

**Forecasting support system**

**combining statistical and judgmental**

**event forecasting techniques**

Guðni Pétur Sigurjónsson

December 2010

**MSc thesis in Decision Engineering**



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**Forecasting support system combining statistical and judgmental event forecasting techniques**

by

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Research thesis submitted to the School of Science and Engineering at Reykjavík University in partial fulfillment of the requirements for the degree of

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Guðni Pétur Sigurjónsson

Master of Science

**Forecasting support system combining statistical and judgmental event forecasting techniques**

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December 2010

**Abstract**

Combining statistical forecasts with judgmental knowledge is widely used in practice to take into account special events such as sales promotions. Forecasters often use passed event information to estimate future effects of events without any aid other than the judgmental view of the forecaster. This paper develops intelligent methods that can analyze past event effects and use that information to aid forecasters in planning future event effects. The methods will form the base for a Forecasting Support System (FSS) which aids forecasters in collecting past event information and provides guidance in similarity judgments and support for adaptation judgments of past events. We discuss the problem of large scale forecasting and offer solutions to that problem that requires as minimal manual work as possible. A binomial programming model is introduced which has the main goal of maximizing the expected profit of a company by identifying the most successful promotions that occurred in the past, and suggesting a preferred promotional calendar for a future period. Some of the methods introduced were tested with a FSS that we developed and implemented on generated data with promising results. The testing results suggest that a simple memory and similarity support can significantly improve forecasting accuracy. The methods introduced in this paper are all relatively easy to implement and we believe a FSS with them included could improve the demand planning process for all companies, since to the best of our knowledge there is no FSS with the presented methods on the market place today.

Keywords; Forecasting Support System, Judgmental forecasting, Statistical forecasting, event effects, event analysis, event forecasting.

**Spáhugbúnaður sem sameinar tölfræðilegar og huglægar spáaðferðir við gerð atburðar spáa**

Guðni Pétur Sigurjónsson

Desember 2010

**Útdráttur**

Sameining tölfræðilegra spáaðferða með huglægri þekkingu er þekkt fyrirbæri og mikið notað af fyrirtækjum sem vilja spá fyrir um sérstaka atburði eins og söluherferðir vara. Greinendur nota oft upplýsingar um sérstaka liðna atburði til að spá fyrir og meta virði framtíðar atburða án nokkurrar aðstoðar annara en huglægs mat greinandans. Þetta verkefni lýsir eiginleikum spáhugbúnaðs sem einfaldar alla framtíðarspágerð fyrirtækja og aðstoðar notendur við að meta vænt virði framtíðar atburða eins og söluherferðra vara. Við kynnum einnig bestunar módel sem hefur það markmiða að hámarka væntan hagnað fyrirtækis með því að benda á þær fortíðar söluherfeðir sem hafa skilað mesta hagnaði og stinga upp á framtíðar söluherferðum. Tilraunar spáhugbúnaður var smíðaður og prófaður á tilbúnum gögnum. Prófaninar leiddu í ljós að einfaldur spáhugbúnaður sem hjálpar notendum að sameina tölfræðilegar og huglægar spáaðferðir getur verulega bætt spáskekkju. Allar aðferðir sem kynntar eru í þessu verkefni eru tiltölulega einfaldar í framkvæmd og við trúum því að spáhugbúnaður gæddur þeim eiginleikum sem við kynnum muni bæta eftirspurnar áætlunargerð allra fyrirtækja.

Lykilorð; Spáhugbúnaður, tölfræðilegar spáaðferðir, huglægar spáaðferðir, eftirspurnar áætlunargerð, áætlunargerð.

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**Contents**

[1. Introduction 1](#_Toc279418247)

[2. Industrial forecasting practice 3](#_Toc279418248)

[2.1 Forecasting practice in mid-sized companies 3](#_Toc279418251)

[2.2 Generic demand planning process 4](#_Toc279418252)

[3. Event Analysis and Forecasting 7](#_Toc279418253)

[3.1 The benefit of combining statistical and judgmental methods 7](#_Toc279418255)

[3.2 Events and database collecting 8](#_Toc279418256)

[3.3 Estimating effects of past events 9](#_Toc279418257)

[3.4 Forecasting in the presence of events 11](#_Toc279418258)

[3.5 Memory, similarity and adaptation support 12](#_Toc279418259)

[3.6 Automation for large scale forecasting 13](#_Toc279418260)

[3.6.1 Multiple criteria ABC analysis 13](#_Toc279418261)

[3.6.2 Identifying successful promotions 15](#_Toc279418262)

[3.7 Pre- and post-event effects 17](#_Toc279418263)

[3.8 Overlapping events 18](#_Toc279418264)

[3.9 Shadow Effects 18](#_Toc279418265)

[3.10 Implementation of a prototype forecasting support system 19](#_Toc279418266)

[4. Testing and results of the prototype forecasting support system 24](#_Toc279418267)

[4.1 The data 24](#_Toc279418269)

[4.2 Event analysis 25](#_Toc279418270)

[4.3 Event forecasting 26](#_Toc279418271)

[5. Discussion 29](#_Toc279418272)

[6. References 31](#_Toc279418273)

**List of figures**

[Figure 1. The workflow of the demand planning process for an updated fixed horizon using a forecasting support system. 5](file:///C:\Users\LENOVO\Desktop\Skóli_vinnur\Skóli%20Master\Meistaraverkefni\Greinin%20mín\newest\final%20vinnumappa\gudniV25.docx#_Toc277257079)

[Figure 2. An example of a baseline time-series compared to actual sales time-series. Event 1 shows a promotional event increase of ca. 20.000 units and event 2 shows a promotional event increase of ca. 13.000 units. 9](#_Toc277257080)

[Figure 3. The workflow of the proposed Forecasting support system with regards to event analysis and forecasting for a single product 11](file:///C:\Users\LENOVO\Desktop\Skóli_vinnur\Skóli%20Master\Meistaraverkefni\Greinin%20mín\newest\final%20vinnumappa\gudniV25.docx#_Toc277257081)

[Figure 4. An example of three most similar chosen events. The average effect of the three events is 80 units, but the forecaster might want to judgmentally alter the future effect to 40 units according to the trend witnessed. 12](#_Toc277257082)

