium (Radio/newspaper/magazine)
  - Small (Web advertisements, social network, in-store displays)
- Flyers
- Coupons
- Incentives

By categorizing promotions in this way, all comparisons are made easier since added similarity is within each group than between them. Discounts have for example more effect in negative purchases shortly after the discount while a campaign may have a more long-term positive effect.

3.1.2 Location of promotion

The location of a promotion is sometimes more descriptive and can have more impact than the type of promotion. This classification also contains two levels. The upper level is descriptive of the geographical location of the promotion, for example, different countries or territories. Sub-level is not in the geographical sense but for example connected to a retailer that is executing the promotion in cooperation with the producer/wholesaler. In the case of a retailer; the sub-level could be different shops. This classification is also highly depended on the business/company in question and needs to be adjusted accordingly to new businesses/companies. An example of classification for a wholesaler in the dimension of location is:

- Iceland
    - HORECA (Hotels, restaurant and catering)
        - Hotel chain 1
        - Hotel chain 2
    - Petrol stations
        - Petrol stations 1
        - Petrol stations 2
- Denmark
    - Supermarkets
        - Supermarket 1
        - Supermarket 2

The primary focus of the classification is to group together promotions that have similar attributes in order to be able to compare them at later stages and use old promotions as a base for new promotions.

3.2 IMPACT ANALYSIS

Impact analysis has the purpose of defining what impact each and every type of promotion has. What happens if a certain product is promoted? The most obvious effect is that it increases sales volume. It is however not the only impact a promotion can have. There might be some pre and post sales effects, some shadow effects on other products and some long-term effects in the case of branding the product.

For clarity impact analysis has been split up into three distinct impact types. First of all and the most obvious one is the sales. To estimate the increase in sales, it is important to know sales numbers had there been no promotion. This is referred to as a baseline sale. Secondly, duration of impact needs to be defined. The duration consists of the time when the promotion is active and which period is affected by this promotion. At last there is the scope of impact, which is what products will be affected by this promotion.

3.2.1 Baseline sales volume

To calculate increase in sales volume, a baseline sale must be known. One way to establish a baseline sale is to forecast the sales volume in a given period. The forecast must take into account aspects like baseline effect, trend effect and seasonal effect. If valuable information about the sales volume for the past three years is available, good statistical forecasting will give an adequate solution. If information about previous sales is unavailable or past sales do not provide a realistic perspective on the future, some expert input on expected sales volume is needed. In some cases, baseline sales must be entered since data is unavailable to make an automated forecast. The main components of calculating baseline sales are historical data, manual adjustment and forecasting technic.

Historical data

When creating a baseline forecast the most important part is the historical data. In order to build a model that has the ability to deal with seasonal variation in sales, data for two years is necessary to develop the model, and more data would help to validate the model.

The historical data can be in many forms. The most common and simplest one is to have the historical sale information in unit quantity. However, when working with real data, this is not a convenient unit. In the consumer packed goods market the products tend to change over time, both in packaging sizes and in different flavours of the same brand. The reason the packaging sizes and the products change so frequently is a subject for another research, but this can both be changes over a short time period, like Easter packaging +33%, and Christmas colour labelling. Or it can be permanent changes like changing the packaging size from 170 gr. to 150 gr. in order to lower the price without giving up on the profit.

Since data of minimum two years is needed in order to create a forecast of seasonal trends, it can be difficult to find products that have stayed unchanged over that period. So usually it is necessary to establish a forecast for a group of products instead of just one. In the case study, there were not many products that had stayed unchanged over the analysed period.

Since there is quite a variance in packaging sizes, a comparison in sale quantity can be misleading. Two other ways are possible, to create the forecast in either volume/weight or by creating a forecast in sales value. The volume/weight makes it easier to forecast for a group of products that might change over time. However, there is always some cost associated with each sale, e.g. it takes more effort to sell four 0,5l of soda than one 2l of soda. The sales value is also usually higher (per unit of volume) in smaller sizes than in the larger sizes. This is even more extreme when the catering or restaurant section is viewed. The difficulties with using the sales value, are that different customers can have different prices, there may be inflation or increase in the cost price. There are some pros and cons for all of these methods and one must choose a method that is best fit with the data and gives the best possible outcome. In this case study working with sales value was selected.

Manual adjustments

An educated guess or adjustment of the forecast by experts is often needed for several reasons. Sometimes an adjustment is required to correct errors in the dataset, e.g. the

historical data does not give a good indication on the future sales. It is also needed for new products where there is no available data.

Historical data is sometimes not the best source for the forecast due to stock out of the product resulting in no sale over some period, or due to some past promotional activity resulting in very high sales over some period. It can also be due to some changes in the past like a new technic that was introduced and resulting in much higher/lower sale before some period. This is also the case for new products where it is either necessary to make an educated guess about estimated sales.

These issues are often not listed in the ERP system, so it is difficult to draw this from raw data. It is therefore often necessary to have an expert validation on the data. This can be done with some DSS system (decision support system) like AGR inventory optimizer. In the case study raw data was used from the system but the expert opinion in the discussion section.

Forecasting model

The model used must be able to deal with the most common factors in forecasting model method, especially consumer packed market. The model must take into account:

- Baseline sale
- Seasonal effects
- Trend in sales

Many forecasting methods are available; the one that usually fits best for estimating sale in consumer goods market and with products that have good historical data is the family of exponential smoothing

- Single exponential smoothing
- Double exponential smoothing (Holt model)
- Triple exponential smoothing (Holt-Winter model)

In the thesis the Holt–Winter model was used since it shows good results when forecasting for fast moving consumer packed goods with trend and seasonality. Other simple models were tested to see if they gave a better forecast but Holt-Winter showed the best result. For the software, a good way would be to let the best forecasting model be drawn from advanced forecasting software like ForecastPro or any other statistical forecasting tool. The forecasting method used is in section 3.4 and the formula for baseline sale is in section 3.5.1.

3.2.2 Duration of promotional impact

In order to analyse the value of promotion, it is essential to know the time period of the promotional impact. The most naïve approach is to use the active time promotion varied. In a more complex world the impact from promotions can be of different time periods. It is possible to see an effect from a promotion before, during and after the actual promotion period. It can, therefore, be categorized as follows:

- Promotional time; that is the time the promotion was active.
- Short term post-promotional impact time; that is the time shortly after the promotion ended where influence from overstocking is still valid

- Long term post-promotional impact time; that is if some of the customers have changed brands due to positive experience during the promotion
- Pre- promotion impact time; that is if customers delay purchase since they suspect a promotion of a certain product is coming up. This can happen when there is a certain routine in promotion on certain products.

For simplification, only two of these time periods were selected, those were promotional time and short-term post-promotional impact time. The reason for long-term post-promotional impact was neglected is that it should come without extra input into the increased sale of the selected product and could, therefore, be picked up by classical forecasting methods. The reason for pre-promotion impact was neglected is that it is difficult to measure. These two remaining time periods can be different between products and promotion types. It is assumed that both of these time periods will be defined for each promotion.

3.2.3 Scope of impact

In order to analyse the impact each promotion had, it was necessary to estimate the extent of the impact. It obviously had the greatest effect on the product that was promoted but was not the only product affected. Promotion can have an impact on other types of products in several ways. It is usually referred to as shadow products and can be categorized in the following way:

- Product on promotion
- Different packaging sizes of the same product, if a promotion is aimed at specific packaging size and not the whole brand.
- A similar product that can be substituted by the promoted product. This could, for example, be other products within the product group
- Products that can follow the promoted product as a side product
    - Cheese and biscuit
    - Chips and dipping sauce

Advanced knowledge about the products is necessary to be able to list up potential shadow products. It is therefore assumed that an expert/brand manager will handpick the affected products with some suggestions from the system like different packaging sizes and products from the same category. In the case study the shadow products were handpicked by a brand manager.

For affected products, baseline sales also had to be conducted so that increase in sales would take all affected products into account. The time period was however only promotional time but short-term post-promotional impact time was neglected.

3.3 VALUE ANALYSIS

Value analysis is done when both classification and impact analysis are ready. It consists of the cost and income of a promotion, resulting in the value of a promotion.

3.3.1 Cost of promotion

Estimating the cost of promotion can either be a fairly straightforward process or it can be a complicated one. The issues that could be taken into a consideration are for example:

- Marketing Cost
    - Direct cost of designing the advertisement
        - Cost from advertising firm
        - Cost of design
    - Cost of publication
        - Production cost
        - Publication cost
    - Direct cost of sales and marketing
        - Incentives

In the case of a discount, if there is a difference in regular price and sale price during the promoted period, the difference needs to be taken into account. If there is a change in the cost price of the promoted product during the promoted period that will also have to be taken into account. This could be due to several reasons, resulting in either increased cost price or decreased cost price. It can for example:

- Increase cost
    - Extra cost for transportation
    - Extra cost for rescheduling the production line
    - Extra cost for early delivery from supplier
- Decrease cost
    - Volume discounts
    - Overstock that would have been sold over a long period of time
    - Overstock that would expire if sold according to baseline sale.

Although all these factors can have an effect on the cost of the promotion, some of this information can be very difficult to attain some are very difficult to measure and are most likely not available in the ERP system. According to the sales and marketing department it was easier to simply obtain one number as the total cost of the promotion, even though the goal is to have the information more broken down in the software for further analysis.

Since the aim is to have the information as easily accessible or obtainable as possible for the first version of the software, it is recommended that this information is either entered into the system when the promotion is defined or when this information is available. In the case study this information is provided by the company and only used for calculation as a total, one number.

3.3.2 Income of promotion

When calculating the income of promotion, information about sales during the promotional time and post-promotional impact time is needed. Sales of shadow products are also needed as well as baseline sales for all products on promotion and shadow products. If the sales history unit is in quantity or volume/weight, the sales price is also needed. To calculate the income the following components are required:

- Promotion sales increase on promoted products:
  - Total sales
    - For promoted period
    - For short term post-promotional impact time
  - Baseline sale
    - For promoted period
    - For short term post-promotional impact time
- Promotion sales increase on affected products:
  - Total sales
    - For promoted period
  - Baseline sale
    - For promoted period

If the total sale in quantity or volume/weight is used, additional information is needed concerning the prices of the promoted products.

- Promotion sales price difference on promoted products:
  - Promoted price
  - Baseline price
- Promotion sales prices on affected products

It is possible that the cost of the product changes significantly during the promotion due to increased cost of production. To fit that into the model, information about regular cost price and cost price during the promotional period is needed:

- Promotion cost price difference on promoted products:
  - Promoted cost
  - Baseline cost
- Promotion cost price on affected products

In the case study it is assumed that any extra cost that increases the cost price of the promoted product would be included in the promotional cost. The next step is to calculate the total sale and baseline sale:

Total sale:

- Total sale of the promoted products during the promotional period
- Total sale of the promoted products during the post-promotional period
- Total sale of the shadow products during the promotional period

The formulas for the model are in section 3.5.1.

Baseline sale:

- Forecast for the promoted products during the promotional period, the forecasted period from the beginning of the promotion.
- Forecast for the promoted products during the post promotional period, the forecasted period from the beginning of the promotion.
- Forecast for the shadow products during the promotional period, the forecasted period from the beginning of the promotion.

If based on the value then the income of the promotion can be calculated by:

- Income of the promotion: Total sale – baseline sale

The formulas for the model are in section 3.5.1.

3.3.3 Profit of promotion

When the income and cost of promotion have been found the increase in sales must be calculated into net profit. Using the margin of the product to find how much profit the extra sale generated. The profit should be of the margin of the extra sale, which is the income of the extra product sold, minus the cost of the extra product sold minus the cost of promotion.

The margin of the product is usually very sensitive information. In the case study an example of margin % is used. For the software it can be either way.

A simple calculation like this can be too naïve of an approach since some soft parameters could be necessary. Like if the main purpose of the promotion was to increase brand awareness. In the case study, the soft parameters are addressed in the discussion section.

The formula for the model can be found in section 3.5.2.

3.4 FORECAST METHOD

To estimate the baseline sale of the promoted products, it was necessary to create a forecast for the promoted products. The method used was as following. A forecast was calculated for the promoted products. The method that was selected was the Holt-Winter method for seasonal series. When building the model the smoothing parameters (alfa, beta, gamma) were set to 0.1. Then the forecasting error and mean square error (MSE) was calculated. To find the best value for the smoothing constant a linear optimization was applied to the model, with the goal to minimize the MSE. In this section, the basic structure of the models will be explained and information on the formula that were used.

3.4.1 Forecasting

There are many ways to create a forecast based on time series data. Few adjustments were made to the classical forecast. The forecast was run at product group level instead of individual products. The main reason for this was to get a better forecast. When forecasting for a group instead of individual it usually gives a better result. The forecast was also done in value but not in sales quantity.

The forecasting model was built by using the Holt-Winter method. It is a very popular and effective method and has been so for over 60 years since first published. There are however slight variations on how it is set up and the results can differ slightly depending on how the smoothing parameters are selected and how the method initialized. The setup in this thesis follows the setup presented in Steven Nahmias' book on production and operation analysis [11].

The model is in the form

$$D_t = (\mu + G_t)c_t + \varepsilon_t \qquad (1)$$

Where:

- D_t is the demand
- μ is the base signal
- G_t is the trend signal
- C_t is the multiplicative seasonal component
- ε_t is the error term
- t is the period
- τ is the number of months the forecast into the future.

The method requires three smoothing parameters (α, β, γ) and three smoothing equations, one for the series, one for the trend and one for the seasonal factors. They are all used to create a forecast for the period.

