Industrial Engineering & Management — Production & Logistics Management
School of Management and Governance

Forecasting:

providing accurate forecasts for an automotive refinish manufacturer

PUBLIC VERSION

Master thesis

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"Prediction is very difficult, especially about the future."
Niels Bohr (1885 — 1962)

ATTENTION: In this public version several business sensitive images and tables have been blacked out, as well as some information on page 31. Appendix E is omitted entirely.

Summary

Valspar b.v. (abbreviation: Valspar) is an internationally operating organization which is specialized in the development, production, and sales of car refinish coatings and ancillary products. The company expects rapid growth in the near-future and aims to have its turnover doubled in five years time, with the financial year (FY) 2009 being the baseline. At the same time, Valspar wants to improve upon its service levels, while keeping a strong focus on safety. Meanwhile, warehouse and production capacity is limited. Valspar also has to deal with a changing distribution model and changing order characteristics. To face these challenges, the company is undertaking various measures, one being the improvement of its ability to forecast future sales in order to decrease the uncertainty in future sales.

Valspar aims to use the more accurate sales forecasts for production planning and inventory management to eventually reduce costs and increase both customer and employee satisfaction. The aggregation level on which we forecast therefore is the individual product level, where different packaging volumes are seen as different end products. Since Valspar sells most of its products world wide (in about 140 countries), we do not focus on specific product-market combinations.

The research goal is to evaluate the current fit between forecasted sales and achieved sales and to design alternative approaches to achieve better forecasting results by combining forecasts based on historic data (the system forecast) with forecasts based on market know-how (judgemental forecasts).

The scope of this project contains the top 20% of products with the highest turnover (or A-items), as well as mixing colours in the remaining 80%, because of the relatively large impact of these slower moving products on production and inventory resources and perceived customer service levels.

Our approach is to develop a software system which incorporates a univariate forecasting method to produce an initial forecast. For key products this forecast can then be adjusted to correct for circumstances expected over the planning horizon or perceived inadequacies in the initial forecast. We also present a flowchart for new product introductions as a means to reduce variability in demand and as such allowing for more accurate forecasts.

The Mean Absolute Deviation divided by the mean (MAD/mean) can be used as a measure for monitoring forecasting quality of individual products as well as entire product categories. It is scale free like the more commonly used Mean Absolute Percentage Error (MAPE) measure, but unlike the MAPE is symmetric and is less influenced by deviations of products with very little demand. We use the MAD/mean to evaluate the performance of the forecast.

The aggregate selection of the damped trend with no seasonality component (DA-N) exponential smoothing model for all products in scope yields a MAD/mean of about 44% for the financial year (FY) 2010, while the currently established forecast has a MAD/mean of 52% for FY 2010. Adding a seasonality exponent does not increase forecasting accuracy. Also, selecting unique exponential smoothing parameters for every product does not yield better results than selecting the same value for the exponential smoothing parameters for all products simultaneously. Using human judgement to adjust the system forecast is likely to improve the accuracy of the forecast, when used properly.

We recommend to use exponential smoothing for item level forecasts on a quarterly basis, since it has increased forecast accuracy compared to the current forecasting system, although we have not achieved our goal of a MAD/mean of 40% with just the system forecast. We also recommend to develop a system forecast for more paint related products, not just the scope items, and focus human adjustment on important items and/or items with a large deviation between forecast and achieved sales.

We also recommend forecasts for new product introduction to be made using an appropriate driver based on the 'newness' and type of products involved. Sales of new product introduction should be monitored carefully, preferably on a more intensive basis than once per quarter, since new product introductions are a major source of variability in sales. Other measures, like coordination with customers can also be taken to reduce this variability. Another measure to reduce uncertainty in future sales is to reduce the number of slow moving items. Demand for slow moving items is less predictable and when sales volume of one item is directed to another similar item, the demand for this similar item may become more stable.

Adjustments to the forecast should be monitored, such that feedback can be given on the adjustments (learning effect) and to check whether the process of adjusting the system forecast is necessary in the first place. The system forecast should be checked likewise and a tracking signal may be incorporated to signal where human judgement might be needed. For good human judgement, one needs adequate understanding of the system forecast to prevent over-adjustment. For this reason we recommend to make use of a single knowledgeable person or small group, for example the sales director, to weigh and interpret information about possible trend breaks.

Integrated forecasting systems based on exponential smoothing in (future) ERP systems to be used by Valspar (such as Oracle 11i) can help to increase automatization of the system forecast and tracking signals.

More and better information tends to lead to better forecasts. Valspar could therefore undertake some efforts to gather information about possible changes in future sales from both within and outside the company and use it to more accurately adjust the system forecast. Especially through sales offices and technicians Valspar could come closer to the end user. The company can also use the fact that the end user needs information from Valspar for every formulation to gather data of mixing colours usage, for example by introducing an online formulation database or by logging the offline data (with the end users consent).

Many of the above mentioned recommendations at least temporarily increase workload, but are helpful for Valspar to meet its ambitions with respect to increased service levels, cost reduction, and expansion of its business. Information which needs to be gathered to improve forecasting accuracy at the same time may lead to valuable knowledge about the needs of its customers and end users.

Samenvatting

Valspar b.v. (afgekort: Valspar) is een internationaal opererende organisatie die gespecialiseerd is in de ontwikkeling, productie en verkoop van autoreparatielakken en bijbehorende producten. De bedrijfsleiding verwacht een snelle groei en heeft zich tot doel gesteld om de omzet te verdubbelen in 5 jaar tijd, gerekend vanaf financieel jaar 2009. Tegelijkertijd wil Valspar de servicegraad verbeteren en de nadruk op veiligheid leggen, terwijl de capaciteit van de productie en de capaciteit van het voorraadmagazijn beperkt zijn. Daarnaast heeft Valspar te maken met een veranderend distributiemodel en gewijzigde bestelkarakteristieken. Valspar neemt verschillende maatregelen om deze uitdagingen aan te kunnen gaan. Eén daarvan is het verbeteren van haar kunde om voorspellingen van toekomstige verkopen te kunnen doen, om zo de onzekerheid in toekomstige verkopen terug te brengen.

Valspar wil nauwkeurigere verkoopvoorspellingen gebruiken voor productieplanning en voorraadbeheer om zo uiteindelijk kosten te reduceren en zowel klant- als werknemertevredenheid te verbeteren. Het aggregatieniveau waarop we voorspellen is daarom het individuele productniveau, waarbij verschillende verpakkingsmaten gezien worden als verschillende eindproducten. Aangezien Valspar de meeste van haar producten wereldwijd verkoopt (in zo'n 140 landen), focussen we ons niet op specifieke product-markt-combinaties.

Het onderzoeksdoel is om de huidige match tussen voorspelde verkopen en behaalde verkopen te evalueren en om alternatieve aanpakken te ontwerpen om betere voorspellingen te kunnen doen, die gebaseerd zijn op de combinatie van historische data (de systeemvoorspelling) en marktkennis (beoordelende voorspellingen).

Dit project omvat zowel de top 20% van producten met de meeste omzet als de mengkleuren in de overige 80%. Dit laatste vanwege de relatief grote invloed van deze langzaamlopende producten op serviceniveaus en productie- en voorraadcapaciteit.

Onze aanpak omvat het ontwikkelen van een softwaresysteem dat een univariate voorspellingmethode omvat om een initiële voorspelling te genereren. Voor belangrijke producten kan vervolgens de voorspelling aangepast worden aan verwachtingen gedurende de voorspelhorizon of aan veronderstelde oneffenheden in de initiële voorspelling. We presenteren ook een hulpmiddel om nauwekeurigere voorspellingen te doen voor productintroducties.

Het gemiddelde absolute verschil gedeeld door het gemiddelde (MAD/mean) is een goede maat om de kwaliteit van de voorspelling voor individuele producten of hele productgroepen te meten. Het is schaalonafhankelijk zoals de veelgebruikte gemiddelde absolute percentage fout (MAPE) maat, maar in tegenstelling tot de MAPE wél symmetrisch en wordt minder beïnvloed door afwijkingen van producten met een zeer lage vraag. We gebruiken de MAD/mean om de prestaties van de voorspelling te evalueren.

Het geaggregeerd selecteren van de gedempte trend zonder seizoenscomponent (DA-N) exponentiele afvlakkingsmodel voor alle producten die dit project omvat levert een MAD/mean op van ongeveer 44% voor het financiële jaar (FY) 2010, terwijl de huidige voorspelling een MAD/mean van ongeveer 52% oplevert. Het toevoegen van een seizoenscomponent verhoogt de voorspelkwaliteit niet. Daarnaast levert het selecteren van unieke exponentiele afvlakkingparameters voor elk product geen betere resultaten op dan het tegelijkertijd selecteren van dezelfde exponentiële afvlakkingscomponenten voor elk product. Het is waarschijnlijk dat de voorspelling beter wordt door het gebruik van menselijke beoordeling om de systeemvoorspelling bij stellen.

We raden het gebruik van de exponentiële afvlakking op individueel productniveau en op kwartaalbasis aan, omdat dit een betere voorspelling oplevert dan het huidige voorspelsysteem, hoewel ons doel van 40% voor de MAD/mean enkel hiermee niet is behaald. We bevelen daarnaast aan om een voorspellingssysteem te implementeren voor alle verfgerelateerde producten, dus niet alleen de producten die wij in dit project beschouwd hebben. Ook kan menselijke bijstelling toegepast worden op belangrijke producten en/of producten met een groot verschil tussen voorspelling en daadwerkelijk gerealiseerde verkopen.