[Figure 5. The shadow effect modul, process and functionality 18](file:///C:\Users\LENOVO\Desktop\Skóli_vinnur\Skóli%20Master\Meistaraverkefni\Greinin%20mín\newest\final%20vinnumappa\gudniV25.docx#_Toc277257083)

[Figure 6. The first graphical user interface (GUI) of the prototype FSS 22](#_Toc277257084)

[Figure 7. The second graphical user interface (GUI) of the prototype FSS 23](#_Toc277257085)

[Figure 8. The generated testing data and the timing of the past events 25](#_Toc277257086)

[Figure 9. The results from the FSS forecast for scenario 1 where the timing of no future or past events are known compared to the actual sales. 27](#_Toc277257087)

[Figure 10. The results from the FSS forecast for scenario 2 where the timing of past events are known but the timing of future events are not known compared to the actual sales 27](#_Toc277257088)

[Figure 11. The results from the FSS forecast for scenario 3 where both the timing of past and future events is known compared to the actual sales. 28](#_Toc277257089)

**List of tables**

Table 1. Summary table of the methods and means the companies visited used for forecasting and event handling. 3

Table 2. An example of the necessary data to be collected on past events for event analysis 8

Table 3. An example of a shadow database table, the setup of the columns. 19

Table 4. Types of generated events and their event effects 25

Table 5. Types of generated events and their event effects versus the forecasted effect 26

Table 6. Error summary for the FSS forecast. 28

**Chapter 1**

# Introduction

Most companies are driven by demand in one way or another, both in manufacturing and service industries. Demand planning is a process of planning all demands for products and services of a company to support the company’s decision making process over some preferred time-horizon [2]. The purpose of demand Planning is to drive the supply chain to meet customer demand with effective management of the company´s resources and to calculate buffer or safety stocks to reach a predefined service level. The expected demand should be the main input for all operational decisions and the demand planning process is therefore of great importance. All decisions in the whole supply chain should be based on already fixed (accepted) customer’s orders and planned sales or forecasts, the latter ones are determined in the Demand Planning process. Therefore the performance of each supply chain entity depends on the quality of the demand plan [1].

Statistical forecasting techniques are widely used for demand planning [2]. In modern marketing theory sales promotions are known to be an effective tool for stimulating sales [1]. Extraordinary conditions such as sales promotions or other events often make the process of demand planning extremely complicated and hard, especially when using statistical forecasting techniques. When dealing with such conditions research has shown that judgmental adjustments to statistical forecasts can improve accuracy [3]. Especially when the forecaster has access to forthcoming information of events that is not included in the historical time-series of the product that is to be forecasted. Quantitative data on such events is possibly scarce or not available because the same event has not been witnessed before or it has only been similar but not the same, those conditions make it difficult to apply statistical techniques to the time-series. In such cases judgmental adjustments can benefit the forecasting process. The judgmental aspect of the forecasting process also gives the forecaster an increased sense of ownership of the forecasting process and therefore the forecast is more likely to be accepted by the forecasters [4]. Judgmental adjustment of statistical forecasts has been the focus of number of research work [5-7], and has often proved to be necessary to obtain an acceptable forecasting result. However there has not been done much research on estimating the effect of individual events on the time series and how to help forecasters in estimating the expected size of future events.

This paper proposes how a forecasting support system should be designed with regards to event analysis. The findings are based on a literature study as well as on an industrial study where several mid-sized companies from different branches were visited and their demand planning challenges analyzed. This research will among other things use the findings of Lee, et al. [8] were they concluded that a forecasting support system that: (i) reduces the demands on memory by providing a database support of past reference cases, (ii) provides guidance to support similarity adjustments and (iii) provides information to support adaptation judgments, is effective in improving the accuracy of judgments in event forecasting. This paper implements and tests their findings on generated data and proposes other features that will enhance and improve the forecasting support system.

In this paper we start by reviewing forecasting practices of five mid-sized companies and illustrate a demand planning process designed for small and mid-sized companies. Event analysis and forecasting will be discussed and a novel forecasting support system (FSS) and its design features introduced. Following our testing method and results from testing the introduced FSS are described. We discuss large scale forecasting and introduce a binomial programming model which aids the forecaster in identifying the most beneficiary sequence and combination of future promotions. Finally the limitations of this research are discussed and its implications for future research and practitioners.

**Chapter 2**

# Industrial forecasting practice

The following chapter describes the industrial forecasting practices of five mid-sized companies that were surveyed in preparation for this project, and introduces a generic demand planning process which can be beneficiary for most small and mid-sized companies.



## Forecasting practice in mid-sized companies

Five mid-sized companies from different industry sectors were surveyed and questioned about their demand planning process, and especially how they incorporated events such as promotions into their demand plans.

The companies have different ways of dealing with forecasting events, but almost all of the companies visited try to learn and save data from previous events. Main findings of the company visits are summarized in table 1 and the industry sectors the companies work in.



Only two of the companies used a FSS, and three of the companies judgmentally changed their forecast with regards to upcoming and planned events. Two of the companies did not take promotions or other events into account while making their demand plans. None of the companies attempted to calculate the effects of the events they had previously witnessed nor store them in a database to use for later reference.

The demand planning workflow was in all cases badly organized and it was often not clear who was responsible for completing various tasks. None of the companies had any documentation of their demand planning process.

All of the companies visited expressed the need for a forecasting support system (FSS) that could help them manage a database of past events, calculate the effect of past events and help in estimating effects of future events.

## Generic demand planning process

The demand planning workflow was in all cases badly organized and it was often not clear who was responsible for completing various tasks. None of the companies had any documentation of their demand planning process.

In the following we propose a simple and efficient demand planning process formed from the industry survey and suggestions from H. Stadtler [1] and C. Crum [2]. The process is designed for small and mid-sized companies and is equally intended for companies that wish to make demand plans;

* For a fixed period of time and do not update the plan.
* For a fixed period of time and update the plan periodically
* For a rolling period of time, that is for example a 12 month demand plan that is constructed each month.

Those demand planning processes are called fixed, updated fixed and rolling horizon respectively.