The series:

$$S_t = \alpha(D_t / c_{t-N}) + (1-\alpha)(S_{t-1} + G_{t-1}) \qquad (2)$$

The trend:

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1} \quad (3)$$

The seasonal factors:

$$c_t = \gamma(D_t / S_t) + (1-\gamma)c_{t-N} \quad (4)$$

Where the constant: ***α, β*** and ***γ*** are the exponential smoothing parameters that take on a value between 0 and 1, and N the number of periods

The forecast

The forecast can then be used for any future period t+τ by using the formula:

$$F_{t,1+\tau} = (S + \tau G_t)c_{t+\tau-N} \quad (5)$$

The initialization procedure:

In order to find the initial values for G_0, S_0 and the seasonal factors c_{-11}, c_{-10}, c_{-9}, c_{-8}, c_{-7}, c_{-6}, c_{-5}, c_{-4}, c_{-3}, c_{-s}, c_{-1}, c_0 the first two years of data was used. The formulas are the following:

The initial value for the growth:

$$G_0 = (V_2 - V_1) \quad (6)$$

The average for year 1:

$$V_1 = \frac{1}{N}\sum_{j=-2N+1}^{-N} D_j \quad (7)$$

The average for year 2:

$$V_2 = \frac{1}{N}\sum_{j=-N+1}^{0} D_j \quad (8)$$

The initial value for the series:

$$S_0 = V_2 + G_0[(N-1)/2] \quad (9)$$

The initial seasonal factors:

$$c_t = \frac{D_t}{V_i - [\frac{N+1}{2} - j]G_0} \text{ for } -2N+1 \leq t \leq 0 \quad (10)$$

The average of the seasonal factors:

$$c_{-N+1} = \frac{C_{-2N+1} + C_{-N+1}}{2}, \ldots\ldots, \frac{C_{-N} + C_0}{2} \quad (11)$$

The normalize of the seasonal factors:

$$c_j = \left[\frac{c_j}{\sum_{i=0}^{-N+1} c_i}\right] N \text{ for } -N+1 \leq j \leq 0 \quad (12)$$

Where i =1 is for the first season i=2 is for the second season and j is for the period of the season.

When the model was ready, the parameter alfa beta and gamma (***α, β, γ)*** were calculated by setting up a linear model where the error was minimized.

3.4.2 Error calculation

Error in the forecast can be calculated in several ways. In the thesis three common methods are used, MAD, MAPE and MSE. Standard deviation is also used, so the formula for that is also given.

Error:

$$E_t = F_t - D_t \tag{13}$$

Mean Absolute Deviation (MAD):

$$MAD_n = \frac{1}{n}\sum_{t=1}^{n}|E_t| \tag{14}$$

Mean Absolute Percentage Error (MAPE):

$$MAPE_n = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{E_t}{D_t}\right| * 100 \tag{15}$$

Mean Squared Error (MSE):

$$MSE_n = \frac{1}{n}\sum_{t=1}^{n}E_t^2 \tag{16}$$

Standard deviation:

$$\sigma = \sqrt{\left[\frac{\sum(X_i-\mu)^2}{(n-1)}\right]} \tag{17}$$

3.4.3 Optimisation of parameters

When the forecasting model was ready and the error had been calculated a simple optimisation model was written to find the best value for the smoothing parameters (***α, β, γ)***

The model was set up as a linear model where the error should be minimized, calculated by MSE, by changing alfa, beta and gamma with the constraint that all of the parameters should be between 0 and 1.

Index

t = period (1…n)

Data

F_t Forecast for period t

D_t Sale for period t

$E_t = F_t - D_t$ Error for period t

Decision variable

The smoothing parameters:

Alfa α,
Beta β
Gamma γ

Objective function

The objective function was to minimize MSE

$$\text{Min } MSE_n = \frac{1}{n}\sum_{t=1}^{n} E_t^2$$

Constraint

Alfa: $0 \leq \alpha \leq 1$
Beta: $0 \leq \alpha \leq 1$
Gamma: $0 \leq \alpha \leq 1$

For each set of data new values were calculated, that is, for every promotion a new forecast and new smoothing parameters were calculated. This was calculated for both the promoted products and potential shadow products. Solver in Excel was used for the calculation.

3.5 VALUE ANALYSIS MODEL

The following model is intended to sum up the structure of the model built to analyse the value of promotion.

3.5.1 Calculation of income

t = time period, where 0 is the start of the promotion.
d = duration of the promotion,
e = duration of the extended period
τ = number of months forecasted ahead.
P = promoted products
S = the shadow products
t = 0; the start of the promotion
$F_{t\tau}$ =Forecast for period t for τ months ahead
D_t = Actual sale for period t
BS = Baseline sale
AS = Actual sale

Formula for baseline sale

$$BS = \sum_P \sum_{\tau=1}^{(d+e)} F_{t\tau} + \sum_S \sum_{\tau=1}^{d} F_{t\tau} \quad for\ t = 0 \tag{18}$$

Formula for actual sale

$$AS = \sum_P \sum_{t=0}^{(d+e)} D_t + \sum_S \sum_{t=0}^{d} D_t \tag{19}$$

3.5.2 Value of the promotion

IP = Income of the promotion
AS = Actual sale
BS = baseline sale
CP = Cost of the promotion
MP = Margin of the promoted products in %
VP = Value of the promotion

Formula for income of the promotion

$$IP = AS - BS \tag{20}$$

Formula for value of the promotion

$$VP = IP * MP - CP \tag{21}$$

4. CASE STUDY

To verify the methodology, data from an Icelandic company was used and the methods tested on real data. The company cooperated by providing data and information about the promotional process as well as valuable insight. This section will cover some basic information about the current process of promotional planning, description of the technic that was used and the data needed to calculate the value of each promotion. The section contains information about the three promotions that were analysed and the sale history of both the promoted and potential shadow products. Due to the sensibility of the data, each promotion has been scaled, so the numbers presented are divided by a factor.

4.1 CURRENT PROCESS OF PROMOTIONAL PLANNING

The company runs a relatively advanced ERP system, Microsoft Dynamics Axapta, which covers most of their needs for daily business. They use a planning tool for sales planning that uses sales from previous years as a base to plan for future months. The plans are made by creating a 12 months rolling plan monthly. The brand managers are responsible for the sales plan of their products with support from the logistic department, production and sales. This 12 months rolling forecast is then used by the logistic department for procurement and the production department for production planning.

However, a more advanced planning tools is needed for planning promotional events. The current process involves an excel sheet for each brand manager where he/she estimates the timing and sales volume for promotions one year ahead. When estimating the increase in sales volume, past promotions are sometimes used for reference if a comparable promotion exists. The estimation of total sales volume is then manually entered into a current planner tool. When the promotion is over no formal validation is made on the outcome of the promotions. When asked, the brand managers agreed on a better overview of the promotions was needed and the process lacked a review of past promotions, in order to create a better estimate for future promotions.

4.2 DATA GATHERING

The data gathering was done in cooperation with employees of the company. Their input was especially vital for the soft parameters and information about the promotions. The data was obtained through two sources; the information about the promotion came from the brand manager and raw data was taken directly from the Dynamics Axapta database.

Data needed for each promotion was:

- Classification of promotion
- Size/type of promotion
- Location of promotion
- Promoted product
- Potential shadow product
- Promoted period
- Post promoted period
- Total cost of promotion
- Sales history for promoted products
  - In value
  - In litres
  - In quantity
- Sales history for the potential shadow products
  - In value
  - In litres
  - In quantity

The marketing department performed valuation of past promotions where they had the possibility to comment on things that are not so easily measured in direct profit/cost. (Soft parameters). That information was only used in the discussion section.

4.3 DATA

For each promotion, the sales history for all the promoted products and potential shadow products were found. The data covered a four-year period, from March 2011 to February 2015. Information about the promoted products and the promotion was also given. All information about sales value, sales quantity, sales volume and the cost of promotion has been scaled to protect classified information. The numbers in this chapter does therefore not represent actual cost or value, but are only to be viewed in proportion to other numbers.

4.3.1 Promotion I

This section contains information about promotion I: the products that were promoted, potential shadow products and sales history both for the promoted products and potential shadow products.

***Promotion I**-Information about the promoted product*

The promoted products are imported products in the snack section. They are sold in most retailer stores, ranging from large supermarkets to small petrol stations. The product group in the market has a few large brands, both Icelandic and imported and some smaller brands as well. The company has two main brands in this product group.

In the analysed period, a total of 19 products had some sales history, in different flavouring of the product and different packaging sizes. During the promoted period, a total of eight products had a sales history. This brand regularly changes packaging sizes so a comparison in sales quantity can be difficult.

Promotion I *- Information about promotion*

This promotion was a small promotion, executed in cooperation with the retailer, by having a point of sale display (POS). No other supporting marketing activity took place for this product group from the company at the same time. The promoted period was April 2013. The total cost of the promotion was estimated to be 100.000, mainly due to POS material in cooperation with the stores. The promotion was not aimed at any one product but for the whole product brand. Other products in the same product group may be affected by shadow effect of the promotions. It was believed that the effect of the promotion was mainly during the promoted period, although there might be some effects in the following month. Table 1 shows a general information summary about the promotion.

Table 1: PI-General information about the promotion.

Classification	Advertisement
Size/type of promotion	Small
Location of promotion	Total market
Promoted period	April 2013
Post-promotional period	May 2013
Promoted product	Whole product brand
Shadow product	Products in the same product group
Total cost of promotion	100.000

Promotion I *- Sale history for promoted products*

Information about the sales history for the promoted products covered a four-year period, from March 2011 through February 2014. Figure 1 shows the sales history, both in quantity and value of the promoted products.

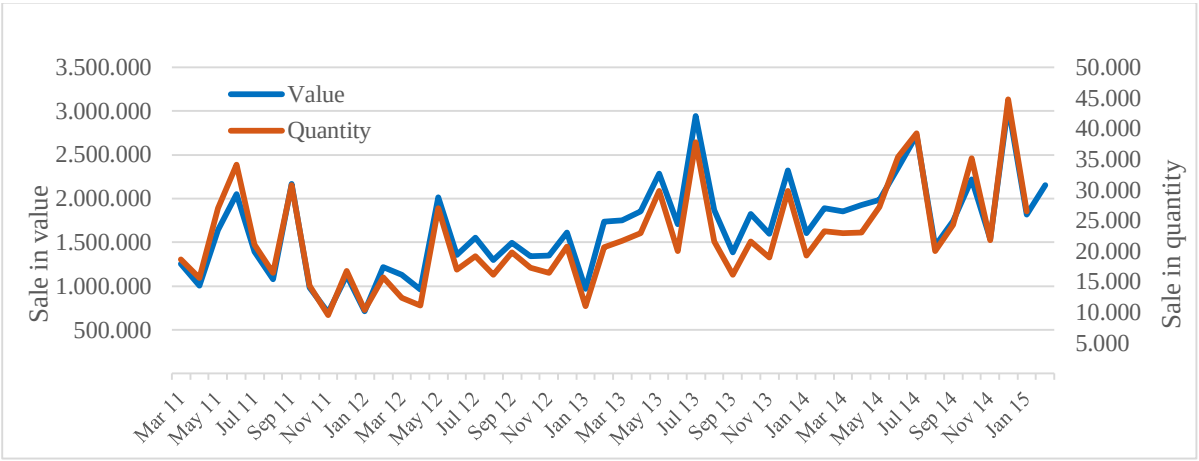

Figure 1: P1-Sales in value and quantity of the promoted products

The figure shows some differences between value and quantity. The reason for that is due to several factors. One of them is that there were/are different sales prices at different times. The

reason for different sales prices can be inflation, different combination of customers or even different prices for customers over some period of time. Another reason for this difference is that sales in quantity is usually not a good measurement for product groups. Products in the consumer packed goods sector usually have a few different packaging sizes that can be aimed at different consumers, like small sizes for selling in patrol stations and family sizes sold in supermarkets. It is also due to frequent changes in packaging sizes from the producer. Those changes and variability in packaging sizes have a much greater impact on the fluctuation in sales history than changes in sales prices. Data analysis is mostly made in value instead of quantity.

***Promotion I** - Sale history for the potential shadow products*

To view the total effect of the promotion for the company, other products that may be affected by the promotion also need to be included. The products that are most sensitive to this promotion were estimated to be other products within the same product group. Figure 2 shows the sales history both in value and quantity for the potential shadow products, that is, products within the same product group as the promoted products, but were not a part of the promotion.

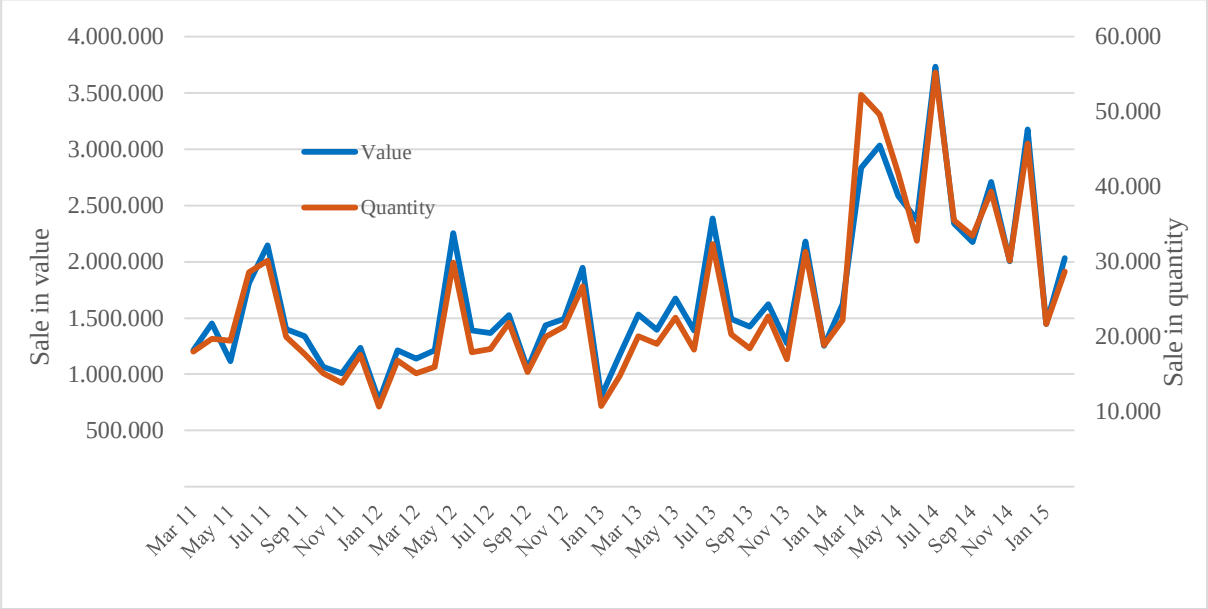

Figure 2: PI-Sales in value and quantity of the shadow products

4.3.2 Promotion II

Information about promotion II can be found in this section, the sales history for the promoted products and the potential shadow products, along with general information about the products and the promotion.