We bevelen ook aan om voorspellingen voor nieuwe productintroducties te baseren op een geschikte onderliggende sleutel afhankelijk van de 'nieuwigheid' van de betrokken producten. Verkopen van nieuwe productintroducties zouden nauwkeurig gevolgd moeten worden, bij voorkeur vaker dan eens per kwartaal, omdat nieuwe productintroducties een grote bron van variabiliteit zijn. Andere maatregelen, zoals coördinatie met klanten kan ook helpen om de variabiliteit terug te dringen. Daarnaast kan ook overwogen worden om het aantal langzaamlopende producten terug te brengen. Vraag voor langzaamlopende producten is minder voorspelbaar en wanneer verkoopvolume van één product naar een ander product geleid wordt kan de vraag voor dit andere product ook stabieler worden.

Aanpassingen aan de voorspellingen zouden bijgehouden kunnen worden, zodat er een leereffect kan ontstaan en om te verifiëren dat het proces van bijstellen überhaupt nuttig is. De systeemvoorspelling zou op een gelijke manier bijgehouden kunnen worden en een tracking signaal kan geïntegreerd worden om aan te geven waar menselijke bijstelling gewenst is. Voor goede bijstelling is adequaat begrip van de systeemvoorspelling vereist om overmatig bijstellen te voorkomen. Daarom bevelen wij aan om gebruik te maken van één persoon (bijvoorbeeld de sales director) of een kleine groep personen om de informatie over mogelijke trendbreuken te wegen en interpreteren.

Geïntegreerde voorspelsystemen gebaseerd op exponentiële afvlakking in (toekomstige) ERP systemen (zoals Oracle 11i) zouden kunnen helpen om de systeemvoorspelling en tracking signalen meer te automatiseren.

Meer en betere informatie leidt vaak tot betere voorspellingen. Valspar zou daarom kunnen investeren in het verzamelen (zowel binnen als buiten het bedrijf zelf) van informatie over mogelijke toekomstige veranderingen in verkopen om daarmee nauwkeurigere bijstellingen te kunnen doen. In het bijzonder door gebruik te maken van haar verkoopkantoren en applicatiespecialisten kan Valspar dichter bij de eindgebruiker komen. Het bedrijf kan ook gebruik maken van het feit dat eindgebruikers informatie van Valspar nodig hebben voor elke kleurformulering door data te verzamelen. Ze kan dit bijvoorbeeld doen door het introduceren van een online kleurenformuledatabase of het bijhouden van offline data (met toestemming van de eindgebruiker).

Veel van de bovengenoemde aanbevelingen vergroten de werklast, in ieder geval tijdelijk, maar kunnen bijdragen aan Valspars ambitie om servicegraden omhoog te brengen, kostenbesparingen teweeg te brengen en de uitbereiding van het bedrijf mogelijk te maken. Informatie die verzameld dient te worden om de voorspelling te verbeteren kan tegelijkertijd leiden tot waardevolle kennis over de behoeften van klanten en eindgebruikers.

Acknowledgements

A student is required to work on his graduation assignment autonomously, but that does not mean that there are not people who have contributed to this report in one way or the other. I would therefore like to take this opportunity to thank them.

Discussion of this project with Henk Sasse has helped me gain insight in what problem I was actually solving, while he also provided me with data. I also recieved some data from Ingrid Hoogland, while Martin ten Berge was kind enough to help me get sales data from the ERP system into a file which I could manipulate and analyse.

I thank Bart de Bruijn, Marco Hoogervorst, and Theo Wemmers for discussing the possibilities for adjusting the forecast by sales managers. Guus Winkelman helped me understand Valspars distribution chain. I would also like thank Debby, Diana, Dirk, George, Janine, Manon, Nicolien, Renata, Shaun, and Wilma at the Product Management and Marketing department for their support and pleasant distractions.

Most importantly, I would like to thank my scientific supervisors Leo van der Wegen and Peter Schuur and my supervisors on behalf of Valspar: Jacco van Geresteyn and Tom Peter Nieuwenhuizen for their time and effort throughout this project.

Lelystad, July 2011

Stephan Domburg

Contents

1

Introduction

1.1 Context Description

Valspar b.v. (abbreviated in this report as Valspar) is an internationally operating organization specialized in the development, production and sales of car refinish coatings and ancillary products. Valspar is a full subsidiary of the Valspar Corporation, a United States based company with over 9,500 employees in 25 countries. The Valspar Corporation is currently the sixth largest paint and coatings company in the world, measured in turnover (*Valspar : Brands & Products*, 2010). The Valspar Corporation has divided its operations in seven market segments:

- Consumer
- Packaging Coatings
- Wood Coatings
- Industrial Coatings
- Automotive Coatings and Refinishing Systems
- Custom Finishing Systems
- Coating Intermediates

Much of the Automotive Coatings and Refinishing System segment is handled by Valspar, which has its main offices and manufacturing plant in Lelystad, the Netherlands. Here it currently employs about 170 employees.

Valspar expects rapid growth in the near-future and aims to have its turnover doubled in five years time, with the financial year (FY) 2009 being the baseline. At the same time, Valspar wants to improve upon its service levels, while keeping a strong focus on safety. To face these challenges, the company is undertaking measures such as extension of offices, production facilities and warehousing capacity. Valspar is also undertaking projects to reduce the number of slow-moving products and to set clear criteria for proposed new products. Furthermore, it wants to improve its ability to forecast future sales. This last issue is directed in this report.

For automotive refinish purposes, several paint and paint-related products are required, all of which are manufactured by Valspar. We here make the distinction between (mixing) colours and ancillary products and briefly discuss them.

Mixing colours are a series of paint products in different colours. The end-user — the person who actually spray-paints a car — can mix these paints together to match the colour of the car. He does this according to a formulation, which is usually generated by a software tool developed by Valspar. Combining the mixing colours in different quantities allows any car colour to be mixed. Valspar also sells some car paints premixed. This group of paints is called ready made. Ready made colours are a relatively small group in volume compared to the mixing colours.

Besides the actual car paints, some ancillary products are required for car refinish. This group includes hardeners, thinners, clear coats, and surfacers. Valspar also manufactures some industrial paint products, which are related to the car refinish products. Valspar sells its products in nearly 140 countries.

1.2 Problem Description

Already briefly discussed in Section 1.1: "Context Description", Valspar wants to use more accurate forecasts. Sales forecasting is performed to decrease uncertainty in future sales. We therefore consider uncertainty in future sales the core problem. A core problem in this report refers to a root cause: an initiating cause which leads to an outcome or effect of interest. The action problem is to reduce this uncertainty. While this implies a forecasting error which does not exceed a certain norm, it is very hard to express the norm and the current deviation from this norm. However, the consequences of the core problem as well as a changing environment hint that there is something to gain from solving the action problem.

We did not find any literature on a norm for uncertainty in future sales in the automotive industry. We therefore choose to have a norm in relative terms: assessment of the current performance on uncertainty of future sales should give at least some insight in what could be achieved.

For the structure of this report we deem it necessary to already divide the core problem into three distinct parts. The first part concerns the input for the forecasts. Specific information of the market can greatly influence the accuracy of the forecasts. Currently specific market information is not incorporated in the forecasts. Secondly, the forecasting techniques used are very basic: more sophisticated techniques may improve forecasts. Thirdly, there is always a stochastic part in forecasting which you cannot predict. We refer to this part as market uncertainty, similar to the name convention in the Capital Asset Pricing Model (*Marcowitz, 1959*).

Uncertainty in future sales leads to inefficient deployment of resources and sub-optimal safety stocks, which in the end leads to less customer and employee satisfaction and avoidable costs. This relationship is described under Section 1.2.1: "Consequences of the core problem". This section also provides insight in why we have chosen this core problem.

A changing environment also has an impact on the core problem and gives a sense of urgency of the core problem, this is discussed in Section 1.2.2: "Coping with a changing environment". Consequences and their relation to the core problem are schematically summarized in Section 1.2.3: "The problem bundle".

The consequences of the core problem are not thoroughly researched, but are established through discussion with the principal and other employees. Within the time schedule for this research, the relationships as described in this section cannot be extensively tested and are therefore assumptions. We feel however that the critical relationships as described here are sufficiently likely to be taken as the starting point for this research.

1.2.1 Consequences of the core problem

Uncertainty in future sales has influence on the inventory: safety stocks increase with increased uncertainty of future sales when a minimum service level is required. For Valspar this service level is measured in OTIF (On Time, In Full at the month end). The OTIF score for FY2011 is set at 96%, while in FY2010 93.7% was achieved. From safety stock theory we know that this increase in service level would require an increase in safety stock when uncertainty (usually measured in standard deviation) does not decrease (*Silver, Pyke and Peterson*, 1998). Since warehouse capacity is limited, this is not desirable.

Sub-optimal safety stocks also require more ad-hoc planning changes, resulting in disturbances, a higher risk of overtime and less optimal production volume (deviation from the Economic Production Quantity).

The inefficient use of resources is another direct consequence of uncertainty in future sales: when we consider human resources for example this might lead to decreased employee satisfaction and avoidable costs. A similar cause is inefficient purchasing of raw materials: additional transportation costs and less quantity discount can be considered avoidable costs.

1.2.2 Coping with a changing environment

The uncertainty in future sales is likely to become a more important issue in the near future. This changing environment is reflected in rapid growth of the production volume in the Lelystad plant, a changing distribution model, changed order patterns of customers, and impact of (environmental) legislation.

Management in Lelystad has set a target for the FY2011 on an increase in turnover of 8% and has expressed ambition to continue with a similar growth over the next few years. While warehouse capacity is limited, efficient warehousing becomes more and more important when service levels need to be met. Meanwhile, the OTIF service level should also increase, as explained in Section 1.2.1: "Consequences of the core problem".