To support the demand planning process a stand-alone FSS is proposed. Most companies have some kind of an Enterprise resource planning (ERP) system but those systems do in our opinion not provide sufficient support. The FSS system requires a two way data link to the ERP system. Figure 1 illustrates the demand planning process for an updated fixed horizon using a Forecasting Support System. All of the functions described in figure 1 the FSS should be able to perform and the first three steps of the demand planning process and their functionality will be the main focus of chapter 3.

**Data preparation:** The FSS provides means for various data preparation tasks such as adding new products at the time they will be introduced to the market, defining if new products are similar enough to get the same sales forecast trend as other existing products. The FSS provides the means of defining the time when obsolete products will be taken from the market. The FSS provides the means of manipulating product groups and a database support of past events. The FSS provides the means for inputting future and past event information that is relevant to a specific product for the purpose of future event or promotional planning.



Figure 1: The workflow of the demand planning process for an updated fixed horizon using a forecasting support system.

Fig. 1. The workflow of the demand planning process for an updated fixed horizon using a forecasting support system.

**Statistical forecast:** After data preparation the FSS creates a statistical forecast on future sales of the product.

**Judgmental forecast:** The FSS provides the forecaster with means of judgmentally altering the statistical forecasts. The FSS also provides the forecaster the means of estimating future event effect and implementing those effects in future forecasts.

**Consensus forecast:** The final step of incorporating the judgmental factors is to have a consensus forecasting meeting where the goal of that meeting is to reach a consensus about open issues like different opinions of the influence of a promotion or other events. The FSS provides a platform to aid the forecaster in collaborative planning and consensus forecast making. It is also important to review past forecasts and their accuracy in these meetings with regards to individual inputs from members of the consensus forecast meeting, to verify if their input is valid.

**Dependent demand:** Next the forecaster has to take into account if there is any dependent demand to be considered. Dependent demand occurs when a demand for an item (called lower level or child item) does not occur until there is a demand for another item (called higher level or parent item). Also, where demand for the higher level or parent item can be satisfied only if the lower level or child items are available. Dependent demand is often defined in the company’s ERP system.

**Using and monitoring the plan:** If then the final forecast is approved the company releases the forecasts to all stakeholders, such as marketing, finance, sales, management or procurement divisions of the company and also their supply chain partners. The FSS then calculates performance measures daily and monitors the actual sales versus the planned sales.

If the company prefers the rolling horizon then this process should be repeated periodically. If the company prefers the fixed horizon method then it is only necessary to implement this process in the beginning of the period.

**Chapter 3**

# Event Analysis and Forecasting

This chapter discusses the benefits of combining statistical and judgmental forecasting methods, how events are defined and how the user will be able to input the necessary event data into the proposed FSS for event analysis. Following there will be a discussion on how the FSS will estimate the values of the past events and use that information to aid the forecaster in predicting future events. We will test some of our proposed solutions and discuss other obstacles the FSS should be able to solve.



## The benefit of combining statistical and judgmental methods

Most forecasting systems use extrapolation methods when forecasting the future. Those methods use only the time series data of the activity itself to generate the forecast. The particular techniques range from the simpler moving averages and exponential smoothing to the more complicated Box-Jenkins approach. Those methods have proved to model and identify time-series patterns of trend, seasonality and autocorrelation successfully, but they do not take into account external factors such as promotions, price change nor other events [9]. Number of studies have shown that people often prefer judgmental methods rather than statistical approaches when forecasting time-series [10, 11], although it is argued that statistical approaches are often more accurate than judgmental [12]. In practice, the forecaster would both use statistical forecast and judgmental data to make the forecast as accurate as possible. The judgmental data would include promotion plans, competitor intelligence, knowledge of stock-outs etc. Judgmental knowledge and adjustments to the statistical forecasts according to that can make substantial improvements to the forecast accuracy [13] and have often proven to be a major factor in determining the final forecast [14, 15]. Graphical user interfaces as well as powerful query tools are very helpful when combining statistical and judgmental forecasts. Much can be achieved by allowing the forecaster to search for past events, analyzing their effects and altering the statistical forecasts with regards to planned events easily. R. Fildes [16] suggested how the ideal attributes of a forecasting support system should work and also concluded that no such system to date exists. The attributes are: (i) acceptable to users, (ii) easy to use, (iii) offers a flexible range of appropriate facilities and methods, (iv) viable for commercial software companies to market and (v) fosters the appropriate mix of judgment and statistical methods. Those attributes are the basis for the proposed forecasting support system.

## Events and database collecting

An event is defined as some circumstances that have an effect on the sales of a product, whether it is an increase or decrease in sales. A typical event in sales forecasting is a sales promotion campaign. Another type of an event might be the world cup series in football. During the series the sales of some products might increase/decrease.

For the purpose of event analysis and event forecasting, it is required to have data of past events and sales. Quantitative data on the effects of such campaigns might be scarce because of their infrequency or their diverse nature. If the forecaster knows the start time, end time and type of the event then the effect can be derived from the time series using the method described in section 3.3. The end result of event analysis is a better understanding of how past promotions affected the historical data. Armed with the knowledge gained by event analysis, the forecaster can better determine the effects of future events and enhance the accuracy of future forecasts.

Events are defined with four attributes which are later used for calculations (see section 3.3); they are event type, event duration, event time of year and event location. Table 2 shows an example of information collected on events. The columns contain the four necessary attributes for the proposed event forecasting method.



Additional event information is not required but could prove to be valuable in future calculations such as a short description of the event and affected items (product, product group, product category) and the cost of the event. Sales price of the product and the cost of goods for the particular product can be derived from the two way data link with the company’s ERP system.

The information on the events is used to build a knowledge base of different types of events and used for further examination. Aiding the forecaster with a database of past cases, where the forecaster can examine and judgmentally choose the appropriate cases when he forecasts future events has proved to significantly improve the forecasting accuracy when the task involved has low level of noise, on the other hand, having the same database can also have a negative effect on the forecast if the task at hand has a high level of noise [17]. It seems that the forecasters will match the target case with just a single case from the database, which can be damaging when the noise is high. It is our assumption that with a properly designed database of calculated event effects and some guidance for the forecaster in choosing past events for future forecasts the forecasting accuracy can be enhanced.