***Promotion II**: Information about the promoted products*

This product is in the carbonated beverage section. The brand owner is a large global company but the product is produced in Iceland. The promoted products are sold in most retailer stores, ranging from large supermarkets to small petrol stations. The product brand is also very big in the HORECA sector (hotels, restaurant and catering).

The market is very brand loyal. Two brands dominate the market with a few other brands, mostly from the same brand owner, also having some market share. The promoted product brand is the main brand in this product group in the company. The product brand holds eight different products, differentiating in product size and type of containers. The sizes do not change very frequently although new product sizes are released on occasions after a long changing process.

***Promotion II**: Information about the promotion*

The promotion was a large world global promotion with support from the brand owner with local customization. The promotion was set up as a game, where there was a code on the label on every bottle in two of the most popular sizes (three SKU). The promotion ran in most media: TV, radio, social media, newspapers, magazines, movie theatres as well as having a point of sale material in stores. The consumers took the code on the label of the product and entered it on a website and got imitate feedback if they had won a prize or not.

The promoted period was April and May 2013, but the effects of the game lasted longer, since the game was active, although the promotion was not running. The total cost of the promotion was estimated to be 70.000 here 15.000 was in prizes, 35.000 for publication and 20.000 for design material and production cost. The products that were most likely to be affected by the promotion were other products in the product brand. In table 2, basic information about the promotion can be seen.

Table 2: PII-General information about the promotion

Classification	Advertisement
Size/type of promotion	Large
Location of promotion	Total market
Promoted period	April and May 2013
Post-promotional period	June 2013
Promoted product	Two sizes of the product
Shadow product	Product in the same product brand
Total cost of promotion	70.000

Sales history for promoted products

Information about the sales history for the promoted products covered a four-year period, from March 2011 through February 2014. Figure 3 shows the sales history, in quantity, volume and value of the promoted products.

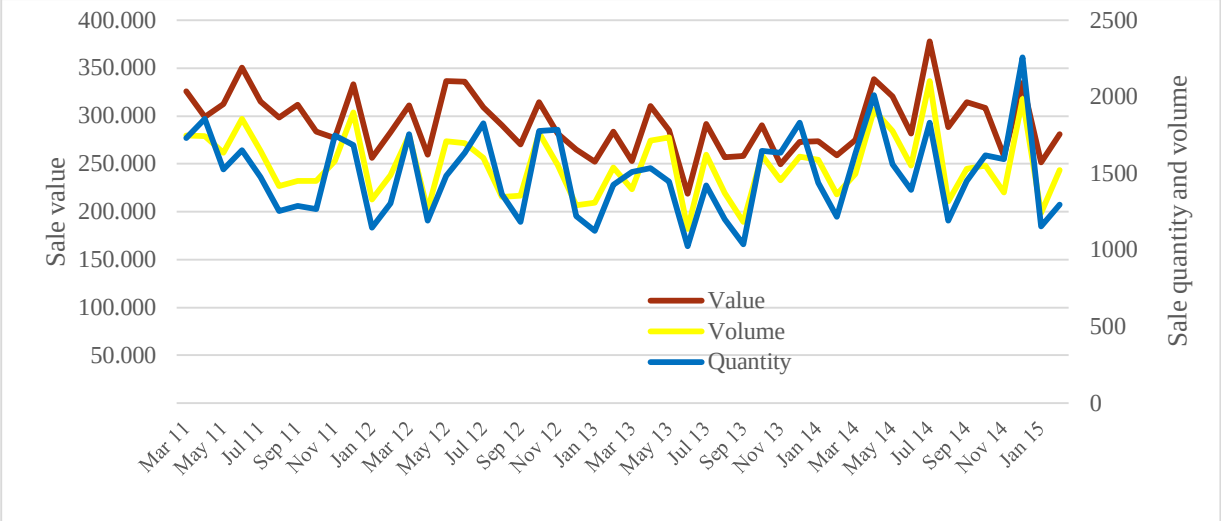

Figure 3: PII- Sales in value, volume and quantity of the promoted products

The difference in value and quantity is for several reasons, one of them being the difference in sales prices at different times. Another reason is that the products are in different container sizes. For these products, there are also quite frequent promotions on different sales units, e.g. a special four pack. This is the main reason quantity is not a feasible measurement for this product group. Another and quite a common way to view these types of products is to use volume instead of quantity. When comparing volume and quantity in figure 4, it can be seen that the volume measurement is more aligned with value than quantity. However, the revenue and profit is usually higher with smaller volume sizes. If performing a value analysis on the promotion by using sales history in litre, then that would have to be adjusted.

When estimating the value of a promotion, it is important to use the best measurement unit for the sales history. Since the bottom line is to make the most profit, the most relevant measurement was chosen as value. The main analysis is therefore mostly done in value instead of quantity or volume.

Sales history for the shadow products

To view the total effects of the promotion for the company, other products that may be affected by the promotion also need to be included. The products that were believed to be the most sensitive to this promotion were other products within the same product brand. Figure 4 shows the sales in value, volume and quantity for the potential shadow products.

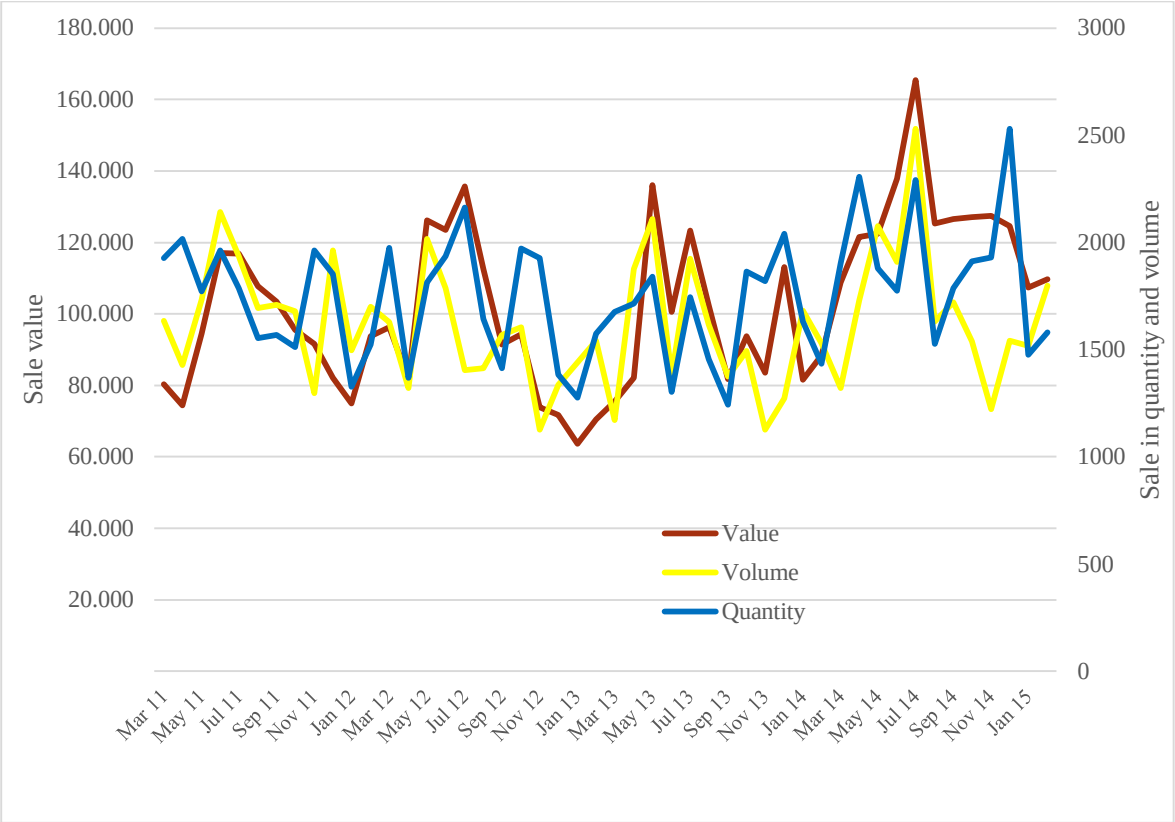

Figure 4: PII-Sales in value, volume and quantity for the shadow products

4.3.3 Promotion III

This section contains information about promotion III. Information about the promoted and potential shadow products are presented, as well as the sales history for the products and basic information about the promotion.

Information about the promoted products

This product is a noncarbonated beverage that is quite sensitive and needs to be kept in a cooler, both during transportation and storage. It has multiple flavours but is only sold in two sizes. The product is mostly sold in small and large supermarkets. It is the company's main product brand in the product group although other products are also included in the product group, both private labels and other small brands. The brand market share of the promoted products was 50% of the total market in that category at the time of the promotion.

In the analysed period a total of 37 products in the product group had some sales history, thereof 28 products of the promoted product brand. In the promoted period 15 out of the 28 products were active while the other ones had some sales history over the four-year period that was analysed.

Information about promotion III

This promotion was a large promotion in the Icelandic market. The promotion was set up as a game, where there was a code on each cap on the promoted products. The customers would enter the code on a website and get imitate feedback if they had won a prize or not. The promotion ran in most media: TV, radio, social media, newspapers and magazines, movie theatres as well as having a point of sale material in stores. The promoted period was nine weeks in June and July 2013. The total cost of the promotion was estimated to be 360.000 Information about the promotion is in table 3.

Table 3: PIII-General information about the promotion

Classification	Advertisement
Size/type of promotion	Large
Location of promotion	Total market
Promoted period	June and July 2013
Post- promotional period	August 2013
Promoted product	Total brand
Shadow product	Product in the same product group
Total cost of promotion	360.000

Sales history for promoted products

Information about the sales history for the promoted products covered a four-year period, from March 2011 through February 2014. Figure 5 shows the sales history in quantity, volume and value of the promoted products.

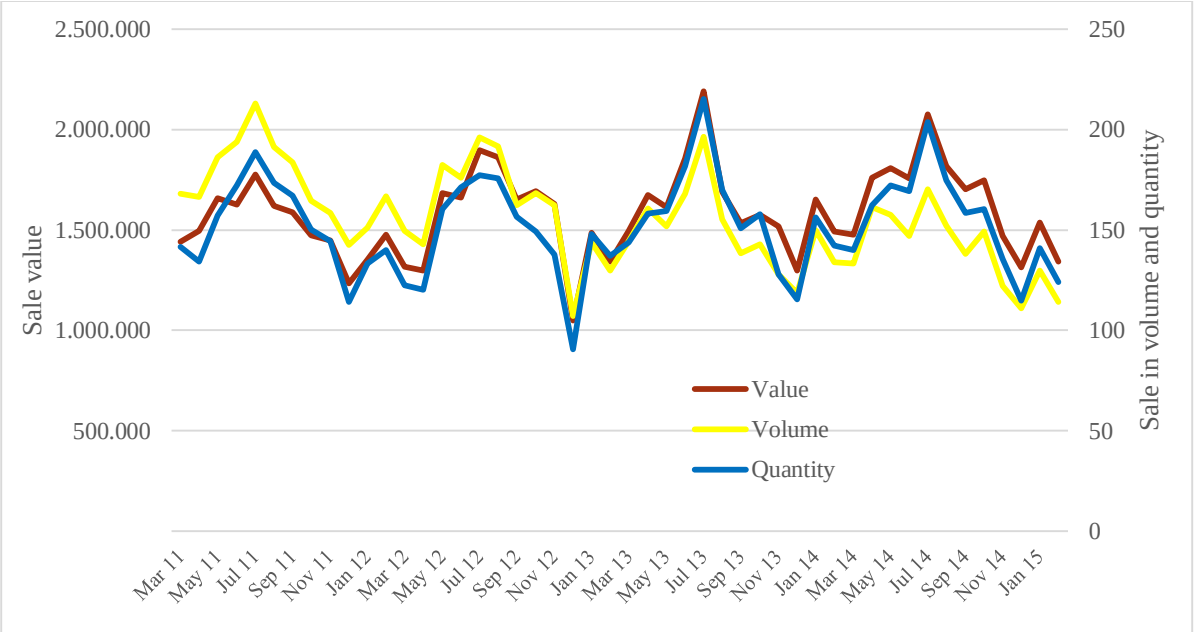

Figure 5: PIII-Sales in value, volume and quantity of promoted products

In figure 5 there is a difference between sales value and sales quantity. This is both due to a difference in sales prices at different times, and the different mix of products for sale at each time. There is also a difference over time in the mix of the product brand because of a new

product sub-brand that was more expensive in production and therefore sold at a higher prize and in smaller quantities. As with other beverage products it is common to view this in volume instead of quantity. Figure 5 shows the sales in volume in comparison to value and quantity. The volume measurement is less aligned with value than quantity. That is mainly due to the more expensive sub-group of the product brand, but also because of the increased cost of the main ingredients.

Sales history for the shadow products

To view the total effects of the promotion for the company, other products that may be affected by the promotion also need to be included. The products that are most sensitive to this promotion were estimated to be other products within the same product group. Figure 6 shows sales in value, volume and quantity for the potential shadow products.