The distribution model is also changing: already sales offices have been setup in some countries to directly supply resellers and cut out the importer and sometimes the dealer. Sales offices are likely to be setup in more and more countries. The proximity to the end-user thus increases and information is more likely to flow back to the company.

Since the financial crisis that started in 2007, order patterns have changed: customers tend to order less, but more frequently. This can be (at least partly) explained by the fact that inventory is more and more considered as locked-up capital that needs to be minimized. Also, freight costs have come down.

While the market for automotive refinish products is relatively calm, rapid changes often come in the form of transitions between products or series of products. When a new, better clear coat is introduced for example, sales may largely move from the 'old' product to the new one. Environmental legislation which limits the amount of Volatile Organic Compounds (VOC) in paints is already in place in the European Union and the US state of California. Similar legislation is likely to be introduced elsewhere in the near future. This legislation has made it illegal to use some entire product series in countries where it is in effect.

The changes in the environment of the company as described here give some sense of urgency in solving the action problem, since it is likely to become more and more important over the next few years. These changes are summarized in *"Table 1: Summary of the effects working in the core problem."*.

Negative effects (—) to the forecasting quality	Positive effects (+) to the forecasting quality
Limited warehouse capacity	Anticipated growth in production volume
Service level increase	More point-of-sale data
Changing distribution model	On the long run: extension of warehouse capacity
Changing order characteristics	
Legislation causes shift in product series	

Table 1: Summary of the effects working in the core problem.

1.2.3 The problem bundle

"Figure 1: The problem bundle." summarizes the issues explained in this chapter in a problem bundle and shows how they are related by arrows. The start of each arrow represents a cause that is directly linked to a consequence at the end of the arrow. Some causes influence consequences both directly and indirectly. In the end, the core problem and subsequent problems all end up in terms of decreased consumer satisfaction, decreased employee satisfaction, or increase in costs.

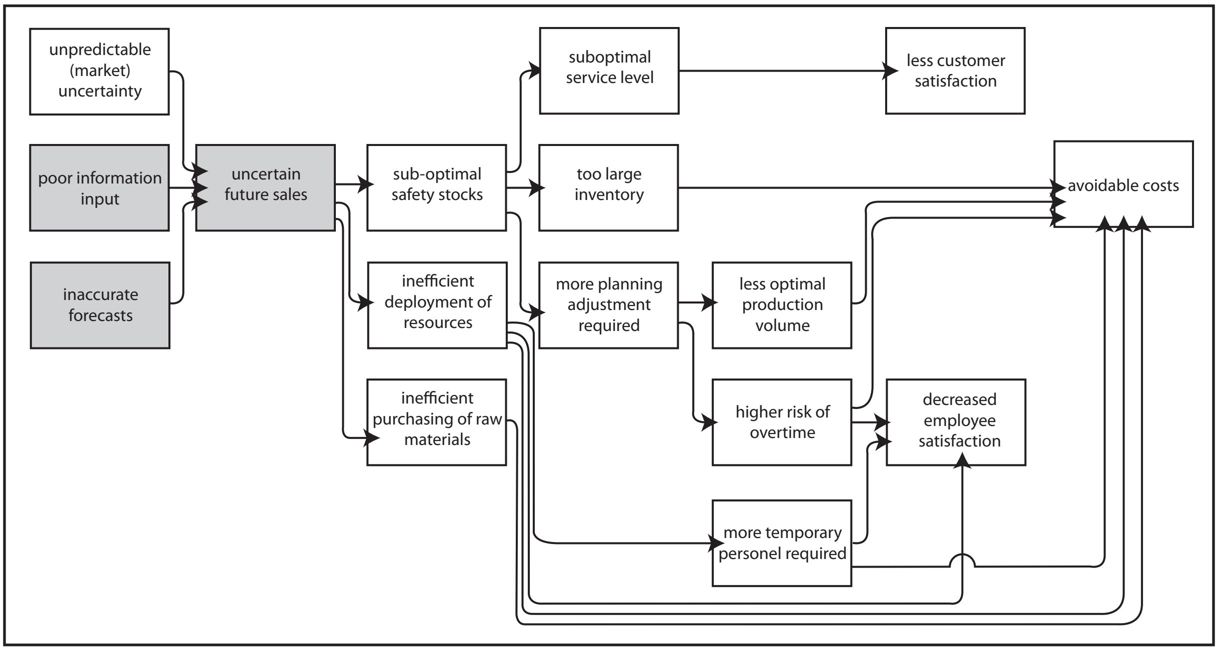


Figure 1: The problem bundle.

The core problem is marked grey in Figure 1 ("uncertain future sales"). It is not displayed as the far left problem as usual, but has already been split up in three parts as explained in Section 1.2: "Problem Description".

1.3 Research Objective

We focus on the core problem: reducing the uncertainty in future sales. The core problem is divided in three parts: poor information input, inaccurate forecasting methods and market uncertainty. Whilst unpredictable (market) uncertainty by definition is not solvable, we choose to focus on the two remaining causes: reducing uncertainty by adding market (judgemental) information in the forecast and by using advanced forecasting techniques on historic data.

However, we first need to know if there is an actual discrepancy between the current forecast quality and the norm. This brings us to the following research objective:

> THE OBJECTIVES OF THIS RESEARCH ARE TO EVALUATE THE CURRENT FIT BETWEEN FORECASTED SALES AND ACHIEVED SALES AND TO DESIGN ALTERNATIVE APPROACHES TO ACHIEVE BETTER FORECASTING RESULTS BY COMBINING FORECASTS BASED ON HISTORIC DATA WITH FORECASTS BASED ON MARKET KNOW-HOW (JUDGEMENTAL FORECASTS).

We try to ease the implementation of such design by developing tools the organization can use to calculate future forecasts.

1.4 Research Questions

To reach the research objective, we introduce three main research questions with corresponding sub-questions:

1. *What is the quality of the current forecast?*
2. *How can (advanced) forecasting methods be used on historic data to help reduce the uncertainty in future sales?*
3. *How can additional information from the market (human judgement) be incorporated in the forecast?*

We answer research question 1 in *Chapter 2: "Current forecast quality"*. In *Chapter 3: "System forecast"* we discuss research question 2, while in *Chapter 4: "Incorporating human judgement"* we answer research question 3.

We define tacit information as information which is readily available within the information: it is already made explicit. Intacit information on the other hand is known by one or more employees, but is more implicit and therefore often requires more effort to gain access to.

1.5 Research scope

Valspar benefits most from accurate sales forecasts on A-products. This group includes about 20% of all products, while accounting for about 80% of the yearly turnover. While most of these A-products are also stock keeping units (SKU's), a more accurate forecast for these products can help decrease safety stocks and/or increase the service level. Demand for B- or C-items is often of a more erratic nature, which makes a reliable forecast much harder. For all A-items, including MTO's, a more accurate forecast can make production planning less prone to last-minute changes. Since A-items account for about 80% of the turnover, we do not consider limiting the scope to only these items a problem. All A-items are produced at least partly in the Lelystad plant. Besides conventional A-items, we would also like to include mixing colours. They are important enough to be considered A-items, even when some of them are not in the top 20% best selling products.

Management is primarily interested in a forecast to aid production planning and inventory management decisions. The focus of our research and the aggregation level of the forecast is therefore on sales forecasting per end product. We use the term end product here, because some products can come in multiple packaging volumes. Each packaging volume is a different end product (or *item*).

Although some products are not sold everywhere in the world, mostly for legislative reasons, most products are sold in many different markets simultaneously. Aggregating over all sales areas usually leads to a more stable demand pattern, which should increase forecasting accuracy. The current forecast also takes this approach, which makes comparison easier.

1.6 Approach

The most common approach when dealing with forecasts for many products is to use a software system which incorporates a univariate forecasting method and to produce an initial forecast. For key products this forecast can then be adjusted to correct expected circumstances expected over the planning horizon or perceived inadequacies in the initial forecast. (*Fildes et al.*, 2009). Since we have to deal with a large number of products, we chose the same approach for this research. This is reflected in the research questions.

Below the research questions are split up in sub questions and a bullet describes how we plan to tackle each research question.

1. *What is the quality of the current forecast?*
   - 1a. *What is a good measure for forecast quality?*
     - *We look in the literature for measures of forecast errors and select the measure which best fits the goal of the research.*
   - 1b. *What data is required for the current forecast and how should this data be processed?*
     - *From the measure of forecasting quality follows the required data. From discussion with the principal we find out what data processing steps are required to get the required data from the available data.*
   - 1c. *How much do the actual achieved sales deviate from the current forecast and how is this forecast setup?*
     - *We gather the forecasts and actual sales data for FY08, FY09 and FY10 and calculate the deviation.*
   - 1d. *What should be the maximum deviation of the actual achieved sales with the forecast after intervention?*
     - *We establish a relative increase in forecasting accuracy as the goal.*
2. *How can (advanced) forecasting methods be used on historic data to help reduce the uncertainty in future sales?*
   - 2a. *What feasible (advanced) forecasting methods are described in the literature?*
     - *We do a literature study to find which feasible (advanced) forecasting methods are described in the literature.*
   - 2b. *How can we find the required parameters for the forecasting methods?*
     - *We find common methods for parameters estimation and find which yields the best results for our data set.*
   - 2c. *How can we apply the forecasting method to our data set?*
     - *We select an implementation method in discussion with the principal.*
   - 2d. *Do the proposed forecasting methods outperform the current simple forecast?*
     - *We do a benchmark where we test the performance of the current forecasting rules to the proposed forecasting method.*
3. *How can additional information from the market (human judgement) be incorporated in the forecast?*

3a. *Does adjustment of the individual product forecast using aggregated forecasts improve the forecast?*
   - *We analyse the aggregated sales volume to correct the individual product sales data. We check whether this correction improves the forecast.*

3b. *How can we use other information than historic data to adjust the forecast?*
   - *We propose a framework for adjusting the system forecast.*

3c. *How should new product introductions be dealt with?*
   - *By analysing a case and literature, we will describe what aspects to take into account.*

We find it important to not only take a measure for forecasting quality for one year, but also to check the measure itself by testing its stability over multiple years. A highly fluctuating forecasting measure is an indicator of a lot of variance in this indicator, which does not make it a good measure to check for improvement. This improvement or lack of improvement might be hidden by the variance of the measure for forecasting quality.