## Estimating effects of past events

The FSS calculates the effects of past events and uses those values to aid the forecaster in constructing future forecasts with planned events (see section 3.4). If the user chooses to forecast a product´s time-series with registered events in its past, the first step for the FSS is to construct a “baseline time-series” for the product and a “best-fit time-series”. The baseline time-series is exactly the same as the actual sales series for all the data points where an event is not present, and where an event is present the value of the baseline time-series is forced to “null”. The best fit time-series is created from the available forecasting method that fits best the past actual time-series. In the case where an event is present and the value of the baseline time-series is “null”, the value of the same period in the best fit time-series is inserted in the baseline time-series. This procedure is then iterated for the whole baseline time-series. The baseline time-series will then represent the expected past sales if the events had not been witnessed. An example of a baseline time-series compared to actual sales time-series can be seen in figure 2. In that example there are two events present; the actual sales series represents the actual sales including the two events. The baseline time-series represents the actual sales in all of the months where an event was not present, if there was an event present then the values of the best-fit time-series in the same month have been inserted, to retrieve the effect of the particular event.



Figure 2: An example of a baseline time-series compared to actual sales time-series. Event 1 shows a promotional event increase of ca. 20.000 units and event 2 shows a promotional event increase of ca. 13.000 units.

After the baseline time-series has been constructed the FSS can calculate the effect of each event by calculating the difference from the actual sales time-series of the product and the baseline time-series when there was an event present (or the percent increase/decrease). The calculated effects of the events will then be stored in the same database table as the event information is stored and described in chapter 3.2. After this process the FSS will have information on all of the events this particular product has witnessed and their effects.

The FSS should be constructed with a number of forecasting methods including exponential smoothing methods such as moving average, simple exponential smoothing, Holt, Winters (equations can be seen in chapter 3.6) and also more complicated statistical methods such as Box-Jenkins (ARIMA). The FSS should then choose the best available forecast by selecting the forecast that has the lowest mean absolute deviation (MAD), Mean absolute percentage error (MAPE) or Mean squared error (MSE).

## Forecasting in the presence of events

Figure 3 shows the workflow of the proposed system with regards to event analysis and forecasting for a single product. Forecasting for multiple products is described in section 3.7. Figure 3 represents the first three steps in figure 1 in section 2.2.

1. The first step of the forecasting process is to select a product. If some sales promotions or other events are foreseen or planned then it is necessary to enter information on the future events as described in section 3.2.
2. A baseline time-series for the product is calculated and the effects of all of the past events are calculated using the method described in section 3.3.
3. Information is displayed on the three most similar past events; the FSS will judge the similarity of the events using the method described in section 3.5.

The FSS will also display a bar chart of the selected most relevant past events, and a trend-line of the bar chart. The trend-line will be there to help the forecaster make a better decision if he/she chooses to alter the value. For example if the values of the events are continually increasing or decreasing, then the forecaster might want to increase or decrease the value of the future event according to his judgment and based on the trend he sees. Figure 4 shows an example of a bar chart of three events.

1. The FSS displays the estimated event effect. The estimated event effect is derived by taking the average of the values of the three chosen events. Requiring forecasters to focus on an average of past cases rather a specific past case, leads to improved forecasts in an unpredictable environment [17]. The forecaster will also have the option of judgmentally altering the value of the future event if the past cases are different in some way from the target case.
2. If the forecaster does not accept the relevance of the three given events, then he will be given the possibility of pressing an advanced button. There the forecaster will be able to see all of the events that the particular product has encountered, and he/she will also be able to select other products that he/she might find relevant and analyze their past events.
3. The forecaster can then select all of the events he/she believes to be relevant and by using the same method as described above he/she can derive the estimated value of the future effect from them.

Figure 3: The workflow of the proposed Forecasting support system with regards to event analysis and forecasting for a single product

1. When the forecaster has finished making the new event, he/she will be asked to accept the future effect.
2. The FSS will then construct a forecast on the baseline time series, and add the effect of the new event at the selected period. A bar chart with the baseline forecast and the estimated new effect will be presented.

If the forecaster accepts the forecast the FSS will save the new event information in the database table presented in section 3.2, and also save the new forecast. If the forecaster chooses to update the forecast in the future because of changed market conditions the new information on the event and the new forecast will overwrite the old forecast.



Figure 4: An example of three most similar chosen events. The average effect of the three events is 80 units, but the forecaster might want to judgmentally alter the future effect to 40 units according to the trend witnessed.

## Memory, similarity and adaptation support

The FSS reduces the demand on memory as discussed in the introduction chapter, by providing memory support. The memory support can be described in such a way that it manages the database of event information introduced in section 3.2, and provides the forecaster with the means of analyzing past event values.

The similarity support works in such a way that the FSS will judge all past events and their similarity to the target case that is to be forecasted. An event has several attributes such as type, duration, time of year and location, so judging events similarity to the target case could prove to be problematic. For example a 10% price change of a product would probably not have the same effect if it took place in January instead of December. Also the effect would not be the same if the particular store was located in a busy shopping center rather than a corner store in a small neighborhood. The similarity module in the FSS is very similar as Lee, et al. [8] suggested, that is a hierarchical rule system is applied to identify the most similar events with regards to the target case. The FSS will examine the database table of past events and compare the attributes of the target case with all of the past events in the database table. The greater the number of matching attributes, the more similar the past events will be. In the case where there are ties in the number of similar attributes, the FSS will intuitively put the most weight on the similarity of the type, followed by the similarity of location, then the similarity of the time of year and the least weight is put on the similarity of duration. This method might often prove useful but would often require the judgmental help from the forecaster.

Letting the FSS select automatically the past events will likely lead to a selection of past events that have several attributes that are identical or at least very similar to the target event. This means that the forecaster can focus on assessing the effect the target event will have on the attribute that is not similar, when all the other attributes are identical or very similar. For example, an upcoming event might have the same duration, location and type as a number of past cases but differed in the time of year. The forecaster than only has to focus on assessing the effect of the time of year on sales with all other attributes held constant.