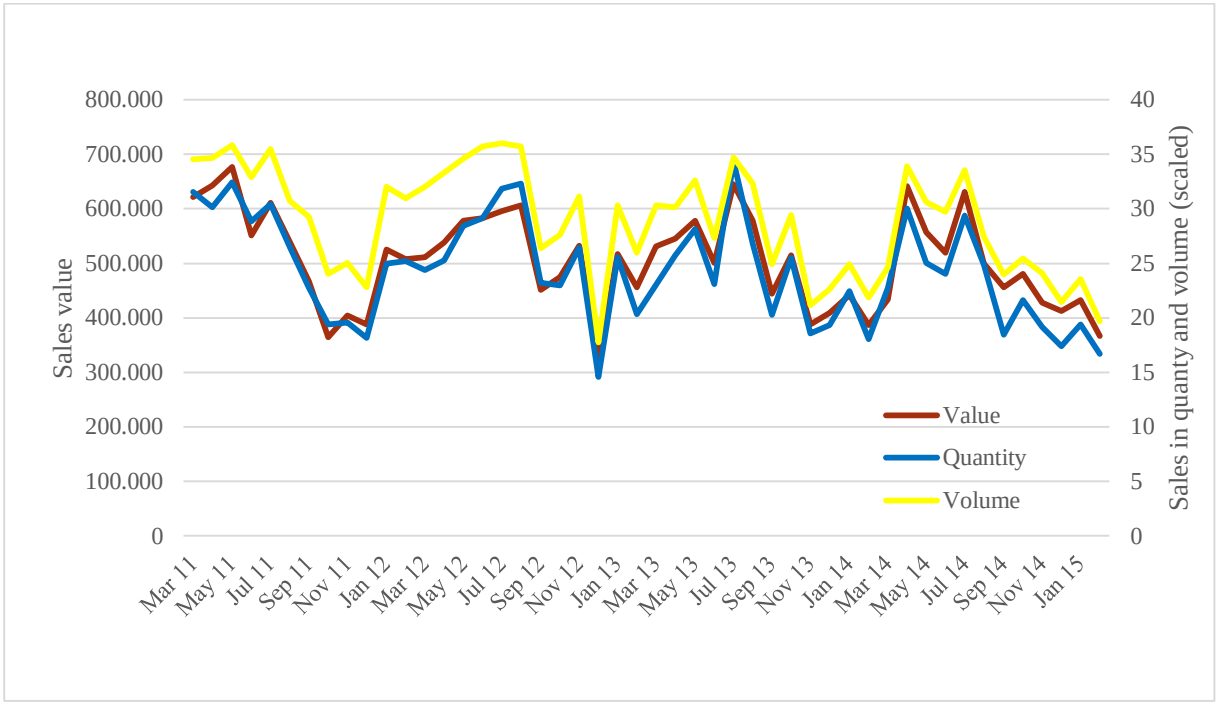

Figure 6: PIII- Sales in value, volume and quantity for the shadow products

5. RESULTS

To calculate the value of the promotion, information about sales history and promotion from the company were used. The baseline sale was calculated by using a forecast based on sales history. Error analysis for each promotion was also performed on the forecasting outcome, and to give some indication whether the difference between actual sale and forecast was due to promotional activity. Lastly, a value calculation of each promotion where the income of the promotions is compared with the cost of the promotion was made.

5.1 DATA ANALYSIS – FORECAST

To calculate the baseline sale a forecast had to be made for both the promoted products and the potential shadow products. The promoted products were all highly seasonal products and the Holt-Winter model is efficient in working with such type of data series.

The forecast was calculated on product group level which generally gives a better forecast than forecasting on a single product, but also because all the promotions were for multiple products. Due to different packaging sizes and the fact that the product group contained different products over time the forecast was calculated in value but not in quantity or volume. Two years of data was used to build a good forecasting model and then the model was used to calculate one month ahead.

To obtain the best-fit model for the data, the exponential smoothing parameters were determined by using linear optimization. In order to calculate the long-term effects of the promotion a forecast of two and three months ahead was also calculated to estimate the following months after the promotion. This was also done for the potential shadow products.

5.1.1 Promotion I

For promotion I a forecast was calculated one, two and three months ahead for the promoted products and the potential shadow products.

Promotion I: Forecast for the promoted products

For promotion I the lowest MSE was obtained when the exponential smoothing parameter took the values shown in table 4.

Table 4: PI-Smoothing parameters for promoted products.

Alfa	α	0,140
Beta	β	0,028
Gamma	γ	0,686

The smoothing parameters show the model's responsiveness. A high value of a constant means that the last value should have high impact on the new forecast and if the value is low, there is a high tendency to smooth out any new data. For products in promotion 1, alfa and beta are low, so the new forecast relies more on past data than the newest data, but the gamma constant is high. That means that the model changes slowly with changes in sales, and growth. The seasonal factor is high, so the model is very responsive to changes in seasonal factors. In figure 7 the forecast for promoted products in promotion I is drawn along with actual sales.

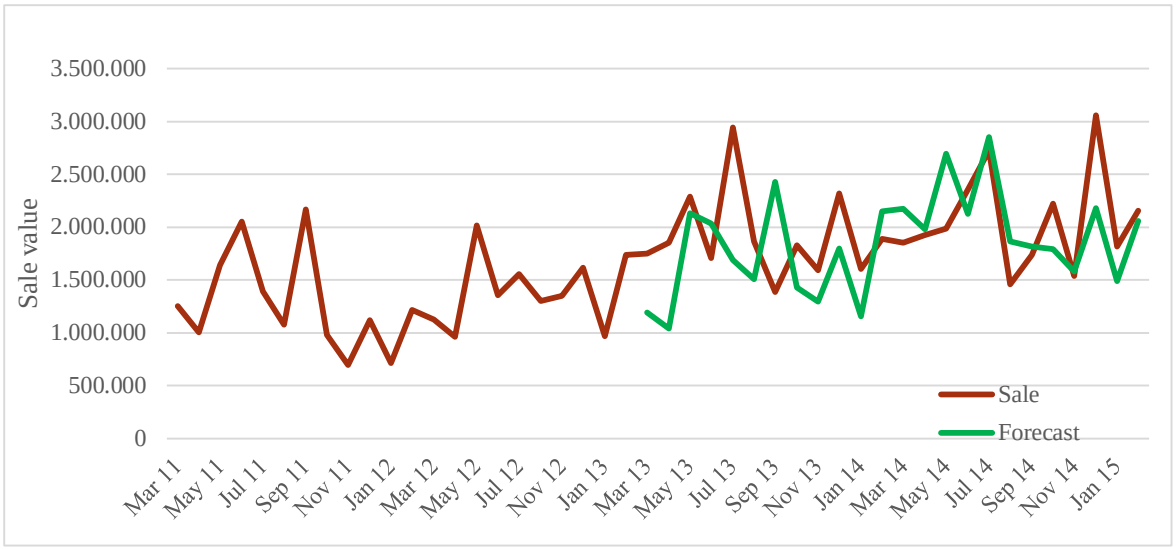

Figure 7: PI-Sales and forecast for the promoted products

The forecast shown in figure 7 was only calculated one month ahead, that is, for every new data a new forecast point was calculated. In order to estimate the effect of the promotion for more than one month ahead it was also necessary to calculate a forecast for two and three months ahead.

In figure 8 a forecast is shown by using the same parameters as before, but calculating for one, two or three months ahead. Forecast 1 is the one month ahead forecasting, forecast 2 is the two months ahead forecasting and forecast 3 is the one calculated three months ahead.

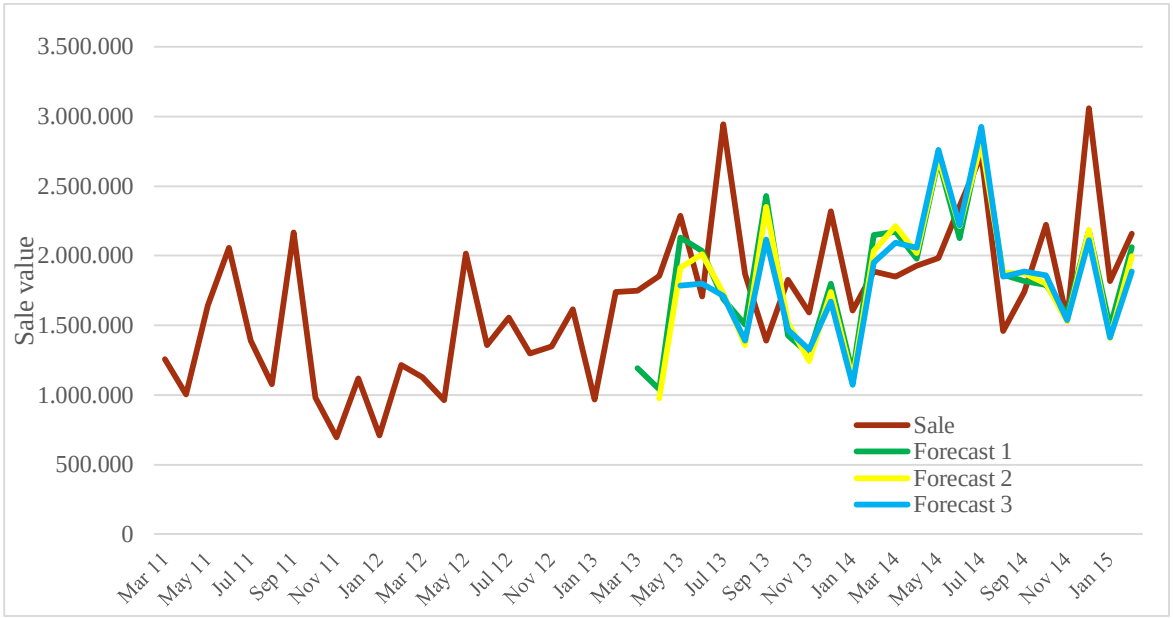

Figure 8: PI-Sales and forecast 1,2,3 months ahead for the promoted products.

As can be seen in figure 8, there is only a slight difference between the forecasts whether they were calculated one, two or three months ahead. The reason for this is the smoothing constant the model uses. The model is not very responsive to changes in growth or changes in last month sales, but only high in the seasonal factors. Since the seasonal factors are for 12

months ahead, changes for calculating the forecast one, two or three months ahead does not differ greatly.

In table 5 the forecasted value for the period around the promoted period can be seen. The promoted month is shown in blue.

Table 5: PI-Sales and forecast 1,2,3 months ahead for the promoted products

	Actual sale	Forecast 1m	Error%	Forecast 2m	Error%	Forecast 3m	Error%
Mars 2013	1.750.568	1.191.899	32%				
April 2013	1.854.503	1.041.515	44%	975.164	47%		
May 2013	2.288.615	2.129.611	7%	1.913.285	16%	1.787.373	22%
June 2013	1.706.953	2.032.648	-19%	2.010.972	-18%	1.800.655	-5%
July 2013	2.945.512	1.690.725	43%	1.730.749	41%	1.711.752	42%
August 2013	1.867.367	1.504.779	19%	1.359.104	27%	1.392.242	25%

From the data in table 5 it can be seen that there is quite a difference between actual sales and forecasted sales. The actual is much higher, so the promotion seems to have a positive effect on the promoted product. The forecasting error is discussed further in chapter 5.2.1

Forecast for the shadow products

When valuing the effect of the promotion it is necessary to also view potential shadow products, that is, products that may be affected by the promotion although not being promoted itself. In figure 9 the sales and forecast for one, two and three months ahead for potential shadow products are shown.

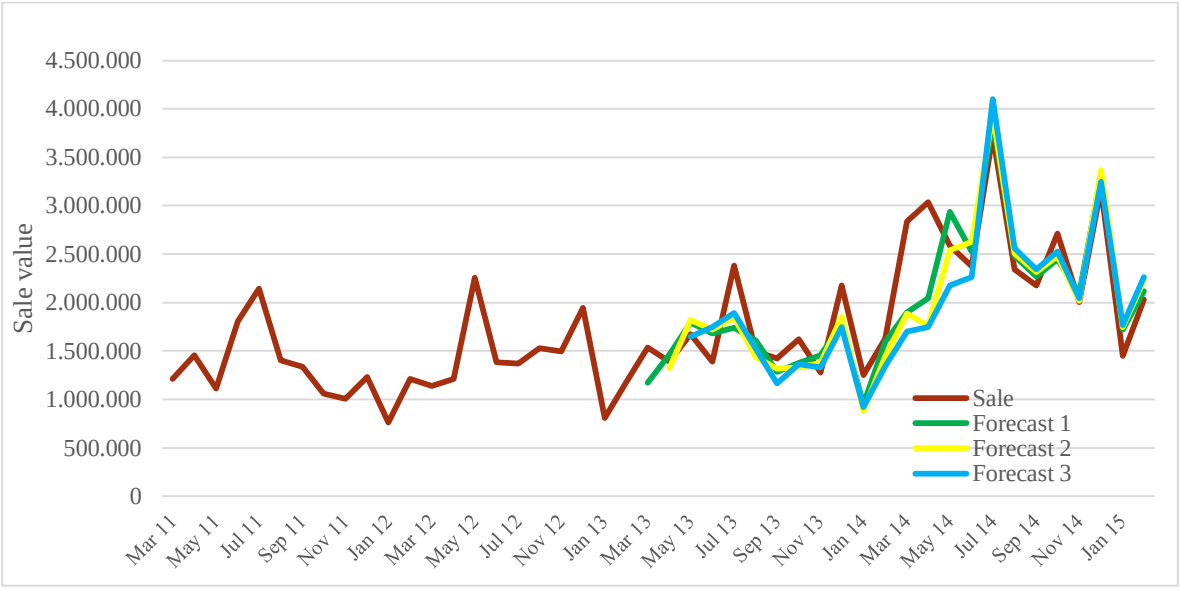

Figure 9: PI-Sales and forecast 1,2,3 months ahead for the shadow products

New smoothing parameters where calculated for the potential shadow products, the new values for alfa, beta and gamma are shown in table 6.