The current forecast is performed on a quarterly basis. To be able to properly compare a new forecasting system to the present one, it is most convenient to also use a quarter based one-period-ahead forecasting system.

1.7 Structure of this thesis

The structure of this report follows the forecasting procedure as displayed in *Figure 2: The structure of this thesis follows the structure of the forecasting procedure*.

To find out to what extend there is uncertainty of future sales, we test the current uncertainty and find a norm to compare it to in *Chapter 2: "Current forecast quality"*.

In *Chapter 3: "System forecast"* we then find a framework from the literature and use it on sales data.

The incorporation of market information (human judgement) is discussed in *Chapter 4: "Incorporating human judgement"*.

In *Chapter 5: "Conclusions and recommendations"* we recapitulate on the most important conclusions and present recommendations.

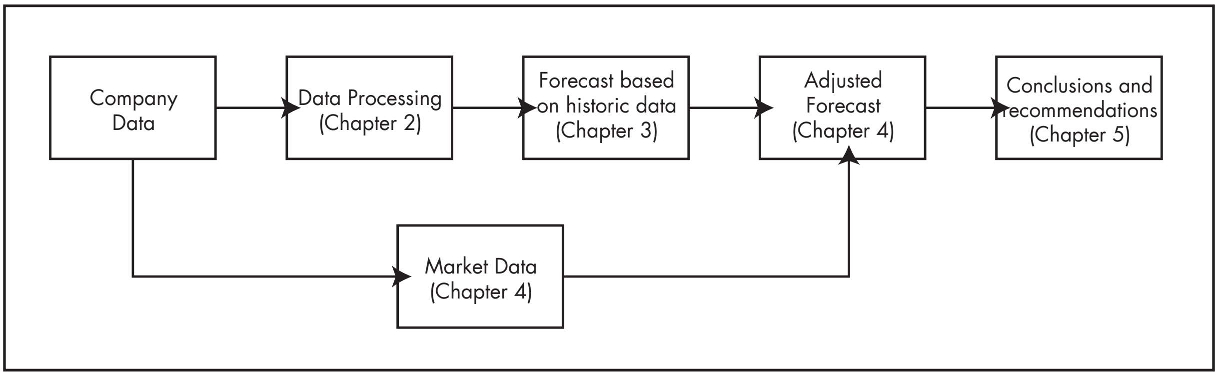


Figure 2: The structure of this thesis follows the structure of the forecasting procedure

2

Current forecast quality

In this chapter we explore the current forecast quality. First, we need to define the forecast quality such that we can quantify the current forecasting quality. Quantifying is essential to measure how our later efforts to improve the forecast work out. We define the measure in *Section 2.1: "Measurement of forecasting quality"*.

Since the data required for the measure turns out to not be readily available, we have to establish a way to get from an aggregate forecast expressed in turnover per product group to individual forecasts expressed in units per product. We do this in *Section 2.2: "Deriving per product forecasts from aggregated forecasts"*.

Since the data set we have acquired contains more data than we require, we need to select which data we find still representable for the current situation. We also need to perform some filter steps to narrow the data set down to the products within scope. We do this in *Section 2.3: "Data selection"* and *Section 2.4: "Data processing"*.

We present the current forecasting quality in *Section 2.5: "Results of the analysis and goal"* and present our conclusions in *Section 2.6: "Conclusions"*. We have elaborated on the problem bundle presented in the previous chapter to gain insight in what causes uncertain future sales through poor information input and inaccurate forecasts in *Appendix A: Causes of the core problem*.

2.1 Measurement of forecasting quality

To be able to improve upon forecasting quality, we must first define what forecasting quality is and how we measure it. We define forecasting quality for an individual product as accuracy of the forecast with respect to the realised sales. Since forecasts in the past have been done on a quarterly basis, we also choose to perform forecasts quarterly (periods of $1/4^{th}$ of a year), so we are able to compare the outcomes.

We would like to find a measure which is not affected by the magnitude of demand, so we are able to aggregate the measurements of all products under consideration into a single value. The mean absolute percentage error (MAPE) is expressed as a percentage and fits this criterion. It is however not appropriate if sales are very low (or worse: zero), because of the division by the actual sales.

Since the MAPE is an intuitive measure and it is not affected by the magnitude of demand, the MAPE is a commonly used measure for forecasting quality. This measure is defined as follows:

Let m be the number of time periods, $x_1, x_2, ..., x_m$ the actual realised sales and $\hat{x}_{0,1}$, $\hat{x}_{1,2}, \ldots$, $\hat{x}_{m-1,m}$ the one-period-ahead forecasts. The MAPE is now given by:

$$MAPE = \left[\frac{1}{m}\sum_{t=1}^{m}\left|\frac{x_t - \hat{x}_{t-1,t}}{x_t}\right|\right] \times 100\%$$

We would like to find an average for not only one product. We therefore aggregate this into one percentage. Now let n be the number of products, the total MAPE is given by:

$$MAPE_{total} = \frac{1}{n}\sum_{s=1}^{n} MAPE_s$$

Since not only A-items but also mixing colours are within scope, the number of products with relatively erratic demand is much higher than first expected. The MAPE measure is sensitive to erratic demand. Also, it is not symmetrical: whereas a negative deviation (meaning the forecast is too low) has an upper limit of 100%, the positive deviation (meaning the forecast is too high) does not have an upper limit and as such can become very high. (*Armstrong & Collopy, 1992*). A symmetric variant of the MAPE has been proposed: the Symmetric Mean Absolute Percentage Error (SMAPE) (*O'Connor et al., 1997*). This variant was shown to be flawed and indeed asymmetric too (*Goodwin & Lawton, 1999*).

Also, since we average the MAPE's into one number, we assign equal weight to all products. This means a relative large penalty is given for very slow moving products (mixing colours). We would like to vary weights somewhat. Kolossa & Schütz (2007) propose to use the MAD/mean ratio. This can effectively be called a generalisation of the MAPE and since it weights individual products is therefore also referred to as Weighted Mean Average Percentage Error (WMAPE). The formula for the MAD/mean ratio is:

$$\frac{MAD}{Mean} = \left[\frac{\sum_{t=1}^{m}|x_t - \hat{x}_{t-1,t}|}{\sum_{t=1}^{m} x_t}\right] \times 100\%$$

In this chapter we will use both the MAPE and the MAD/mean measure to analyse the data. We will use the MAD/mean for comparing the current performance with the performance after the intervention, because it is a more intuitive measure than the MAPE when a low sales volume is considered and because the impact of very slow moving products is not as large compared to the MAPE.

2.2 Deriving per product forecasts from aggregated forecasts

In order to calculate the MAD/mean we need to have data on the sales per product (expressed in units) and also a forecasted number of units per product. Unfortunately, only an aggregated forecast is available, which expresses the expected turnover in Euro per product group. We therefore have to recalculate the forecast on a number-of-items-per-product-level, which requires some additional data and some assumptions to be made.

Product group #	Group # assignment	Product group name
1	21XXXX	Thinners
2	26XXXX	Primers
3	22XXXX	Hardeners
4	22XXXX	Clear Coats
5	28XXXX	Topcoat (ready made colours)
6	27XXXX (not 275XXX)	Topcoat (mixing colours except water base)
7	275XXX	Topcoat (water based mixing colours)
8	24XXXX & 29XXXX	Other Professional

Table 2: Summary of product groups

Let p be the product number ($p = 1, 2, \ldots, 14456$), t the time period ($t = 0, 1, \ldots 12$), and g the product group ($g = 1, 2, \ldots 8$). The product groups are listed in *"Table 2: Summary of product groups"*. These groups have been assigned according to their subgroup numbers in the ERP (Enterprise Resource Planning) system. Now let $T_{t,p,g}$ be the turnover at time t for product p in product group g, $FT_{t,p,g}$ the forecasted turnover at time t for product p in product group g, $P_{t,p,g}$ the number of products sold at time t for product p in product group g, and $FP_{t,p,g}$ the forecasted number of products sold at time t for product p in product group g. This brings us at the following function to calculate $FP_{t,p,g}$:

$$FP_{t,p,g} = \frac{\dfrac{T_{t-1,p,g}}{\sum_p T_{t-1,p,g}} \times \sum_p FT_{t,p,g}}{\dfrac{T_{t-1,p,g}}{P_{t-1,p,g}}}$$

The numerator of this formula can be interpreted as the fraction of turnover of a product within a product group in a previous period times the forecast for the current period for that product group. This is the forecasted turnover per product. The denominator is the mean sales price for that product in the previous period. For practical reasons, we choose the previous period mean sales price representative for the current period. We find this assumption holds within 10% average deviation for the 100 products with most turnover in FY 2010.

Some products are not produced locally but purchased elsewhere. These products have product group 'various' assigned to them. In the previous forecast these products were however assigned to other product groups, depending on the product. We therefore need to repeat this exercise to get realistic figures. In the data set, we have identified the 6 products in the 'various' group and assigned them to a one of the groups listed in *"Table 2: Summary of product groups"*, depending on the product characteristics. Because turnover for products which are bought elsewhere is very low in the ERP system, the derivation of individual forecasts from the group forecasts results in huge discrepancies.