The FSS will also provide the user with an adaptation module. It will provide adaptation support to the forecaster by two means. First it will add the previously discussed trend-line to the bar chart of selected similar events; this will help the forecaster judgmentally choose the estimated value of the target case. Secondly the FSS will examine the database table for the selected product for pairs of cases that differ in only one attribute. The FSS will then for each pair calculate the ratio difference of the events effects. Finally the FSS will calculate the mean ratio for all of the pairs that only differ in the same attribute. This will give the forecaster the option of examining how much effect different attributes can have on the product sales. For example the FSS might show that a 15% discount on the chosen product has a 1.5 times greater effect on the product than a 10% discount.

The FSS that provides memory, similarity and adaptation support can produce significantly more accurate forecasts and appears to be highly acceptable to forecaster [8].

## Automation for large scale forecasting

For most mid-sized and large companies the process described in section 3.4 could prove to be too time consuming, because those companies should create and manage forecasts for all of their products which could range from hundreds to millions. For this reason the FSS should aim to be as automatic and require as minimal manual work as possible without losing much accuracy.

### Multiple criteria ABC analysis

ABC analysis is a method of classifying a company’s existing stock with regards to its value. The FSS will offer the simple ABC classifier for multiple criteria introduced by W. L. Ng [18]. ABC analysis is well known and is based on the Pareto principle. The most common interpretation of ABC analysis states that inventory items in category A make about 80% of the business but are about 20% of the inventory. Inventory items in category B make about 15% of the company´s business and are about 15% of the inventory and finally category C make about 5% of the business but are about 65% of the inventory. However ABC analysis is based on a single measurement such as annual profitability but there are a number of other measurements that are important as well, for example inventory cost, lead time, obsolescence, number of request per year, scarcity, order size requirement and stock out penalty. W. L. Ng [18] proposed a weighted linear model for the multi-criteria inventory classification (MCIC) which converts all criteria measures of an inventory item into a scalar score. The classification based on the calculated scores using ABC principle is then applied. A company might for example not only want to make an ABC analysis on the basis of only annual profitability but rather annual profitability, average unit cost and lead time.

The whole process is easy to implement in the proposed FSS.

First all criteria measures are transformed to a comparable base by using F. Y. Partovi and W. E. Hopton [19] transformation which converts all measurement to a 0-1 scale for all items:

(1)

Where the measurement of the *i*th item under the *j*th criteria is denoted as *yij*. For example if we were transforming average unit cost of all products, and product i had a unit cost of 49.92 dollars, the maximum average unit cost is 210 dollars and the minimum average unit cost is 5.12 dollars then would be 0.22. The same procedure would be iterated for all the criteria selected.

After the transformation following steps are performed for each inventory item:

* Calculate all partial averages, (2)
* Compare and locate the maximum among these partial averages. The corresponding value is the score Si of the *i*th item.
* Sort the scores Si in the descending order.
* Group the inventory items by principle of the ABC analysis.

After the FSS has ABC classified all of the company’s products and the forecaster chooses to make forecasts for the whole products line the FSS makes a baseline forecast for all of the products that do not have registered upcoming events. If a product has registered upcoming events, then the FSS creates the baseline as described in chapter 3.3 and when there is an event present the FSS takes the average increase/decrease effect of the past three events it deems most relevant using the similarity hierarchal rule weighting system described in section 3.5, and adds it to the baseline forecast where the event is supposed to take place.

The FSS will collect information on the names of all the products that had planned upcoming events and the summarized similarity grade for each event (as described in section 3.5) of each product were the three most relevant events were not identical to the attributes of the planned event.

The FSS will then construct a report for the forecaster which is ABC classified with the names of products and their similarity grade in ascending order. With that report the forecaster should more easily get an overview of the products he has to focus on and he can manually manipulate all of the products he chooses and he believes that require more attention.

The process described in this chapter for automatically making forecasts for a company’s complete product line offers a great deal of possibilities, such as aggregating data with dimensions for analyzing purposes. Three most practical dimensions should be:

* Product dimension: product -> product group -> product family -> product line
* Geographic dimension: customer -> sales region -> country
* Time dimension: different bucket size (days -> weeks -> years) and horizon

When a company has aggregated its data in such a way, it can more easily examine it and optimize all operational decisions with regards to expected demand.

### Identifying successful promotions

Sales promotions, in general, are meant to stimulate stronger target market response than would otherwise occur without the promotions. Promotion costs can be significant, whether that cost is calculated as lost profit when a product is put on discount, advertising cost to stimulate the sales of a product or extra inventory holding cost. After our survey of the companies visited and introduced in section 2.1 we recognized the need marketers have of identifying successful promotions. Often marketers did not know whether a particular promotion could be justified with regards to promotional cost versus the sales increase gain. Because of this lack of information it has been suggested that high levels of promotional activity can lead to a loss of control over a company’s supply chain and hence to their cash flow crisis [20]. All the companies visited did some kind of a promotional calendar plan for the whole year at some time point, and they based their promotional decisions on purely judgmental intuition. Using the data derived from event analysis a binomial programming model is proposed that can identify the most beneficiary promotions and aid marketers in making an optimal promotional calendar. The main goal of the model is to maximize the companies expected profit by identifying the most successful promotions that occurred in the past. Marketers can then use that information to build a promotional calendar for future periods.

The database described in section 3.2 has information on the sales increase or decrease that occurred as a result of a particular event that took place. Section 3.2 discussed the benefit of collecting additional data and storing it in the database, such as event costs. The FSS also has a two way data link with the companies ERP system and all ERP systems have information such as sale price of a particular product and the cost of goods. The indexes and data needed for the model is listed in the following.

**Indexes:**

* p = product: p =1,2,….,n
* i = event type: i=1,2,....,q
* t = month: t=1,2,…..,12
* d = duration: d = 1,2,3,4
* s = affected location: s = 1,2,….,r

**Data:**

* Cp,i,t,d,s = Average cost of event on product p for event type i, in month t, with duration d for location s
* Vp,i,t,d,s = Average event value on product p, for event type i, in month t, with duration d for location s
* Rp = Sales price of product p
* Gp = Cost of goods of product p
* Dp,i = Size of discount on product p for event type I (if event type is 2 for 1 set discount as 50% etc.)

Where Cp,i,t,d,s and Vp,i,t,d,s is the average effect of exactly matching events.

**Decision variable:**

The model has only one binomial decision variable which is described below.