Table 6: PI-Smoothing parameters for shadow products

Alfa	α	0,317
Beta	β	0,036
Gamma	γ	1,000

As with the promoted products, the model is very responsive to seasonal changes (γ). The trend parameter (β) is very low, so changes in trend appear slowly in the forecast, but the level (α) parameter is higher in the shadow products than the promoted products, so changes in sales have more effect in this forecast.

In table 7 the actual sales and forecasting values for the one, two and three months ahead forecasts along with calculated errors compared with actual sales is shown. The promoted month is shown in blue.

Table 7: PI-Sales and forecast 1,2,3 months ahead for the shadow products

	Actual sale	**Forecast 1m**	**Error %**	**Forecast 2m**	**Error %**	**Forecast 3m**	**Error %**
Mars 2013	1.533.368	1.174.615	23%				
April 2013	1.392.550	1.460.759	-5%	1.326.950	5%		
May 2013	1.671.908	1.790.919	-7%	1.818.858	-9%	1.646.186	2%
June 2013	1.390.626	1.681.929	-21%	1.719.540	-24%	1.747.357	-26%
July 2013	2.383.794	1.743.029	27%	1.848.494	22%	1.891.394	21%
August 2013	1.494.165	1.609.245	-8%	1.435.057	4%	1.525.381	-2%

The data in table 7 shows very little difference between actual sales and forecast in the potential shadow products. So, the promotion seems to have had only a small effect on the potential shadow products.

5.1.2 Promotion II

For promotion II, a forecast was calculated one, two and three months ahead for the promoted products and potential shadow products.

Forecast for the promoted products

For promotion II the lowest MSE was obtained when the smoothing constant took the values shown in table 8.

Table 8: PII-Smoothing parameters for promoted products

Alfa	α	0,349
Beta	β	0
Gamma	γ	0,932

The smoothing constant shows which factors the model is responsive to. If a value is high, the best forecast is to have high weight on that part of the model, if low, the model reacts slowly to changes in that part. For products in promotion II, the level parameter (α) is quite high so the forecast will change when new sales points come in. Since the growth parameter (β) is 0, the model will not change according to changes in growth, but changes in seasonal factors have an effect.

Figure 10 shows the forecast for the promoted products by using a smoothing constant in table 8.

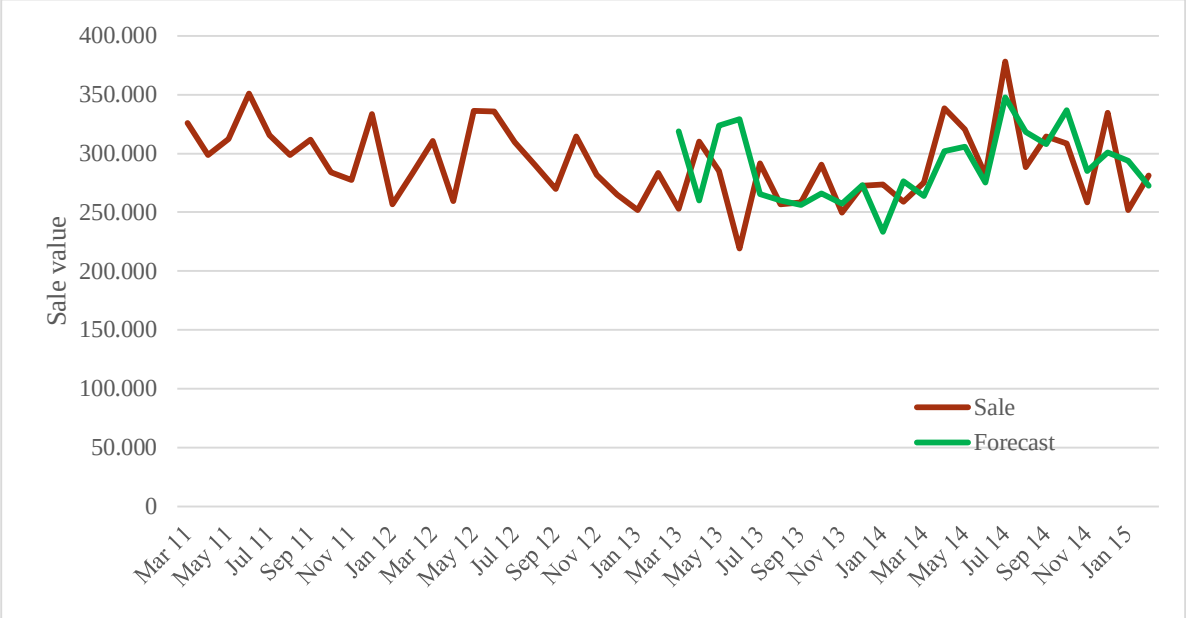

Figure 10: PII-Sales and forecast for the promoted products

It is also necessary to calculate the forecast not only for one month ahead but also two and three months ahead. In figure 11, a forecast is shown by using the same parameters as before, but calculating for one, two or three months ahead. Forecast 1 is the one month ahead forecasting, forecast 2 is the two months ahead forecasting and forecast 3 is the one calculated three months ahead.

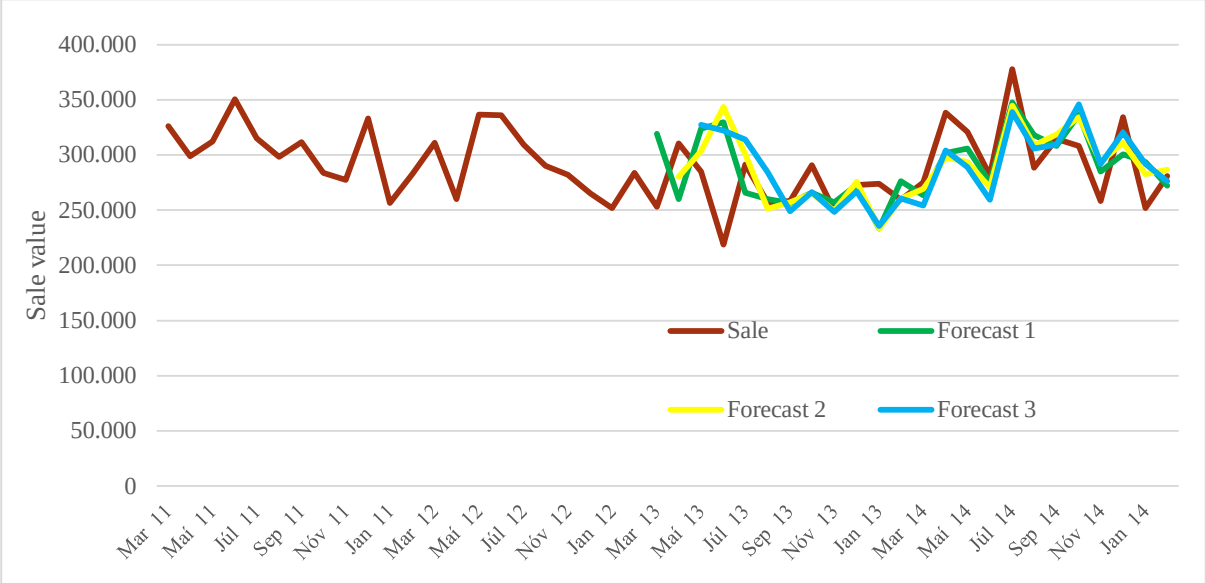

Figure 11: PII-Sales and forecast 1,2,3 months ahead for the promoted products

There are some differences between the forecasts whether they were calculated one, two, or three months ahead, but still they are similar. The reason is the value of the smoothing constant the model used.

In table 9 the actual sales and the forecasted value for the period around the promotion can be seen. The promoted months are shown in blue.

Table 9: PII- Sales and forecast 1,2,3 months ahead for the promoted products

	Actual sale	Forecast 1m	Error%	Forecast 2m	Error%	Forecast 3m	Error%
Mars 2013	252.789	318.848	-26%				
April 2013	310.148	260.103	16%	280.328	10%		
May 2013	284.994	323.950	-14%	303.613	-7%	327.140	-15%
June 2013	219.005	329.295	-50%	343.688	-57%	322.180	-47%
July 2013	291.487	265.614	9%	300.679	-3%	313.777	-8%
August 2013	256.868	259.736	-1%	251.219	2%	284.259	-11%

As can be seen it table 9, the forecast for April is lower than actual sales so the promotion might have had a positive effect, but if May is viewed, the actual sale is lower than was expected in the forecast made before the promotion started. What is, however, most troubling is the actual sale in June, where the actual sale is much lower than it should be in a regular June month.

Forecast for the shadow products

When viewing the promotion it is also possible to view potential shadow products. That is, products that may be affected by the promotion although not being a part of the promotion. In figure 12 the potential shadow products for promotion II are shown.

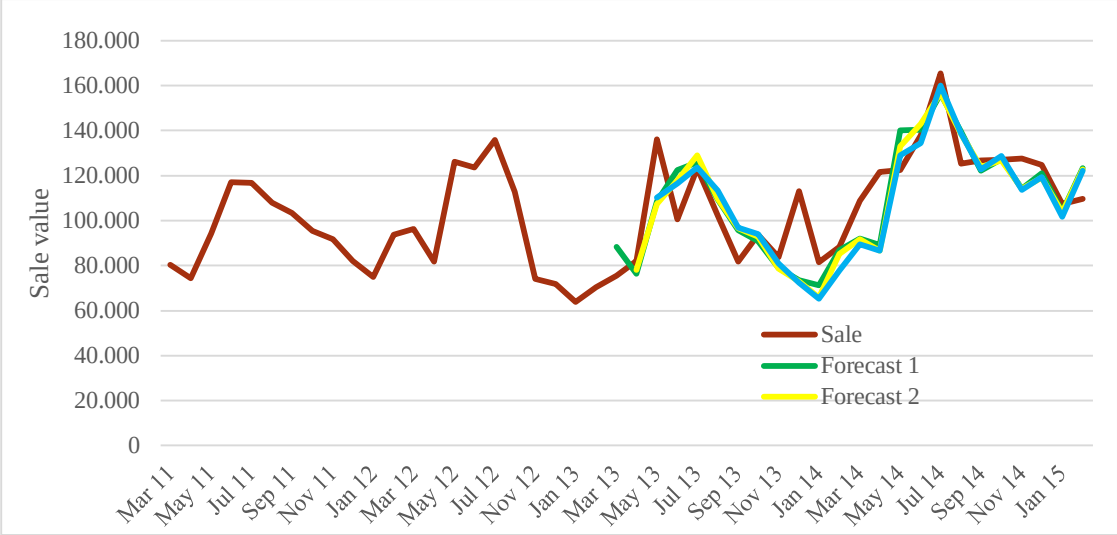

Figure 12: PII-Sales and forecast 1,2,3 months ahead for the shadow products

New parameters were calculated for the potential shadow products, shown in table 10.

Table 10: PII-Smoothing parameters for the shadow products

Alfa	α	0,115
Beta	β	0,271
Gamma	γ	0,254

The smoothing parameters give the indication that those products have greater sensitivity to growth but less sensitivity to new values for seasonal factors than the promoted products.

During the promotional period, the potential shadow products have greater sales than was expected; sales are higher than the forecasted value. The promotion might, therefore, have had a positive effect on other products in the product brand although not being promoted. It could have an increased brand awareness. In table 11 values for the period around the promotion are shown.

Table 11: PII- Sales value and forecast 1,2,3 months ahead for the shadow products

	Actual sale	**Forecast 1m**	**Error%**	**Forecast 2m**	**Error%**	**Forecast 3m**	**Error%**
Mars 2013	75.505	88.262	-17%				
April 2013	82.151	76.358	7%	78.001	5%		
May 2013	136.014	108.465	20%	107.274	21%	110.090	19%
June 2013	100.497	122.311	-22%	117.935	-17%	116.359	-16%
July 2013	123.344	125.711	-2%	129.047	-5%	123.472	-0%
August 2013	102.295	109.363	-7%	109.664	-7%	113.198	-11%

5.1.3 Promotion III

For promotion III a forecast was calculated one, two and three months ahead for the promoted products and potential shadow products.

Forecast for the promoted products

For promotion III the lowest MSE was obtained when the smoothing constant took the values shown in table 12.

Table 12: PIII-Smoothing parameters for promoted products

Alfa	α	0,162
Beta	β	0,000
Gamma	γ	0,522

The smoothing constant shows the factors that the model is responsive to. For products in promotion III, the level parameter (α) is quite low, there is no growth parameter (β) in the model but changes in seasonal factors (γ) have quite an effect.

In figure 13 the forecast that resulted in the lowest MSE is shown by using the smoothing constant in table 12.