2.3 Data selection

The data set we use in this report contains quarterly sales data for the financial years 2006, 2007, 2008, 2009, and 2010. Although sales data from earlier years is available, there are two reasons we do not use this data.

Firstly, the forecasts have not been stored in the ERP system, but have been stored separately. We could only retrieve forecasts on quarterly or monthly basis from 2008, 2009, 2010, and

2011. Since we use this forecast as a benchmark in this report, we can only use data from previous periods for initialization.

Secondly, many changes in the product range have occurred since 2006. Only 47.6% of the turnover in 2010 is generated by products which already existed in 2006. We therefore regard data previous to 2006 on item level not representative for use in forecasts.

Forecasts usually require demand data as opposed to sales data. This demand data is not available within the company, but we expect sales and demand data to be very similar, since the service level used is high (93.7% On Time, In Full for FY 2010).

2.4 Data processing

The data we use is extracted from the companies ERP-system, Baan IV B40c.46. No selection on specific products was made, filtering of out-of-scope items is performed after extracting the sales data.

In *"Table 3: Overview of data filtering steps."* each consecutive step in the data filtering is shown.

Step #	Filter criteria	Number of items filtered	Number of items left
0	None	0	14687
1	Discontinued items as per 01-2011	7006	7681
2	No turnover in FY08, FY09 and FY10	5473	2208
3	Mean sales price in FY10 < 3 Euro	31	2177
4	Non-paint items removed	141	2036
5	B and C items that are not mixing colours removed	578	1476

Table 3: Overview of data filtering steps.

In the first step all discontinued items at the time of the data extraction from the ERP system (January 2011) are filtered out, because these items are not relevant for future forecasting. In the second step we have eliminated all items which have not been sold in all three years. Keeping them in would indeed lower the MAD/mean score, without these items actually benefitting the company.

By filtering out items which have an average sales price of less than three Euro in FY10 many erroneous items are removed from the data set. All relevant items in the data set are considered by the company to have an average sales price of at least three Euro. An example of an item which did not meet this criterion is an item which has been given a cost price of 0.01 Euro to be able to administer a transport to a different production location. Using this filter criteria, these administration errors are effectively removed.

A-items have been defined by Valspar as the items with most turnover who together account for 80% of the turnover. B-items are the next-up items with most turnover who together account for 15% of the turnover, whereas the remaining 5% of turnover is generated by C-items.

This definition of the classification is typical. The classification usually leads to A-items containing 20% of the total number of items, B-items 30% and 50% by the C-items (*Silver, Pyke and Peterson*, 1998). From *"Table 4: A, B and C items in the data set of 1476 scope items" on page 12* we can see that these typical numbers do not match closely with the remaining products after step 5 of the filter process is performed. The number of B-items is less than expected, whilst the number of A items is larger than expected. We expect this to be the result of the filtering of products with no sales over the last three years.

Item group:	Number of items:	% of total:	Typical % of total:
A	367	25	20
B	300	20	30
C	809	54	50
Total (A+B+C)	1476	100	100
Mixing Colours	1333	90	-

Table 4: A, B and C items in the data set of 1476 scope items

The remaining number of items within scope (1476) is the union of A-items and Mixing Colours, as presented in *"Figure 3: The scope shown in a Venn diagram."*. Since there is overlap in Mixing Colours and A-items the total items within scope is not just the sum of these two categories.

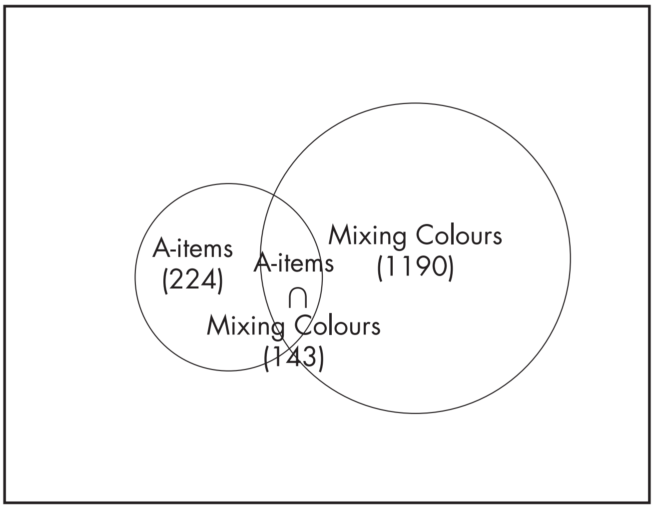


Figure 3: The scope shown in a Venn diagram.

To get a feeling how the items within scope are spread across the A, B and C-items we present a distribution-by-value diagram in *"Figure 4: Distribution by value." on page 13*. This diagram shows the cumulative turnover with respect to the cumulative percentage of items. As was to be expected from the data in *Table 4: A, B and C items in the data set of 1476 scope items*, the curve is also typical for a distribution-by-value diagram.

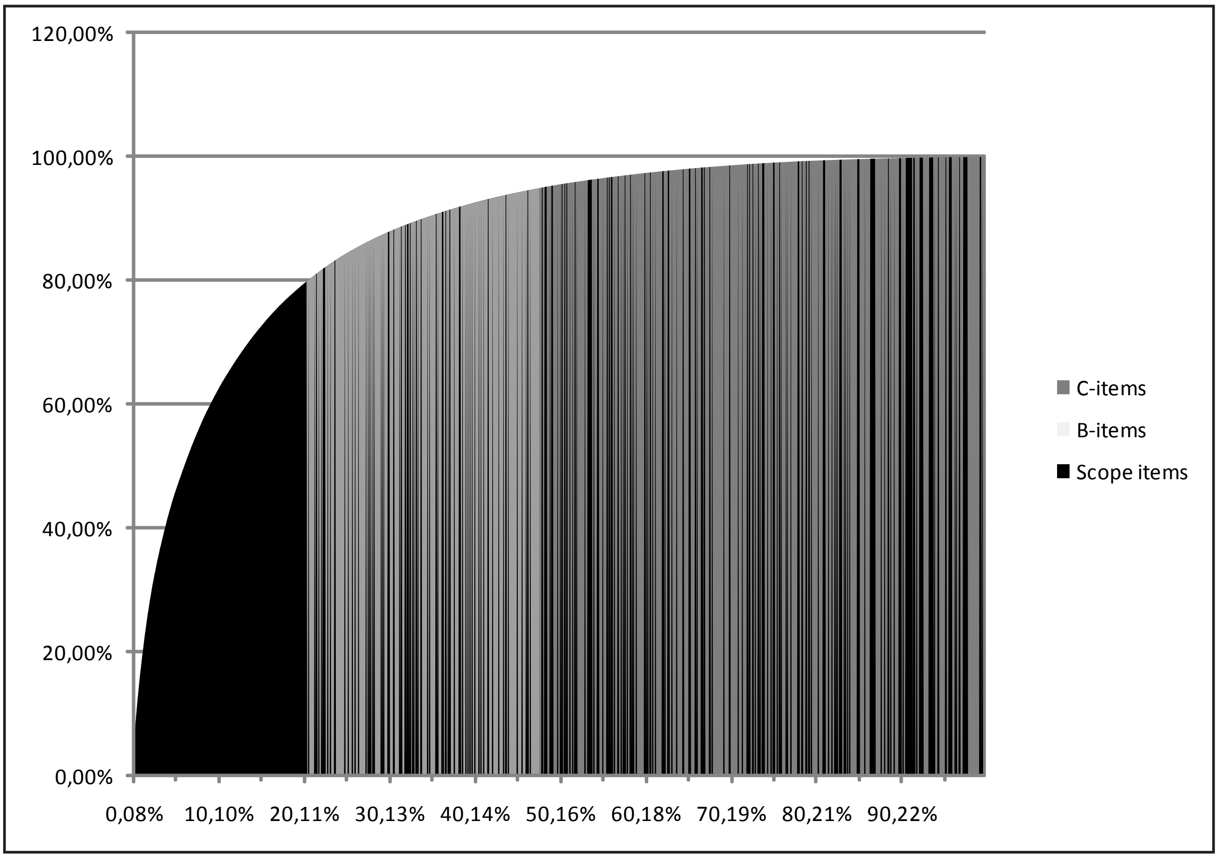


Figure 4: Distribution by value.

2.5 Results of the analysis and goal

In *"Table 5: MAPE and MAD/mean scores for 12 periods."* the MAPE scores and their respective biases are presented, as well as the MAD/mean ratio. All numbers are based on the 1476 paint products (A, B, and C items).

Period	MAPE (%)	MAD/mean (%)
Quarter 1, 2008	182.09	84.74
Quarter 2, 2008	201.05	47.27
Quarter 3, 2008	121.63	37.72
Quarter 4, 2008	95.55	36.99
Quarter 1, 2009	197.41	65.69
Quarter 2, 2009	135.49	65.73
Quarter 3, 2009	152.96	59.94
Quarter 4, 2009	127.09	54.91
Quarter 1, 2010	109.01	56.17
Quarter 2, 2010	139.19	53.70
Quarter 3, 2010	97.83	46.57
Quarter 4, 2010	82.28	51.27
Total	136.80	55.06

Table 5: MAPE and MAD/mean scores for 12 periods.

From *"Table 5: MAPE and MAD/mean scores for 12 periods." on page 13* we see that the MAPE varies greatly each quarter, while the MAD/mean ratio is a much more stable measure.