Xp,i,t,d,s =

1 if we decide to have event for product p for event type i, in month t, with duration d for location s

0 otherwise

**Objective function:**

The objective function (3) describes the total profit which is to be maximized. The total profit is formed by multiplying the decision variable with the value of the particular event, the sales price of the product and one minus the size of the discount if there is any. Next the cost is subtracted by multiplying the decision variable with the cost of the particular event and the cost of goods of the product.

MAX (3)

**Constraints:**

The constraints for this model would have to be formulated and custom made for each company’s preference, and can be as many and as elaborated as each company chooses. Constraints 4-7 describe some possible constraints that might be beneficiary for most mid-sized companies.

Equation (20) guaranties that a company may have no more than ‘n’ event types present in each month.

(4)

Equation (21) guaranties that a company may only have one or less event on a particular product in the same month, for example a company would not want to have both an ad-campaign and a 2 for 1 promotion on the same product in the same month.

(5)

Equation (22) guaranties that the company has at least one event for each of its locations per year, for example if the company wants to make sure that it will have an event at each store at some time of the year.

(6)

Equation (23) guaranties that the company does not spend more than ‘k’ each month in events or any amount of money the company wants to spend.

(7)

The binomial programming model described is very efficient in helping the user identifying the most successful events that have been witnessed in each month in the past, and using that information to suggest the attributes of future events. As previously stated the data used for this model would be derived from the continually increasing event database described in section 3.2. Therefore the shortcomings of this model would be the fact it can only suggest exactly matching events that have occurred in the past, it would not suggest implementing a particular event in a future time period if the exact event has not been witnessed before in the past. Therefore the forecaster or marketers would have to judgmentally adapt the value of past events they would like to plan for if they wanted to alter its future timing.

## Pre- and post-event effects

Often when an event takes place there are changes in the sales time series both before and after the event. A company might for example put one of its products on a large discount, and the company’s customers might not buy that product just before the discount begins. Also the customers would overstock on the product when it is in its promotion period and therefore not buy it in the following period. One way that the FSS could offer to analyze these pre- and post-event effects, is to automatically code the pre- and post-event effects as event types of their own, to explain for example a drop in sales of a product in the periods before and after a promotion. The FSS then analyses all pre- and post-event effects of all past events and offers the forecaster a knowledge base of those effects.

## Overlapping events

In a real world situation, companies often face the problem of overlapping events. For example a particular store might have a big promotion campaign currently running, and also a large discount on one of its products at the same time. It would be extremely difficult or impossible to try to sufficiently estimate the effects one event would have on the time series over the other. That’s why the FSS will offer the solution of combining those events and coding them as one event. That way the FSS can estimate the value of the combined effect and save it in the database table for later reference.

## Shadow effects

Researchers and retailers acknowledge that the impact of marketing actions goes beyond the individual product. Often when a product is affected by an event it will have an effect on other products, this effect is often referred to as the shadow effect. For example if a hardware store would have a large discount on a paint product, the event would probably affect the sales on paint brushes or painting trays also, regardless if those products are in a state of event or not. Price promotion of a certain product boosts both sales of the promoted product itself and sales of (non-promoted, full-margin) complementary products [21]. The FSS will provide the forecaster with a shadow effect module that will aid the forecaster in analyzing those shadow effects. An understanding of how products interrelate and how these interrelationships can be exploited by price and promotion strategies can help forecasters in driving purchase behavior, and make optimal use of promotional resources. These interrelationships also work in such a way that if a company would decide to promote one of its products then sales of a complementary product might decrease. Following is a description on how the shadow effect module in the FSS will work and figure 5 describes the process.

When the forecaster is in the process of defining a new event, the FSS will provide the forecaster with the means of choosing products that he/she believes will be affected by that event. The forecaster will judgmentally choose all of the products he/she believes will be affected. The FSS will then populate the information needed in database table referred as the shadow table. Table 3 shows an example of a shadow table. One line will be made in the shadow table for each selected shadow product. When the event passes the FSS will automatically calculate the shadow effect of all the selected products by taking the difference of actual sales from the previously made forecast, and insert the value into the shadow table seen in table 3.

Figure 5: The shadow effect module, process and functionality

Next time a similar event is produced the FSS will prompt the user of the shadow effects previously witnessed, and give the forecaster the possibility of altering the forecast of the selected products accordingly.



## Implementation of a prototype forecasting support system

For testing purposes a prototype forecasting support system (FSS) was developed and implemented in Matlab 7.1. The FSS was constructed with four forecasting methods;

**Moving average:**

(8)

Where Lt is the average of the demand Dt at last N periods, and the forecast becomes:

 (9)

**Simple exponential smoothing:**

Where the previously stated same moving average is used to make the forecast Ft.

 (10)

The forecast is then adapted with the following formula:

 (12)

Where α is the exponential smoothing parameter; 0 < α < 1

**Trend-corrected exponential smoothing – Holt:**

The forecast is calculated by:

 (13)

The estimation is adapted for the level (L) and the trend (T):

 (14)

 (15)

Where α and are the exponential smoothing parameters; 0 < α,  < 1 .

**Trend and seasonality corrected exponential smoothing – Winter:**

The forecast is calculated for any period t+l with:

 (16)

The level (L), trend (T) and seasonal factor (S) is adapted with:

 (17)

 (18)

 (19)

Whereα, and  are the exponential smoothing parameters; 0 < α, ,  < 1

The exponential smoothing parameters used are estimated by minimizing the sum of MSE over the historic data using an iterative search method. The FSS chooses the best available forecast by calculating those error measurements listed below and taking the weighted average of them:

**Error:**

 (20)

**Mean Absolute Deviation (MAD):**

 (21)

**Mean Absolute Percentage Error (MAPE):**

 (22)

**Mean Squared Error (MSE):**

 (23)

The test FSS requires two documents for input, one document is the sales history of the product that is to be forecasted, and the second document is the event log of the product.