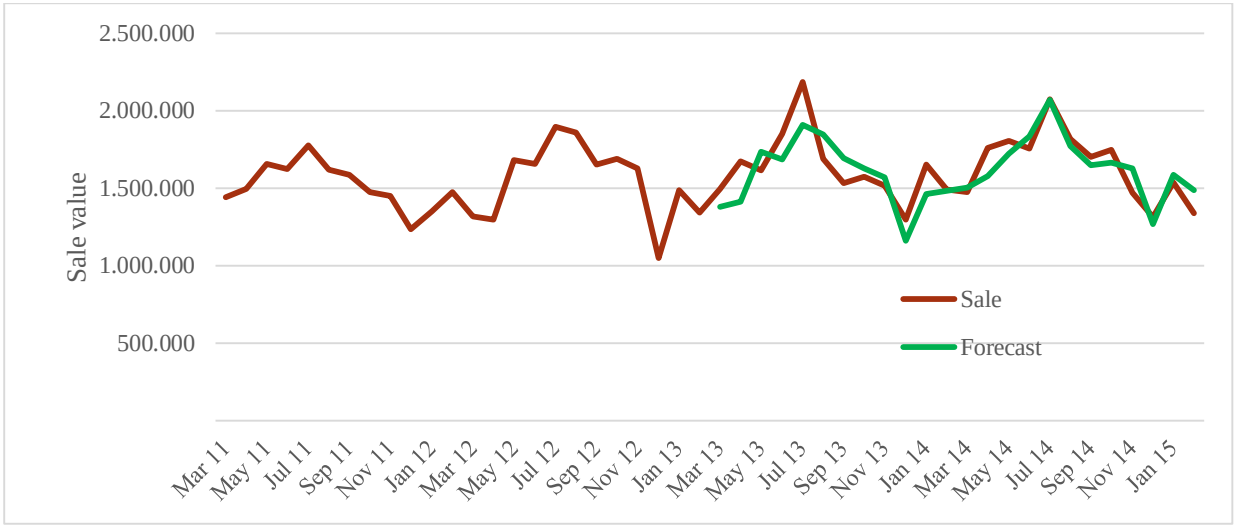

Figure 13: PIII-Sales and forecast for promoted products

It is also necessary to calculate the forecast not only with one month ahead but also two and three months ahead. Figure 14 shows a forecast by using the same parameters as before, but calculating one, two or three months ahead.

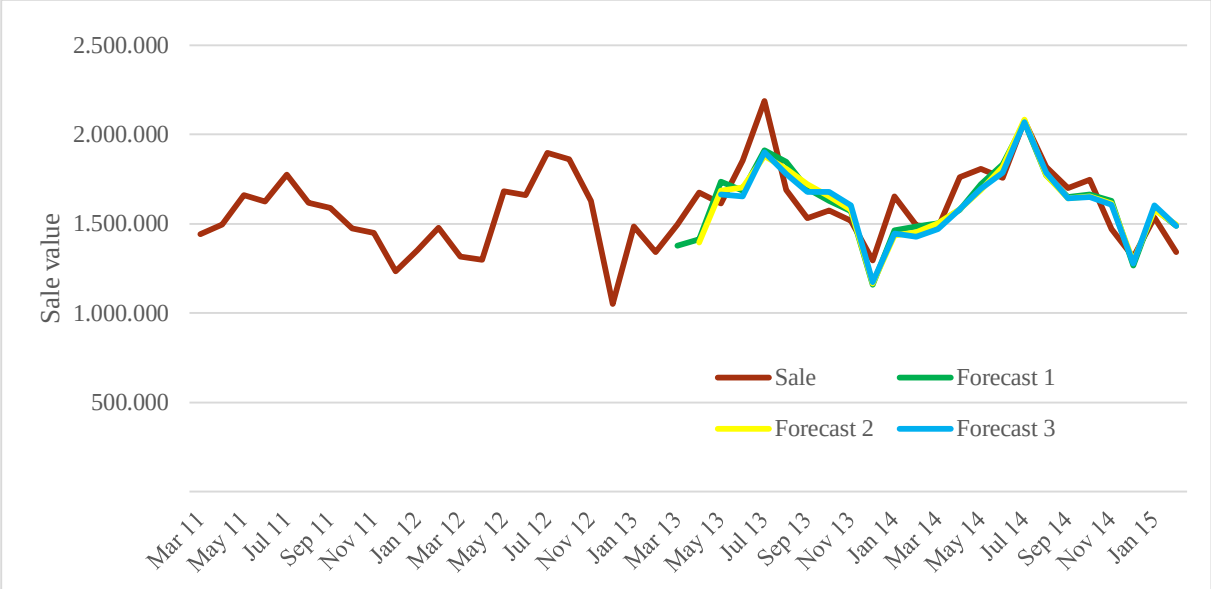

Figure 14: PIII-Sales and forecast 1,2,3 months ahead for the promoted products

There is only a small difference between the forecasts whether it was calculated one, two, and three months ahead. The reason being the value of the smoothing constant the model used. The model is not very responsive to changes in growth, but seasonal factors have a high impact. Since they are for 12 months ahead, changes in calculating the forecast one, two or three months ahead do not make much of a difference. Table 13 shows the actual sales and the forecasted value for the period around the promotion. The promoted months are shown in blue.

Table 13: PIII-Sales and forecast 1,2,3 months ahead for the promoted products

	Actual sale	**Forecast 1m**	**Error%**	**Forecast 2m**	**Error%**	**Forecast 3m**	**Error%**
Mars 2013	1.496.128	1.379.452	8%				
April 2013	1.674.327	1.413.336	16%	1.394.238	17%		
May 2013	1.614.360	1.737.785	-8%	1.687.326	-5%	1.664.478	-3%
June 2013	1.853.906	1.684.611	9%	1.704.211	8%	1.654.625	11%
July 2013	2.188.897	1.911.210	13%	1.880.606	14%	1.902.532	13%
August 2013	1.689.810	1.849.244	-9%	1.806.736	-7%	1.777.745	-5%

If the data in table 13 is viewed, actual sales are higher than the forecasted value. So, the promotion probably had some positive effects on sales volume during the promoted months. However, if the forecast 3m in August is viewed, sales are less than was forecasted in the beginning of the promotion. So, the promotion may have caused some purchases to be borrowed from the following month.

Forecast for the shadow products

The potential shadow products can also be views along with the promotion. In figure 15 the potential shadow products for promotion III are shown.

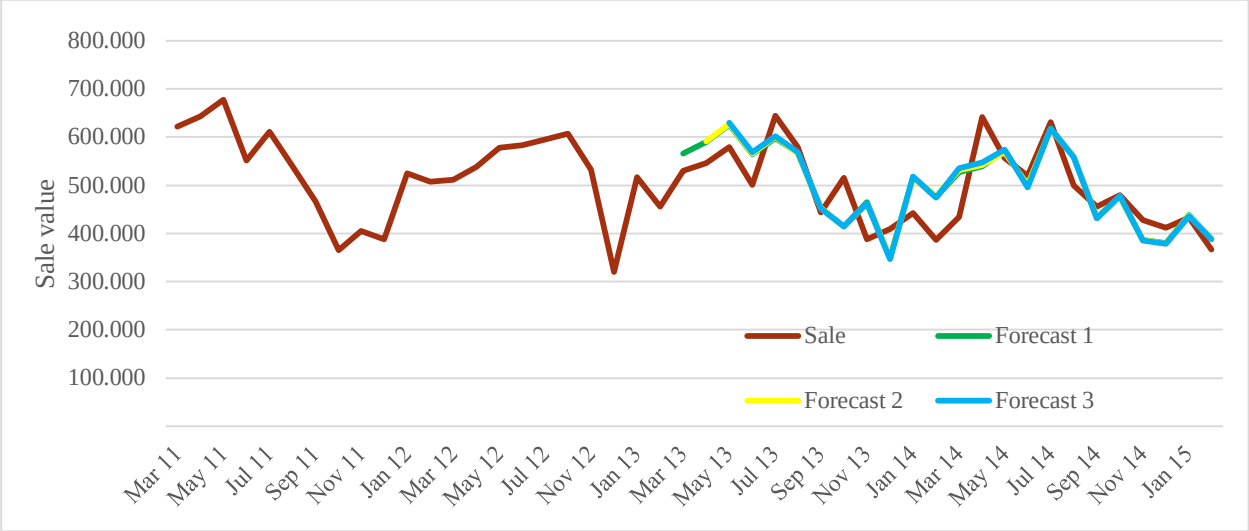

Figure 15: PIII-Sales and forecast 1,2,3 months ahead for shadow products

New parameters were calculated for the potential shadow products, shown in table 14.

Table 14: PIII-Smoothing parameters for the shadow products

Alfa	α	0,017
Beta	β	1,000
Gamma	γ	0,794

Table 14 gives the indication that this forecast is sensitive to new data in growth and seasonal factors but with alfa being very low, it is not responsive to last month's sales. This explains why there is such a small change between the forecasts created for one, two or three months ahead.

It is noticeable that during the promotional period, the forecast is quite higher than the actual sales. That gives an indication that the promotion had a negative impact on those products. It is therefore possible that cannibalisation may have occurred in this product group. Information about actual sales and forecast is in table 15. The promoted months are in blue.

Table 15: PIII- Sales and forecast 1,2,3 months ahead for shadow products

	Actual sale	Forecast 1m	Error%	Forecast 2m	Error%	Forecast 3m	Error%
Mars 2013	530.669	566.359	-7%				
April 2013	545.471	590.303	-8%	591.551	-8%		
May 2013	578.698	626.161	-8%	627.760	-8%	629.750	-9%
June 2013	500.919	565.004	-13%	566.446	-13%	568.617	-14%
July 2013	644.658	597.622	7%	599.910	7%	602.210	7%
August 2013	578.612	567.388	2%	565.887	2%	569.149	2%

5.2 Data Analysis – Forecasting error

An error analysis for each promotion was done on the forecasting outcome. It was used to give some indication whether the difference between actual sales and forecast was due to the promotional activity or other factors. Since this is not an isolated system, many activities are taking place simultaneously. It is, therefore, impossible to isolate a promotion out of the sales history data. The difference in forecast and actual sales can, however, give some indication.

There are always some forecasting errors associated with forecast calculation. In order to estimate whether the difference between actual sales and forecast is only due to regular fluctuation in data (buzz) or to promotional activity, an average forecasting error and standard deviation for the forecast was calculated. The total errors of the forecast were also calculated, by using MAD, MAPE and MSE.

The forecasting calculation used is shown in method section 3.4. For every promotion, the average forecasting error and standard deviation was calculated.

5.2.1 Promotion I

For promotion I the forecasting error for each month was calculated. Since the promotional period was in April 2013 the main question is whether the difference in actual sales and forecast is higher in that month than other months. The calculated forecasting error for the promoted products is shown in figure 16.

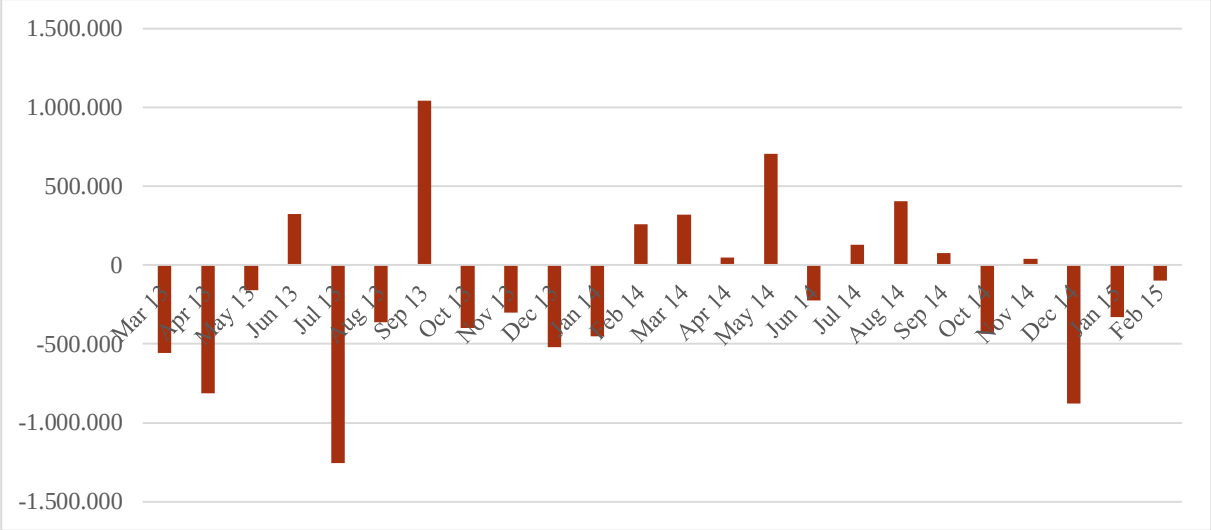

Figure 16: PI-Forecasting error.

In figure 16 it can be seen that out of 24 forecasted values, the promoted month had the 4th highest error. That could indicate that this is a high error for these products. If the data was analysed further the average error for these products is high. This means that these products were difficult to forecast for, even though a forecast was made on product group level and best practice used.

Table 16 shows some of the calculated error values for the promoted products in promotion I

Table 16: PI-Forecasting error

Average error	422.451
Average forecast	1.852.037
Average sale	1.994.759
Standard deviation	318.071
Error in April 2013	-812.987
Error in % April 2013	43,8%
Error in STD in April 2013	2,6
MSE	275.418.586.333
MAD	422.451
MAPE	21,6%

As can be seen in table 16 the forecasting error in April is quite high. There is, however, not enough data available in order to estimate whether this is statistically significant or not. The error is higher than average so it is likely that the increase in sales was due to the promotion.

5.2.2 Promotion II

For promotion II the forecasting error for each month was calculated. The promotional period was in April and May 2013. The calculated forecasting error for the promoted products is shown in figure 17.