Our goal for improving the forecasts accuracy is to go from an average MAD/mean of about 55% to an average of about 40% over all scope items. *Kahn (1998)* suggests that the industry average is about 33%. While we believe the specific volatility in sales of individual products is higher than average for the automotive refinish industry in general and Valspar as a somewhat smaller player in specific, we do not aim to achieve this average. Instead, we would like to achieve a significant reduction using both a better system forecast and human adjustment.

2.6 Conclusions

We require a measurement of forecasting quality to be able to benchmark the current forecasting quality with the forecasting quality after intervention. The Mean Absolute Percentage Error (MAPE) is an intuitive measure which is also not affected by the magnitude of demand. For these properties, the MAPE is often used to measure forecast accuracy.

The MAPE is however not a good measure when we consider products with low magnitudes of demand. A small deviation in terms of numbers can lead to a large percentage deviation. In periods where there is no demand at all, the MAPE is even undefined. Large deviations on products with low magnitudes of demand have a high impact on the total MAPE too, since products are not weighed. Also, the MAPE is shown to be asymmetrical: while negative deviations can result in a maximum MAPE of 100%, positive deviations in theory can be infinite.

We therefore choose to use the ratio of Mean Absolute Deviation (MAD) by the mean magnitude of demand, since it is essentially a weighed version of the MAPE. For the data under consideration, we find that this forecasting quality measure is much more stable over 12 quarterly periods in the financial years 2008, 2009, and 2010.

For the current forecasting quality for the quarters of financial year 2008, 2009, and 2010 based on the MAD/mean we find a mean of 55.06% with a standard deviation of 13.17%. We aim to reduce the MAD/mean from 55.06% to 40%.

3

System forecast

Sylver, Pyke and Peterson (1998) describe three steps involved in statistically forecasting a time series. These steps are:

1. Select an appropriate underlying model of the demand pattern through time.
2. Select the values for the parameters inherent in the model.
3. Use the model and the parameter values to forecast the future demands.

The sub chapters in this chapter are setup as to follow these basic steps. We start with *Section 3.1: "Method selection"*, where we explore the literature to find what underlying models of the demand patterns can be used and how they typically perform. In *Section 3.2: "Forecast model parameter estimation"* we discuss two models which we will try with our data set. The practicalities of the implementation thereof are discussed in *Section 3.3: "Implementation of the system forecast"*. In *Section 3.4: "Results of future demand forecasting"* we present and discuss the results. Section 3.5: "Smooth error tracking signal" presents a way to find a bias in the forecast. Finally, we give our conclusions from this chapter in Section 3.6: "Conclusions".

3.1 Method selection

Although ARIMA models have been used for forecasting and have been thought of as more sophisticated, *Gardner (2006)* shows that these traditionally used models, despite being more complicated, are indeed a subset of exponential smoothing techniques. This understanding gives a theoretical foundation to the finding that exponential smoothing usually outperforms these models. Also, ARIMA models are harder to implement.

Neural networks have more recently been proposed as a tool for forecasting, but *Fildes (2001)* remarks that at least with data of the M3-competition there exists an 'unexciting performance of neural networks'. The M3-competition features 3003 data sets and has been used to benchmark forecasting methods. Furthermore, the implementation of neural networks is not very easy and its non-intuitive nature makes it harder to get management support.

Pegels (1969) has proposed a framework for standard exponential smoothing methods which has later been extended by *Gardner (1985)* and *Gardner (2006)*. We follow the naming convention by Gardner. This extended framework is presented in *"Table 6: Standard exponential smoothing methods"*.

Trend component	Seasonality component N (None)	A (Additive)	M (Multiplicative)
N (None)	N-N	N-A	N-M
A (Additive)	A-N	A-A	A-M
DA (Damped Additive)	DA-N	DA-A	DA-M
M (Multiplicative)	M-N	M-A	M-M
DM (Damped Multiplicative)	DM-N	DM-A	DM-M

Table 6: Standard exponential smoothing methods

When selecting a model, it is important that it gives a good forecast, not only a good model fit. The model fit refers to how well the model fits the actual sales data. We can judge the fit visually from the graph, or we can use a measure of forecasting quality to determine the fit. A more complicated model generally leads to a better fit, but the model might not describe the underlying relationship. Instead, it describes random error or noise. This is known as *overfitting*. A more complicated model may not result in a more accurate forecast. We therefore test the forecast quality using data which has not been used for fitting the model.

In a review paper on exponential smoothing *Gardner (2006)* lists 65 papers that present empirical studies for exponential smoothing from 1985 to 2006. Gardner finds that "In most cases, little attention was given to method selection, a generalization substantiated by the large number of studies with only one method listed."

Hyndman et al. (2002) propose to select the method individually for each product under consideration which best fits the data. They introduce a selection algorithm based on the Aikaike Information Criterion (AIC) (*Aikaike, 1974*) to do so. This tool for model selection weighs the goodness-of-fit and the number of parameters in the model. Later, *Billah et al. (2005)* have extended this by using other information criteria, like the Empirical Information Criteria (EIC). However, *Gardner (2006*) concludes that "Although the EIC criteria performed better than the others, this study is not benchmarked, and we do not know whether the EIC criteria picked methods better than aggregate selection of the DA-N method." The aggregated selection means applying the same method (in this case the damped trend model without seasonality) to all time series data.

Fildes (2001) concludes on this topic: "There is just too small a gain from selecting the 'best' method compared to selecting damped trend for all data series." This is why we choose to select the damped additive model without seasonality component (DA-N) for the bulk of the products within scope. We try to fit a damped additive model with seasonality exponent to products which we expect to have an underlying seasonality component to see whether this might improve the forecast.

3.2 Forecast model parameter estimation

Typical products that we expect to show a seasonal behaviour are hardeners. Hardeners come in a variety of different drying speeds: very slow, slow, standard, medium fast, fast, and very fast. The use of a specific hardener depends mostly on the temperature in the place of application. Although products are sold in both the northern and southern hemisphere, most products are sold in the northern hemisphere. This is why we expect to still see a seasonal component in the magnitude of demand. We therefore try a method besides the recommended DA-N method which includes a seasonality exponent on a few of these products, namely the A-M method (known as Holt-Winters), since this is the classical method used when a seasonal component is expected.

In this section we explore the A-M and DA-N methods and estimate their optimal relevant parameters. For comparison, we also use the A-N method in our discussion of the A-M method. Since the A-N method is a simplification of the A-M method (the seasonality component is omitted), we do not explicitly describe this method. It gives quick insight in whether the seasonality component is worth considering though.

We choose not to use adaptive smoothing—where we adjust the forecasting parameters during the forecast — since adaptive methods are not necessarily better than regular, nonadaptive smoothing and there is a risk of introducing instabilities (*Chatfield 1978*).

For both methods, we use the same aggregation level as in Chapter *2*: we focus on all end products within scope and want to arrive at sixteen individual one-quarter ahead forecasts per end product. After initialization, we find the first one-quarter ahead forecast. We update the forecasts using the appropriate procedure and get the second one-quarter ahead forecasts. We continue this process until the sixteenth one-quarter ahead forecast. The first twelve one-quarter ahead forecasts are used for model fitting: the parameters of the model are set such that the MAD/mean in the first twelve one-quarter-ahead forecasts is as low as possible. The thirteenth to sixteenth one-quarter-ahead forecasts are used to check the forecast performance.

In *Section 3.2.1: "Parameter estimation for the DA-N model"* we give the formulas for the DA-N method. The parameters of this method are estimated using a grid search. Using the grid search, we find both a single set of values for the three parameters for all products combined (so every product has the same parameters) and sets of values for individual parameters for each product (so every product is allowed to have different parameters). This is achieved using an implementation in Microsoft Excel, as described in *Section 3.3.1: "Implementation of the DA-N method"*.

In *Section 3.2.2: "Parameter estimation for the A-M method"* we give the relevant formulas for the AM method and try it on some products that we expect show seasonal behaviour.

3.2.1 Parameter estimation for the DA-N model

In this section we apply the DA-N model, known as the damped trend model. To obtain the initial values for a and b, named $\hat{a}_0$ and $\hat{b}_0$ respectively, we again use the following formula's (*Brown, 1963*):

$$\hat{a}_0 = \frac{6}{n(n+1)}\sum_t tx_t + \frac{2(2n-1)}{n(n+1)}\sum_t x_t$$

$$\hat{b}_0 = \frac{12}{n(n^2-1)}\sum_t tx_t + \frac{6}{n(n+1)}\sum_t x_t$$

We sum period t=1 to 16, since we choose to have 4 complete seasons for initialization. We do not choose to use the ratio to moving average procedure, since this is only helpful when there is a seasonal effect in the historic data which needs to be separated from the trend.

Then we use the following updating formulas:

$$\hat{a}_t = \alpha_{HW} x_t + (1-\alpha_{HW})(\hat{a}_{t-1} + \phi \hat{b}_{t-1})$$

$$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1}) + (1 - \beta_{HW})\phi\hat{b}_{t-1}$$

$$\hat{x}_{t,t+\tau} = \hat{a}_t + \sum_{i=1}^{\tau}\phi^i\hat{b}_t$$

The damped trend model requires three parameters: α_{HW}, β_{HW}, and ϕ.Using a simultaneous grid search for all scope products, we find the following values for all end products combined: α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8. The grid search assesses combinations of α_{HW}, β_{HW}, and ϕ simultaneously for all products, so each product has the same value for α_{HW}, β_{HW}, and ϕ. It judges the outcome based on the lowest total MAD/mean. For the implementation, see Section 3.3: "Implementation of the system forecast". We present an example of how this works out for one particular product, the 47-50/1 in *"Table 7: Example of calculation of forecast using the DA-N model for Hardener 47-50/1 with standard parameters"*. We find a MAD/mean of 22.03% for this example.