After the data for a single product has been loaded into the test FSS, the system uses the method described in section 3.3 to construct a baseline and calculate the values of past events. The FSS makes a new 12 month forecast for the baseline by using the most recent 24 months. The forecaster is then presented with a number of options to judgmentally change the baseline forecast if he has knowledge of upcoming events that are similar to past events, or he can stick to the baseline forecast if he believes there are no upcoming events in the next 12 month period. If the forecaster has information of an upcoming event he can insert the necessary event data and the FSS finds the three most relevant events by using the similarity support described in section 3.5. The forecaster can also visually examine all the past events and their effect via the memory support.

Figure 6 shows the Graphical User Interface (GUI) of the prototype FSS. The forecaster can visually examine the whole actual sales time-series, the effects of each individual event and the 12 month forecast of the baseline on the graph. The forecaster is also presented with a table containing each past event, the period the event took place, type of the event, location of the event and the value of the event. Another table is also presented which shows the forecaster the value of each period in the 12 month forecast. If the forecaster for example knows that a promotion will take place in month 9, that is similar to the events that are named “1” in this example, he can simply insert the new event name, choose month 9, choose all of the events in the event table that are called “1” and click on “Make new event”. The FSS will then take the average of all the selected past events named “1” and add it to the 12 month baseline forecast in month 9 The forecaster can continue and judgmentally change all of the months he chooses. When the adjustments are finished the forecaster can press “Final Forecast”.

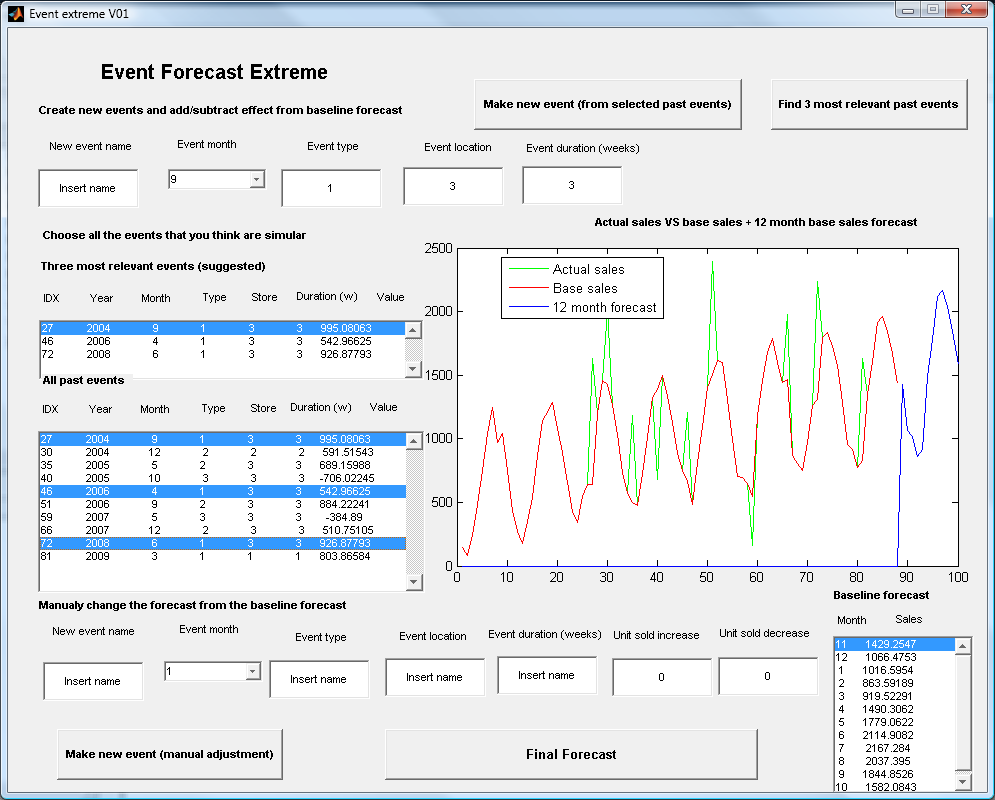


Figure 6: The first graphical user interface (GUI) of the prototype FSS

After the forecaster has pressed “Final Forecast” the forecaster is presented with a new GUI which contains a graph of the original baseline forecast versus the new judgmentally changed forecast (see figure 7). The forecaster is also presented with a table containing the forecasted values, and can export his findings into Microsoft Excel.

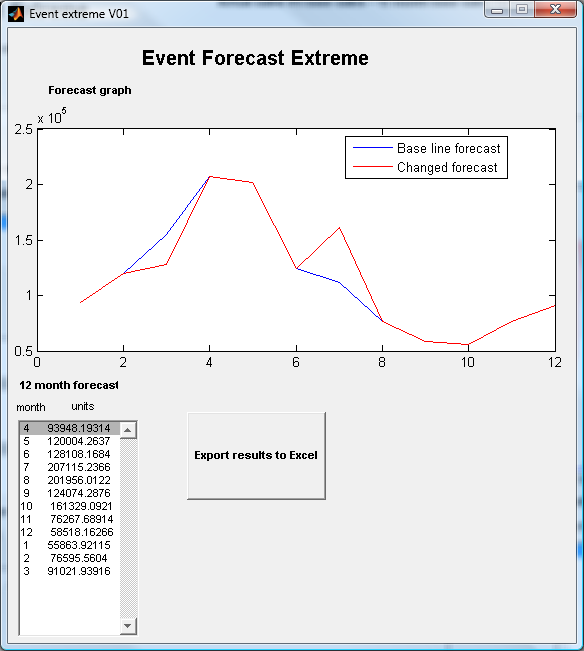


Figure 7: The second graphical user interface (GUI) of the prototype FSS

**Chapter 4**

# Testing and results of the prototype forecasting support system

The following chapter describes the testing process of the prototype FSS and evaluates the procedure used for forecasting in the presence of events. The first section describes how the testing data was generated. The second section describes the results from the event analysis of the testing data, and the third section describes the results from event forecasting using the FSS.



## The data

A data series was generated that would represent the sales for one product over a period of 100 months. It was assumed that the generated data series would represent the cumulative sales for a company which had number of stores. A data series with 100 values from a normal distribution with mean 200 and standard deviation of 75 N(200,75) was generated. A sinus wave with an angular frequency of 12 and a phase of 100 was added to the time-series. The series was shifted up by adding the value 600 to all of the data points and finally we added an increasing trend to the series. Formula number (24) represents the data generated where A is the random variable from N(200,75), is the angular frequency of 12 and is the phase of 100.