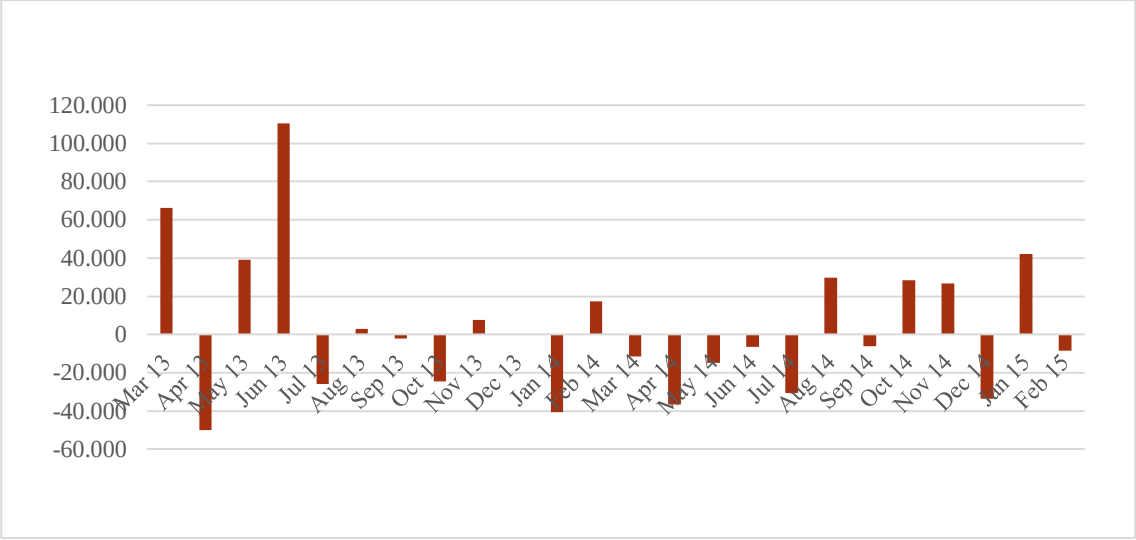

Figure 17: PII-Forecasting error

In figure 17 it can be seen that out of 24 forecasted values, the first promoted month had the 3rd highest error. The second promoted month had also a high forecasting error, but in the opposite direction. That is, the forecast was higher than the actual sales. During a promotion one would expect the sales to exceed the forecasted value.

In this case, a forecast for two months ahead would be more appropriate. This is due to the fact that if a forecast is calculated only one month ahead the new sales figures in April have an impact on the forecast for May.

In figure 18 the error for forecasting one and two months ahead is shown together in the same graph.

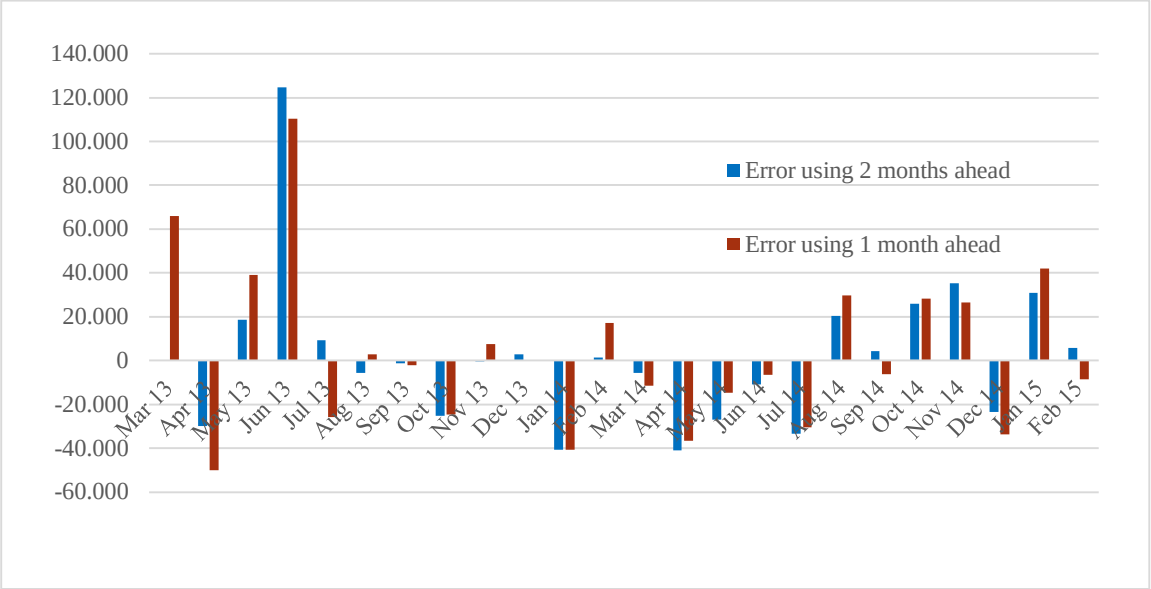

Figure 18: PII-Forecasting error one and two months ahead

Figure 18 shows a very high error in June, both for the error for the forecast using one month ahead and the one for two months ahead. Whether that is due to the promotion in earlier months or another reason is difficult to say

In table 17 some of the calculated value is shown. The calculation used a forecast that was made one month ahead, except in May where the forecast calculated two months ahead.

Table 17: PII-Forecasting error

Average error	27.544
Average forecast	288.662
Average sale	285.399
Standard deviation	24.395
Error in April 2013 (F1)	50.045
Error in May 2013 (F2)	18.618
MSE for F1	1.329.013.741
MAD for F1	27.544
MAPE for F1	10%

5.2.3 Promotion III

For promotion III, the promotional period was June and July 2013. The calculated forecasting error for the forecast is shown in figure 19. The figure shows a forecasting error both for the forecast created one month ahead and the one created two months ahead. It is necessary to use both in later calculations since the promoted period is two months and the first promoted month would have an impact on the forecasted value for the second month.

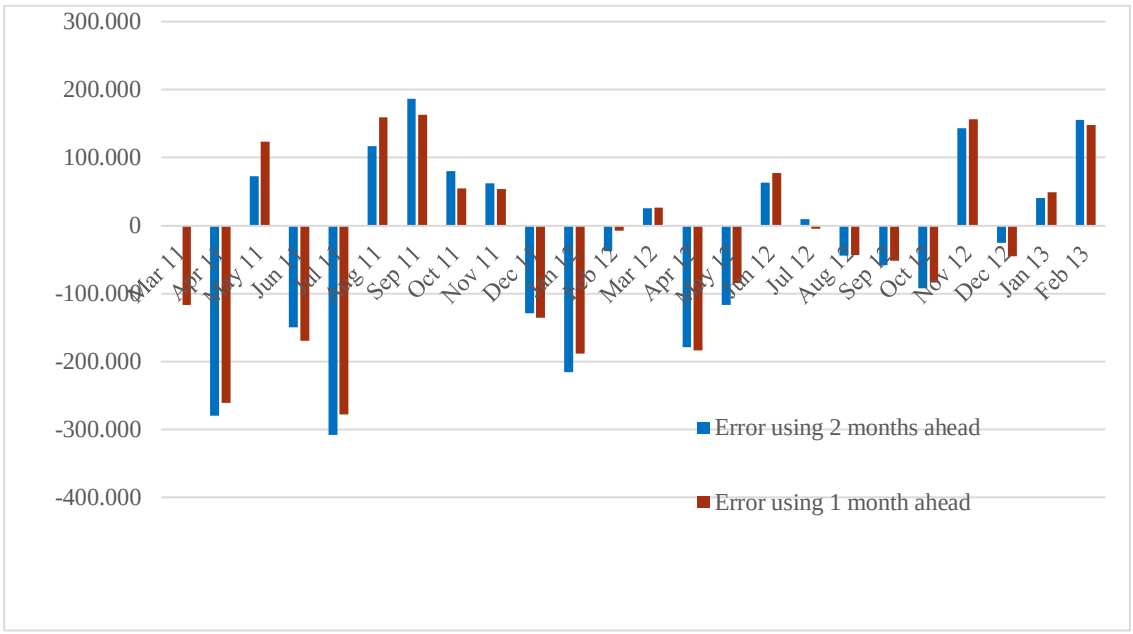

Figure 19: PIII-Forecasting error one and two months ahead

In table 18 some of the calculated value is shown, the calculation is done by using a forecast that was made one month ahead, except for the error in July. The error shown in figure 19 indicates that the promotion did have an impact. The error in July is the highest one out of the 24 values, and the error in June is more the two standard deviation from the mean.

Table 18: PIII-Forecasting error

Average error	111.091
Average forecast	1.614.573
Average sale	1.641.393
Standard deviation	74.740
Error in June 2013 (F1)	169.295
Error in July 2013 (F2)	308.292
MSE for F1	17.694.435.436
MAD for F1	111.091
MAPE for F1	6,8%

5.3 VALUE ANALYSIS OF PROMOTIONS

The value of the promotion is calculated by using the income of the promotion and the promotional cost. The formulas for the calculation are shown in section 3.5.

5.3.1 Promotion I

For promotion I the basic information about the promotion is given in section 4.3.1, including the cost of the promotion. The income of the promotion is found, taking into account both the potential shadow products and the sales during the post-promoted period. The value of the promotion can then be summed up.

Income of the promotion:

The income of the promotion is the difference between the baseline sale and actual sale during the promotional period and the post-promotional period (if that is defined). It is also the difference between the baseline sale and actual sale of the potential shadow products.

Actual sales can be seen in table 19. It contains actual sales of the promoted products both for the promotional period and the post-promoted period and actual sales of the shadow products during the promotional period.

Table 19: PI-Actual sales

	Promoted period	Post promoted period	Total
Actual sales of the promoted products	1.854.503	2.288.615	4.143.118
Actual sales of the shadow products	1.392.550		1.392.550
Total	3.247.052	2.288.615	5.535.667

The baseline sale was calculated by the forecasting model described in section 3.4. For each forecasted value, the model uses the forecast created at the beginning of the promotion. In the case of promotion I this is the one-month forecast for the promoted period and the two month ahead forecast for the post-promoted period. In table 20 the value for the baseline sale is shown.

Table 20: PI-Baseline sale

	Promoted period	Post-promoted period	Total
Forecast of the promoted products	1.041.515	1.913.285	2.954.801
Forecast of the shadow products	1.460.759		1.460.759
Total	2.502.274	1.913.285	4.415.559

The calculation for the income of the promotion is the actual sale minus the baseline sale. Table 21 shows the income of the promotion for different products and period.

Table 21: PI-Income of the promotion

	Promoted period	Post-promoted period	Total
Actual sale- baseline sale of the promoted products	812.987	375.330	1.188.317
Actual sale – baseline sale of the shadow products	-68.209		-68.209
Total	744.779	375.330	1.120.108

Value of the promotion:

To calculate the value of the promotion the profit from the additional sales during the promotion is used. The calculation is then the income of the promotion multiplied with the margin minus the promotional cost. Because the margin % of the company is confidential this is set up by viewing different margins %. The results are also shown as a proportion to the average monthly sales. The average of four years' sales history was used. In table 22 the value of the promotion is shown for different margins.

Table 22: PI-Value of promotion using different margins

	20% margin		30% margin		40% margin	
	Value of promotion	% of average monthly sale	Value of promotion	% of average monthly sale	Value of promotion	% of average monthly sale
Only promoted products during the promoted period	62.597	4%	143.896	9%	225.195	14%
Only promoted products during the extended period	137.663	8%	256.495	15%	375.327	23%
Promoted and shadow products during the promoted period	48.956	3%	123.434	7%	197.911	12%
Promoted and shadow products during the extended period	**124.022**	**7%**	**236.032**	**14%**	**348.043**	**21%**

For promotion I the results are positive for the value of the promotion. It does not matter if it is viewed with or without the shadow products or by viewing the extended period, that is, the post-promotional period. Promotion 1 seems to be quite a profitable promotion according to the method proposed here for evaluation of the promotion value.

5.3.2 Promotion II

For promotion II the basic information about the promotion is given in section 4.3.2, including the cost of the promotion. The income of the promotion is found, taking into account both the potential shadow products and sales during the post-promoted period. The value of the promotion can then be calculated by using different margins %.

Income of the promotion:

The income of the promotion is the difference between the baseline sale and actual sale during the promotional period and the post-promotional period (if that is defined). It is also the difference between the baseline sale and actual sale of the potential shadow products.

Actual sales can be seen in table 23. It contains actual sales of the promoted products both for the promotional period and the post-promoted period and the actual sales of the shadow products during the promotional period.

Table 23: PII-Actual sales

	Promoted period	Post promoted period	Total
Actual sales of the promoted products	595.142	219.005	814.147
Actual sales of the shadow products	218.165		218.165
Total	813.306	219.005	1.032.311

In table 23 actual sales during the promoted period is for both April and May and sales for the post-promotional period is in June.

The baseline sale was calculated by the forecasting model described in section 3.4.1. For each value the forecast used is the one from the beginning of the promotion. In the case of promotion II this is the forecast done with March data, calculating for April one month ahead and May two months ahead. For the post-promotional period the forecast calculated with March data was used, calculating three months ahead. In table 24 the value for the baseline sale is shown.

Table 24: PII-Baseline sale

	Promoted period	Post promoted period	Total
Forecast of the promoted products	563.716	322.180	885.896
Forecast of the shadow products	183.632		183.632
Total	747.348	322.180	1.069.528

The calculation for the income of the promotion is the actual sale minus the baseline sale. Table 25 shows the income of the promotion.

Table 25: PII-Income of the promotion

	Promoted period	Post promoted period	Total
Actual sale- baseline sale of the promoted products	31.426	-103.175	-71.749
Actual sale – baseline sale of the shadow products	34.533		34.533
Total	65.959	-103.175	-37.216

As can be seen in table 25 the income of the promotion is negative. The forecasted sale without the promotion was higher than actual sales with the promotion. If only the promoted period is viewed it is positive, but when viewing the post-promotional period the outcome is negative. The shadow products seem to have benefitted from the promotion, as they increased in sales.

Value of the promotion:

Calculations of the value of the promotion is the income of the promotion multiplied with the margin for this product group, minus the cost of the promotion as seen in the formulas in section 3.5. The results are also shown with different margins used and as a proportion of the average monthly sale, the average of a four year sales history was used. In table 26 the value of the promotion is shown.