We have also used a grid search on every individual end product to determine the end product specific smoothing parameters. When we apply this to the same example product, this yields the damped trend forecast as displayed in *"Table 8: Example of calculation of forecast using the DA-N model for Hardener 47-50/1 with parameters found using grid search" on page 19*. In this specific case we find α_{HW} = 0, β_{HW} = 0, and ϕ = 1, effectively reducing the damped trend to a linear trend model, which does not update for new values. We find a MAD/mean of 20.21% for this example.

We will present the results with respect to the forecast quality of using these different smoothing parameters in Section 3.4: "Results of future demand forecasting".

Year	Quarter	Demand xt	Damped Trend Forecast	Error et	MAD
2006	-15	[redacted]			
	-14				
	-13				
	-12				
2007	-11				
	-10				
	-9				
	-8				
2008	-7				
	-6				
	-5				
	-4				
2009	-3				
	-2				
	-1				
	0				
2010	1				
	2				
	3				

Year	Quarter	Demand xt	Damped Trend Forecast	Error et	MAD
	4	[redacted]	[redacted]	[redacted]	[redacted]
MAD/mean					22.03%

Table 7: Example of calculation of forecast using the DA-N model for Hardener 47-50/1 with standard parameters

Year	Quarter	Demand xt	Damped Trend Forecast	Error et	MAD
2006	-15	[redacted]	[redacted]	[redacted]	[redacted]
	-14	[redacted]	[redacted]	[redacted]	[redacted]
	-13	[redacted]	[redacted]	[redacted]	[redacted]
	-12	[redacted]	[redacted]	[redacted]	[redacted]
2007	-11	[redacted]	[redacted]	[redacted]	[redacted]
	-10	[redacted]	[redacted]	[redacted]	[redacted]
	-9	[redacted]	[redacted]	[redacted]	[redacted]
	-8	[redacted]	[redacted]	[redacted]	[redacted]
2008	-7	[redacted]	[redacted]	[redacted]	[redacted]
	-6	[redacted]	[redacted]	[redacted]	[redacted]
	-5	[redacted]	[redacted]	[redacted]	[redacted]
	-4	[redacted]	[redacted]	[redacted]	[redacted]
2009	-3	[redacted]	[redacted]	[redacted]	[redacted]
	-2	[redacted]	[redacted]	[redacted]	[redacted]
	-1	[redacted]	[redacted]	[redacted]	[redacted]
	0	[redacted]	[redacted]	[redacted]	[redacted]
2010	1	[redacted]	[redacted]	[redacted]	[redacted]
	2	[redacted]	[redacted]	[redacted]	[redacted]
	3	[redacted]	[redacted]	[redacted]	[redacted]
	4	[redacted]	[redacted]	[redacted]	[redacted]
MAD/mean					20.21%

Table 8: Example of calculation of forecast using the DA-N model for Hardener 47-50/1 with parameters found using grid search

3.2.2 Parameter estimation for the A-M method

We use AM method in this section, otherwise known as the Holt-Winter exponential smoothing procedure for a seasonal model. *Sylver, Pyke and Peterson (1998)* recommend using at least four complete seasons and maximal six complete seasons for this procedure. In our case, a complete season consists of one year of four quarters, so in total we would need 16 to 24 quarters. Since there is reason to believe (for example due to the introduction of new products) that sales characteristics are changing rapidly, we choose to take four complete seasons, or 16 periods, as the initialization period.

Model:

$$x_t = (a + bt)F_t + \varepsilon_t$$

Where a is the level, b is the linear trend, F_t a seasonal index (coefficient) appropriate for period t, and ε_t are independent random variables with mean 0 and constant variance σ^2. The seasonality effects are assumed to be yearly, such that it has a length of *P* = 4 periods.

For the initialization, we use the most commonly used method: the ratio to moving average procedure. This method is recommended, because the trend and seasonal components in the historic data used for initialization need to be separated (*Hamburg and Young 1994*). To eliminate the trend component, a 4-period moving average is used. Since we have four periods per season (an even number) we have to do this twice and average the results to get a centred 4-period moving average. We get an estimate of F_t by dividing the demand x_t by the centred 4-period moving average. By averaging these values for the estimated F_t and normalizing, we get a 'true' F_t value. By dividing again the demand x_t by the 'true' value for F_t we have found, we get an estimate for the level. To obtain the initial values for a and b, named $\hat{a}_0$ and $\hat{b}_0$ respectively, we use the following formula's (*Brown, 1963*) on the estimates of level we found:

$$\hat{a}_0 = \frac{6}{n(n+1)}\sum_t tx_t + \frac{2(2n-1)}{n(n+1)}\sum_t x_t$$

$$\hat{b}_0 = \frac{12}{n(n^2-1)}\sum_t tx_t + \frac{6}{n(n+1)}\sum_t x_t$$

We sum period t=1 to 16, since we choose to have 4 complete seasons for initialization.

To update the parameter after new information has arrived (so after each quarter), we use the following formulas:

$$\hat{a}_t = \alpha_{HW}(x_t/\hat{F}_{t-P}) + (1-\alpha_{HW})(\hat{a}_{t-1} + \hat{b}_{t-1})$$

$$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1}) + (1-\beta_{HW})\hat{b}_{t-1}$$

$$\hat{F}_t = \gamma_{HW}(x_t/\hat{a}_t) + (1-\gamma_{HW})\hat{F}_{t-P}$$

The smoothing constants α_{HW}, β_{HW}, and γ_{HW} should be set relatively high to emphasize more recent data, whilst it should be set relatively low to make the model less sensitive to random fluctuations. We have found that most products demand characteristics change much over time: that is why we guess the smoothing constants will be relatively high. *Sylver, Pyke, and Peterson (1998)* recommend $0.02 \le \alpha_{HW} \le 0.51$, $0.005 \le \beta_{HW} \le 0.176$, and $0.05 \le \gamma_{HW} \le 0.50$. We choose to use a grid search algorithm on the top 10 of best selling products to produce values for α_{HW}, β_{HW}, and γ_{HW} that are best suitable for this data set. We find the following values: $\alpha_{HW} = 0.2$, $\beta_{HW} = 0.2$, and $\gamma_{HW} = 0.05$.

This is worked out the same example as earlier in *"Table 9: Example of calculation of forecast using the A-M model for Hardener 47-50/1" on page 21*. We find a MAD/mean of 28.33% for 2010.

Year	Quarter	Period t	Demand x_t	Centred 4-Period Moving Average	Estimate of F_t	F_t	Estimate of Level	HW Forecast of Demand	Error e_t
2006	1	-15				0,560			
	2	-14				1,054			
	3	-13			0,888	0,956			
	4	-12			1,625	1,430			
2007	1	-11			0,563	0,560			
	2	-10			1,058	1,054			
	3	-9			1,088	0,956			
	4	-8			1,328	1,430			
2008	1	-7			0,390	0,560			
	2	-6			1,087	1,054			
	3	-5			0,964	0,956			
	4	-4			1,443	1,430			
2009	1	-3			0,769	0,560			
	2	-2			1,096	1,054			
	3	-1				0,956			
	4	0				1,430			
2010	1	1				0,560			
	2	2				1,054			
	3	3				0,956			
	4	4				1,430			
MAD/MEAN									28.33

Table 9: Example of calculation of forecast using the A-M model for Hardener 47-50/1

When we apply the seasonal model to several items of which we expect some form of seasonality (for example hardeners which come in several, temperature dependent variants) we do not find a better MAD/mean for these products in FY2010 compared to a simple linear fit. Some products do however show some sign of seasonality, such as the 47-50/1 Hardener shown in *"Figure 5: Actual demand compared to forecast for 47-50/1 Hardener" on page 22.*

[redacted]

Figure 5: Actual demand compared to forecast for 47-50/1 Hardener

Although the *model fit* for this example in 2006-2009 is reasonable, the actual performance on forecasting 2010 sales under performs a simple linear trend forecast, so while the model fit is good, the forecasts is not.

We have plotted the error for the 47-50/1 example product in *"Figure 6: The error for the both DA-N forecasts and A-M forecast of the 47-50/1 Hardener"*. Since all three methods fluctuate around zero, we consider all of them to be without bias in this example.

[redacted]

Figure 6: The error for the both DA-N forecasts and A-M forecast of the 47-50/1 Hardener

3.3 Implementation of the system forecast

In *Section 3.3.1: "Implementation of the DA-N method"* we explain the way we have implemented the DA-N method itself, while we discuss the specifics of the grid search algorithm we have implemented to find the best parameters (α_{HW} , β_{HW} , and ϕ) in *Section 3.3.2: "Grid search implementation"*.

The implementation of the forecasting method should (preferably) be:

1. As simple as possible, such that others can easily understand the implementation and/or

update the forecast with new data.
2. Versatile enough, such that different initialization periods, parameters etc. can be easily used.
3. Be automated.
4. Be executed on software currently available within the company.

We therefore choose to use Microsoft Excel for implementation.

3.3.1 Implementation of the DA-N method

The DA-N method can easily be implemented in Microsoft Excel. It can however not easily be implemented such that it allows for performing a grid search on all data. We therefore choose to use a User Defined Function (UDF) called TrendForecast in Visual Basic for Applications (VBA). This function requires two arrays and allows for three optional parameters. The syntax is as follows:

```
TrendForecast(InitSales [required array], NewSales [required array],
alpha [optional parameter], beta [optional parameter], phi [optional
parameter])
```

The function returns a one-period-ahead forecast using the DA-N method. The first array required for input is the sales data which should be used for initialization. The initial forecast is then updated as new data comes in as specified in the second array. Parameters alpha, beta and phi can optionally be defined, otherwise the function will default to alpha = 0.2, beta = 0.2 and phi = 0.8. We have found these values to give an overall good performance.