(24)

The first 88 months of the generated data series was used as training data, and the last 12 months as testing data.

Five types of events were generated and distributed randomly at fourteen dates within the time-series. Ten events were placed within the training data and four events were placed within the testing data. This was done in order to forecast the last twelve months using the FSS and compare it to the generated data. The types of generated events can be seen in table 4 with their event effects which we assigned to each event. The first line in the table represents that a discount took place in store one and had the event effect of 500 units sales increase. The event type “Discount” is known by the FSS as (1), that explains the numbers in the table.



The event effect of a particular event was added to the value of the data point in the generated time-series were an event was placed. For example if in march 2008 an discount in all stores was placed, the value of the testing data that represents that month was increased by 700 units. Figure 8 shows the plot of the training data and the timing of the ten events we wanted to analyze.



Figure 8: The generated testing data and the timing of the past events

## Event analysis

The FSS was used to analyze the training data and estimate the effects of the past events. Figure 4 in chapter 3.6 shows the GUI from the FSS with the generated data. Table 5 shows the average effects of the past events as the FSS forecasted versus the real event effects as was assigned to the generated data. The average effects of the past events were derived by using the similarity support described in chapter 3.5.



We believe that the error of the event analysis from the FSS is acceptable for all of the events with an exception of the first event (Discount in store 1). The reason for such a high error for the first event might be explained with the fact that an event like that had only been witnessed once before in the past time-series and therefore we only had one reference case, and could not take the average of past cases. Also the actual sales data was constructed with a fairly high standard deviation, and therefore makes all forecasts more difficult.

## Event forecasting

The prototype FSS was tested with regards to its event forecasting capabilities for three scenarios:

1. **Timing of no future or past events known.** In practice this is the way practitioners would forecast their product line if they were using a commercial FSS, with no event analysis capabilities.
2. **Timing of past events known but not the timing of future events.** In practice this would be called a baseline forecast, were the past data has been analyzed and outliers adjusted.
3. **Both the timing of past and future events known.** This scenario shows the capabilities of the proposed FSS, both analyzing past events and using the average values of similar past events to help forecast future events.

Figures 9-11 display the results from the FSS for all of the scenarios. Figure 9 shows the forecast versus actual sales for scenario 1. The figure displays the results most FSS system on the market today would forecast for a time-series like this, the forecast picks up the trend and seasonality of the data series but is still not acceptable because of the event errors.



Figure 9: The results from the FSS forecast for scenario 1 where the timing of no future or past events are known compared to the actual sales.

Figure 10 displays the forecast versus actual sales for scenario 2. This forecast is a baseline forecast and therefore the past data has been stripped of any unexpected outliers such as promotions or stock-outs. These results are better with regards to forecast error than the results from scenario 1.



Figure 10: The results from the FSS forecast for scenario 2 where the timing of past events are known but the timing of future events are not known compared to the actual sales

Figure 11 displays the forecast versus actual sales for scenario 3. The FSS picks up the trend and seasonality of the data series and also adjusts the forecast for future planned events. From this figure it can be seen that these results are better with regards to forecast error than the results from scenario 2 or scenario 1.



Figure 11: The results from the FSS forecast for scenario 3 where both the timing of past and future events is known compared to the actual sales.

Figures 9-11 clearly display the benefit of using the FSS with regards to event forecasting. Figure 10 shows the results from scenario 3 which gives the best results of the three scenarios.

Table 6 displays the error summary for the twelve month forecast. The table shows that scenario 3 where both the timing of past and future events is known, is the best scenario with regards to total error, MAD and MAPE.



**Chapter 5**

# Discussion

In this paper we have described all the features we believe is necessary to have in an FSS. We recognize that operationally, it is clear that the accuracy of the forecast directly contributes to higher profits by reducing stock-out situations and lowering the level of safety inventory. With fewer stock-outs the profit of any company increases and also customer’s satisfaction [9]. However, the cost due to the complexity of system in terms of data preparation, setup and maintenance of sophisticated models requiring expert analysts also has an impact on the profitability of operations, given an incentive for simpler data and models. In practice, simpler models and FSS are more used and desirable. That’s why we have always strived in the design of the FSS to have it as simple and user-friendly as possible.

We showed that using the novel approach of estimating the effects of past events and the similarity support when forecasting for future events, resulted in increased forecasting accuracy. Those approaches are also applicable and we believe very beneficiary in large scale forecasting. With regards to forecasting accuracy and time consumption, when the FSS is set to automatically choose its reference cases when forecasting for future events. We recognize the risks when the FSS selects past reference cases automatically. We know it would be optimal to have the forecaster go through each individual product forecast. But with regards to today´s market behavior and the need to save as much time as possible in the manual work of making forecasts, we accept those risks and believe we will have a more practical and user friendly FSS in return.

The hierarchical rule system applied in the similarity module presented section 3.5 and implemented in the prototype FSS was purely based on the intuition of the authors and practitioners of forecasting in the companies visited. In the prototype FSS we put the most weight on the similarity of event type, followed by the similarity of location, then the similarity of the time of year and the least weight was put on the similarity of duration. For future work it would be needed to analyze a company’s sales and event history and use data mining and regression techniques to estimate the optimal hierarchal rule system.

We introduced a binomial programming model that identifies the most successful past promotions of a company. The model uses the data retrieved from the continually increasing database of the FSS and is relatively easy to implement. The benefits of using a model like the model presented could be substantial, since all of the companies we surveyed had difficulties or did not try to estimate the value of past events. From our discussions with the surveyed companies we also sensed that most companies have difficulties in deciding upon future events and making a promotional calendar, since they do not estimate the effects of past events. In such cases the proposed model could prove very useful.

In the process of this project and our company visits we continually came across the problem of data shortage at the companies. We are concerned that many companies do not have much data on past events and would have a hard time changing their demand planning process to start collecting that data. It will take time and effort to manage and continually update a FSS like this but we believe it is fully worth the time and effort.

The methods introduced in this paper are all relatively easy to implement and we believe a FSS with them included could improve the demand planning process for all companies, since to the best of our knowledge there is no FSS with those methods present on the market place today.

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