Table 26: PII-Value of promotion using different margins

	20% margin		30% margin		40% margin	
	Value of promotion	% of average monthly sale	Value of promotion	% of average monthly sale	Value of promotion	% of average monthly sale
Only promoted products during the promoted period	-63.715	-22%	-60.572	-21%	-57.430	-20%
Only promoted products during the extended period	-84.350	-29%	-91.525	-31%	-98.700	-34%
Promoted and shadow products during the promoted period	-56.808	-19%	-50.212	-17%	-43.617	-15%
Promoted and shadow products during the extended period	**-77.443**	**-27%**	**-81.165**	**-28%**	**-84.887**	**-29%**

For promotion II the results are negative for the value of the promotion. If the promotional period is viewed only then the loss is not great, but if the extended period is viewed then the loss is greater.

5.3.3 Promotions III

For promotion III the basic information about the promotion is given in section 4.3.3, including the cost of the promotion. The income of the promotion is found, taking into account both the potential shadow products and the sale during the post-promoted period. The value of the promotions is viewed by using different margins %.

Income of the promotion:

The income of the promotion is the difference between the baseline sale and the actual sale during the promotional period and the post-promotional period (if that is defined). It is also the difference between the baseline sale and the actual sale of potential shadow products.

The actual sale can be seen in table 27. It contains the actual sale of the promoted products during the promotional period, and the post-promotional period and the actual sale of the shadow products during the promotional period.

Table 27: PIII-Actual sale

	Promoted period	Post promoted period	Total
Actual sale of the promoted products	4.042.804	1.689.810	5.732.614
Actual sale of the shadow products	1.145.577		1.145.577
Total	5.188.381	1.689.810	6.878.191

Table 27 shows the actual sale during the promoted period for both June and July and the sale for the post-promotional period in August.

The baseline sale was calculated with the forecasting model described in section 3.4. For each value the forecast used is the one from the beginning of the promotion. In the case of promotion III this is the forecast calculated with May data calculating for June one month ahead and July two months ahead. For the post-promotional period the forecast calculated with May data was used, calculating three months ahead. In table 28 the value for the baseline sale is shown.

Table 28: PIII-Baseline sale

	Promoted period	Post promoted period	Total
Forecast of the promoted products	3.565.217	1.777.745	5.342.961
Forecast of the shadow products	1.164.914		1.164.914
Total	4.730.131	1.777.745	6.507.875

The income of the promotion is calculated as the actual sale minus the baseline sale. Table 29 shows the income of the promotion.

Table 29: PIII-Income of the promotion

	Promoted period	Post promoted period	Total
Actual sale- baseline sale of the promoted products	477.587	-87.935	389.652
Actual sale – baseline sale of the shadow products	-19.337		-19.337
Total	458.251	-87.935	370.316

Value of the promotion:

Calculations of the value of the promotion are shown in method section 3.5. The income of the promotion multiplied with the margin %, minus the cost of the promotion. In table 30 the value of the promotion is shown.

Table 30: PIII-Value of promotion using different margins

	20% margin		30% margin		40% margin	
	Value of promotion	% of average monthly sale	Value of promotion	% of average monthly sale	Value of promotion	% of average monthly sale
Only promoted products during the promoted period	-264.483	-17%	-216.724	-14%	-168.965	-11%
Only promoted products during the extended period	-282.070	-18%	-243.104	-15%	-204.139	-13%
Promoted and shadow products during the promoted period	-268.350	-17%	-222.525	-14%	-176.700	-11%
Promoted and shadow products during the extended period	**-285.937**	**-18%**	**-248.905**	**-16%**	**-211.874**	**-13%**

The promotion showed some increase in sales, during the promotional period, but still not high enough to make the margin of the increase in sales pay the promotional cost. Therefore, the value analysis of the promotion is negative.

5.4 PROMOTION RESULTS

The promotions did show different results with both good and bad outcomes. Those findings were compared with the view of the market department on the promotions. Although the marketing department did not have a formal review for each promotion, it did have a feeling whether the promotion was good or bad.

5.4.1 Promotion I

Promotion I was very successful, from every perspective. It was a small promotion with low cost, but highly efficient. The sale increased significantly and when the cost of the products and the promotion has been subtracted the value of the promotion is positive. There was a substantial increase in sales during the promotional period and also during the post-promotional period, so there was a positive effect on the promoted product after the promotions. The sales of the shadow products were however slightly less than expected so the sales of the promoted brand seem to have taken some sales from the shadow brand. The marketing department agrees that this was a very successful promotion. It increased sales and brand awareness with very low cost and little effort.

5.4.2 Promotion II

The outcome of promotion II was not positive. During the promotion the sale did increase compared to the forecast, but when taking into account the following month, sales were significantly lower. The promotion seems to have taken sale from the following month. For the total period, the forecast was higher than actual sales, that is, during the promotion the sales decreased compared to what was expected. There was, however, a small increase in sales of the shadow products, so the total brand seems to have had some benefit from the promotion although not all products in the product brand were promoted.

The marketing department agrees that this was not a successful promotion, even though there are some positive signs. In fact, the main task of this promotion was to increase brand awareness, using marketing support from the global brand owner. So, even though the model and sales figures during the promoted period do not show a positive outcome, the purpose of the promotion might have been successful. However, it is necessary to measure that with other means than used in this thesis.

Concurrent external events, like a marketing activity from the main competitions, could also have effected this. That possibility is, however, not documented so it cannot be confirmed.

5.4.3 Promotion III

In promotion III there was some increase in sales and the extra income of the promotion did cover the cost of the promotion, but if the cost price of the promoted product was subtracted, the profit of additional sales did not exceed the cost of the promotion. Sales during the post-promotional period were slightly lower than expected, which could be because of customers advance buying. That is, sales during the promotional period did borrow sales from the post-promotional period. There was also some cannibalization in this promotion as other products in the same product group did sell less than expected. The marketing department agreed with these findings. That is, it would have liked sales during the promotional period to be higher and the increase in sales to continue into August. Despite that, the promotion was considered successful. The image of the promoted brand had improved and the brand awareness increased. According to the marketing department the whole product group had been declining in the Icelandic market and the promotion helped the product brand to increase market share although the sales volume perhaps did not increase.

6. CONCLUSION

The case study was successful; it was possible to calculate the value of the promotion by the methods that were proposed in this thesis. The promotions did show different results, with both good and bad outcomes. The marketing department mostly agreed with the findings although its perspective was a little bit more on the soft parameters, like brand awareness. The model was easy to implement but needs more testing.

The model setup was easy to apply and use in practice. The aim of the structure was to have the model only based on information easily available in the ERP system of the company with a little additional information from the marketing department. That was successful. The calculation only needed data about sales value of the promoted products and potential shadow products. The information from the marketing department, a list of eight issues, was easily obtained. The results from the case study indicated that the model is useful and the results were confirmed by the views of the marketing department. There are, however, some soft parameters that were not addressed in this analysis, like the increase of brand awareness, but it is likely that this will always be very difficult to measure with an analytic model like the one proposed in this work. The model was built by using value of sales and would not need many adjustments to change the unit into quantity or volume. That would, however, require more information like cost and sale price. It would also be necessary for products within the promoted group to have a great similarity, or a method to adjust different packaging sizes and sale prices.

There are several limitations and risks that need to be considered. The literature about how to estimate the value of promotion was very scarce; this might be due to wrong keyword search or others means, but even with expanded search little was found. This model was only tested for three promotions at one company in the food and beverage industry in consumer packed goods. All of the promotions were advertisements. The outcome of the promotions might have shown different results if they had only been in the form of discounts or flyers since the cost of the promotions might not have as much impact. It is, therefore, necessary to test this with more data and make adjustments to the model after that iteration.

The next step is to have this model tested on more promotions. This model could, however, be a good starting point for a beta version of the software and to have a Beta customer analyse their own data with the system and see what may be improved. That would probably give a new perspective on the problem and the model could be adjusted accordingly.

7. REFERENCES

[1] M. A. Moon, J. T. Mentzer and C. D.Smith, „Conducting a sales forecasting audit," *International Journal of Forecasting,* b. 19, nr. 1, pp. 5-25, 2003.

[2] R. Fildes and R. Hastings, „The Organization and Improvements of Market Forecasting," *The Journal of the Operational Research Society,* b. 45, nr. 1, pp. 1-16, 1994.

[3] J. T.Mentzer, C. C. Blenstock and K. B. Kahn, „Benchmarking Sales Forecasting management," *Business Horizon,* b. 42, nr. 3, pp. 48-56, 1999.

[4] D. Önkal, M. Lawrence, K. Z. Sayim, "Influence of differentiated roles on group forecasting accuracy," *International journal of forecasting,* vol. 27, no. 1, pp. 50-68, 2011.

[5] J. R. Trapero, D. J. Pedegral, R. Fildes and N. Kourentzes, „Analysis of judgmental adjustments in the presence of promotions," *International Journal of Forecasting,* b. 29, pp. 234-243, 2013.

[6] R. Fildes and P. Goodwin, „Against your better Judgment? How Organization can improve their use of management judgment in forecasting," *Interfaces,* b. 37, nr. 6, pp. 570-576, 2007.

[7] R. Fildes, P. Goodwin, M. Lawrence and Konstantinos Nikolopoulos, „Effective forecasting and judgmental adjustments: an emperical evaluation and straegies for improving in supply-chain planning," *International Journal of Forecasting,* b. 25, nr. 1, pp. 3-23, 2009.

[8] P. H. Franses and R. Legerstee, „Properties of expert adjustments on model-based SKU-level forecasts," *International Journal of Forecasting,* b. 25, nr. 1, pp. 35-47, 2009.

[9] Editorial: R. Fildes and P. Goodwin, „Forecasting support system: What we know, what we need to know," *International Journal of Forecasting,* b. 29, pp. 290-294, 2013.

[10] R. T. Clemen, „Combining forecast," *International Journal of Forecasting,* b. 5, nr. 4, pp. 559-583, 1989.

[11] S. Nahmias, Production and operations analysis, New York: McGraw-Hill/Irwin, 2005.

[12] J. S. Armstrong, „Forecasting by Extrapolation: Conclusions from 25 Years of Research," *Interfaces,* b. 14, nr. 6, pp. 52-66, 1984.

[13] K. C. Green and J. S. Armstrong, „Simple versus complex forecasting: The evidence," *Journal of Buisiness Research,* p. In press, 2015.

[14] M. Lawerence, P. Goodwin, M. O'Connor, D. Önkal, „Judgmental forecasting,“ *International Journal of Forecasting,* b. 22, nr. 3, pp. 493-518, 2006.

[15] A. Davydenko, R. Fildes and J. Trapero Arenas, „Judgmental Adjustments to Demand Forecast: Accuracy Evaluation and Bias Correction,“ *The Department of Management Sience, Lancaster University Management School, Working paper,* b. 003, pp. 1-20, 2010.

[16] R. Fildes and A. Davydenko, „Measuring forecasting accuracy: The case of judgmental adjustments to SKU-level demand forecast,“ *International Journal of Forecasting,* b. 29, nr. 3, pp. 510-522, 2013.

[17] N. R. Sanders and L. P. Ritzman, „Judgmental adjustment of statistical forecasts,“ *Principles of Forecasting,* b. 30, pp. 405-416, 2001.

[18] R. Webby and M. O'Connor, „Judgemental and statistical time series forecasting: a review of the literature,“ *International Journal of Forecasting,* b. 12, nr. 1, pp. 91-118, 1996.

[19] M. Lawrence, M. O'Connor and B. Edmundson, „A field study of sales forecasting accuracy and processes,“ *European Journal of Operational Research,* b. 122, nr. 1, pp. 151-160, 2000.

[20] M. O'Connor, W. Remus and K. Griggs, „Judgemental forecasting in times of change,“ *International Journal of Forecasting,* b. 9, nr. 2, pp. 163-172, 1993.

[21] D. Önkal, P. Goodwin, M. Thomsson, S. Gönul and Andrew Pollock, „The relative influence of advice from human experts and statistical methods on forecast adjustments,“ *Journal of Behavioral Decision Making,* b. 22, nr. 4, pp. 390-409, 2009.

[22] P. Goodwin, R. Fildes, M. Lawrence and G. Stephens, „Restrictiveness and guidance in support system,“ *Omega,* b. 39, nr. 3, pp. 242-253, 2011.

[23] A. E. Mannes, „Are We Wise About the Wisdom of Crowds? The Use of Goup Judgments in Belief Revision,“ *Management Sience,* b. 55, nr. 8, pp. 1267-1279, 2009.

[24] J.M. Silva-Risso, R. E. Bucklin and D. G. Morrison, „A Decision Support System for Planning Manufacturers' Sales Promotion Calenders,“ *Marketing Sience,* b. 18, nr. 3, pp. 274-300, 1999.

[25] K. L. Ailawadi., S. A. Neslin and K. Gedenk, „Pursuing the value-conscious consumer: store brands versus national brand promotions,“ *Journal of Marketing,* b. 61, nr. 1, pp. 71-89, 2001.

[26] L. G. Cooper, P. Baron, W. Levy, M. Swisher and P. Gogos, „PromoCast: A new forecasting method for promotion planning,“ *Marketing science,* b. 18, nr. 3, pp. 301-316, 1999.

[27] G. Sigurjónsson, „Forecasting support system combining statistical and judgmental event forecasting techniques,“ School of Sience and Engineering at Reykjavik University, Reykjavík, 2010.

[28] Ö. G. Ali, S. Sayin, T. van Woensel and J. Fransoo, „SKU demand forecasting in the presense of promotion,“ *Expert System with Application,* b. 36, nr. 10, pp. 12340-12348, 2001.

[29] H. J. van Heerde, P. S.H. Leefland and D. R. Wittink, „How Promotions Work: SCAN*PRO-Based Evolutionary Model Building,“ *Schmalenbach Buissness Review,* b. 54, nr. 3, pp. 198-220, 2002.

[30] S. Divaker, B. Ratchford and V. Shankar, „CHAN4CAST: A Multichannel, Multiregion Sale Forecasting Model and Decision Support System for Consumer Packaged Goods,“ *Marketing Sience,* b. 24, nr. 3, pp. 334-350, 2005.