The VBA code of this UDF (TrendForecast) can be found in *Appendix B: "VBA code"*. The ParameterSolver code in the same appendix is used to automate the Excel Solver to determine the best smoothing parameters.

3.3.2 Grid search implementation

We have found that the Excel Solver is sometimes not able to find the optimal parameters which lead to the lowest sum of errors, even when using nonlinear solving methods introduced in Microsoft Excel 2010. We have therefore implemented a basic grid search in Excel, which enumerates all combinations of three variables: α_{HW} = [0.00,0.05, 0.10,...0.50], β_{HW} = [0.00, 0.05, 0.10,...0.50], and ϕ = [1.00, 0.95, 0.90,...0.70]. These arrays contain all 'reasonable' typical values. Per quarter and per end product a total of 11 x 11 x 7 = 847 forecasts are made.

The arrays are easily graphically represented as 7 matrices of 11 x 11 cells. Using colour coding (the lower the MAD/mean value, the greener the cell) we can easily see which combinations of parameters yield good results. We present an example for one end product in *Appendix D: "Example of the graphical representation of the Grid Search results"*.

We have taken this graphical representation as the basis to automate the Grid Search and select the lowest value. The VBA code of this UDF (FindLowest) can also be found in *Appendix B: "VBA code"*.

3.4 Results of future demand forecasting

We would like to see how our efforts to improve the system forecast have worked out if we try it on the same data set used in the previous chapter (sales data from the financial years 2006, 2007, 2008, 2009 and 2010). We therefore summarize the MAD/mean of the forecast as was previously used (forecast established by MT), the DA-N method with 'standard' parameters (α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8) for all products, the DA-N method with individual parameters through the Excel Solver, and the DA-N method with individual parameters through the grid search. We distinguish the estimation interval FY06 - FY09 and the forecast interval FY10.

Forecasting method	MAD/mean FY06 - FY09	MAD/mean FY10
Same quarter as last year ($Q_t = Q_{t-4}$)	60.15%	52.58%
Forecast established by MT	60.74%	51.93%
DA-N method with (α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8)	52.09%	43.93%
DA-N method with individual parameters (Excel Solver)	51.41%	62.50%
DA-N method with individual parameters (grid search)	45.55%	46.11%

Table 10: Overview of future demand forecasting performance

The implementation of the DA-N method with the grid search and the implementation with the standard parameters do not perform very differently, although the individual parameters for every product approach does show a better model fit, as expected. Since using the same parameter values for all products is a much simpler implementation, we choose to use this implementation.

We have calculated the cost savings on inventory in *Appendix E: "Cost savings on inventory"*.

Reporting on a survey with 40 respondents, Kahn (1998) reports a 77% accuracy on forecasts. This accuracy is measured in different ways, but the (weighed) MAPE is the most commonly used measure. While the paper does not explicitly state how accuracy is calculated from the MAPE, we assume the following formula:

$$\text{Accuracy} = 100\% - \text{MAPE}$$

This way, the original forecasts has achieved an accuracy of about 48% (because of a MAD/mean of about 52%), while our best exponential smoothing procedure is accurate about 56%. Both scores are considerably less than one would expect from the 77% accuracy as stated by Kahn.

3.4.1 Discussion of the results

Why is the unexplained variability that much higher with this data set? We discuss some reasons. First of all we recognise that though the variability on an individual product level is very high, the variability on a product group level is very moderate. Secondly, new product introductions increase variability, although this effect can be limited by manually adjusting the system forecast.

We have already stated in Section 2.3: "Data selection" that there is a rapid pace of new product introductions. While new product introduction have limited or no previous sales data, forecasts are less accurate. In our calculations, new product introductions are not included until the time it first generates sales. At that moment, the forecasts is off 100%. The next period has a level the same as the initial period and no trend. Only after two periods of non-zero sales a trend can be calculated.

New product introductions can however impede the forecast, because demand for the new product can be negatively correlated to another product. For example: a newly introduced hardener might cannibalize other hardeners. Such errors could be corrected by adjusting the system forecast, as described in *Chapter 4: "Incorporating human judgement".*

A third issue is the Make-to-Order (MTO) versus Deliver-from-Stock (DFS) decisions. Decisions whether a particular order should be delivered from stock or made to order are made ad-hoc. Although differentiating between these order types does not change the demand pattern, it can be argued that DFS items are more important to forecast accurately, because only those orders should influence safety stock levels. When you take out the MTO orders, you take out a major source of variability. For an extreme example, we have plotted the quarterly sales from financial year 1999 to the second quarter of 2011 for a 1 Litre thinner in *"Figure 7: A relatively stable demand is offset by 1 big customer, which increases variability"*.

[redacted]

Figure 7: A relatively stable demand is offset by 1 big customer, which increases variability

We cannot easily correct for these effects, since MTO decisions are made ad-hoc and no policy regarding when an order should be MTO or DFS exists. Also, outliers are not easy to detect.

We expect one of the causes of the current variability in demand to be the *bullwhip effect (Forrester, 1961)*. The bullwhip effect is a phenomenon in forecast driven distribution systems, which magnifies variability in demand upstream from the end user. The bullwhip effect increases with the number of steps between the company and the end user. In Valspars case, this is typically three steps. See *"Figure 8: Valspars distribution channels. The thickness of the connecting lines indicate the relative volume of products that use that particular link."*.

[redacted]

Figure 8: Valspars distribution channels. The thickness of the connecting lines indicate the relative volume of products that use that particular link.

Typical measures to reduce the bullwhip effect by reducing uncertainty, variability and lead time are given in *Appendix C: Reducing the bullwhip effect*.

3.5 Smooth error tracking signal

When the forecast shows sign of bias, i.e. has a deviation that is either continuously above the actual sales level or below it, we would like to manually interfere. We do not want to monitor all items by hand, thus we need a way for the system to inform us of such bias. *Trigg (1964)* proposes to use a tracking signal for this exact purpose. He defines the following formula:

$$T_t = z_t / MAD_t \text{ where}$$

$$z_t = \omega(x_t - \hat{x}_{t-1,t}) + (1-\omega) z_{t-1}$$

T_t fluctuates between -1 and 1 and is near-zero when there is no bias present in the forecast. We implement a threshold value (actually two, a negative and positive threshold value) for T_t when manual adjustment is required on a specific item. This way monitoring of the forecast can be more effective.

3.6 Conclusions

Forecasting using exponential smoothing has been shown to usually outperform both ARIMA models and neural networks. Furthermore, exponential smoothing is easier to implement. Therefore we choose to establish a system forecast using exponential smoothing. The combination of five trend and three seasonality components leads to a framework containing fifteen main exponential smoothing methods. While it is possible to select a different model for each product in scope, the literature suggests aggregate selection of the damped trend model with no seasonality component (the DA-N method).

We choose to follow this recommendation, but we also like to check whether there might still be a benefit for using a seasonal component. We have therefore implemented the A-M method (the classical Holt-Winters method) for a few preselected products. We hypothesise these products show a seasonal trend. We have not found any benefit of using the A-M method over the DA-N method for these preselected products, so we choose to stick to the recommendation of the aggregate selection of the DA-N method.

The specific implementation of the DA-N method depends on parameter selection. We use two approaches: using the same values for the parameters of all products and using parameters found specifically for each product in scope. For both approaches, we use a grid search to find the best parameters. We choose Microsoft Excel for implementing the DA-N method, since it best fits the requirements that the implementation should be as simple as possible yet versatile enough, be automated and can be executed on the software currently available within the company.

We find that for all products in scope, both implementations of the DA-N method do not perform very differently, although the individual parameters for every product approach does show a better model fit, as expected. Since using the same parameter values for all products is a much simpler implementation, we choose to use this implementation.

Using this approach, we have achieved a MAD/mean score for the system forecast that is about 8% better than the original forecast that was used before this project. The accuracy of both the currently used forecast (48.5%) and the best performing alternative forecast (56%) are poor compared to the general industrial average of 77%. The poor accuracy on an individual product level is mainly caused by the volatility of the individual product sales. We find that the variance on individual products is very high, whereas the variance on a product group level is much lower.

Relatively many new product introductions over the last couple of years can be pointed out as one of the reasons for the sales volatility. Another reason is the offset of sales data by customers who buy a relatively large proportion of a product, which is not easily filtered out. The bullwhip effect may also increase variability, since there 3 to 4 steps between Valspar and the end user. We hope to reduce these effects by incorporating human judgement in the next chapter, so we can achieve our goal of a MAD/mean of 40%. The system forecast by itself with a MAD/mean of about 44% does not meet the goal.

4

Incorporating human judgement

The system forecast we have found in *Chapter 3: "System forecast"* is based solely on historic sales data. We refer to this forecasts as the system forecast. Trends found are extended to future periods to achieve a forecast, although these trends are damped to improve overall performance. Since this system forecast cannot account for recent changes, some expert adjustment may be required. Does adjustment however equal improvement?

Fildes et al. (2009) have summarized on this topic that there is "substantial evidence" from the economic forecasting literature that adjusting of forecasts indeed improves forecasts, although it may also introduce bias. *Sylver, Pyke and Peterson (1998)* distinguish factors internal and external to the organization which may require judgemental input in the system forecasts. We have adapted these factors to the automotive refinish business. The factors external to the organization are:

- The general economic situation (inflation rate, exchange rates, costs of borrowing capital, unemployment rates etc.)
- Government regulations (VOC legislation, import duties/quotas, safety standards etc.)
- Competitor actions (for example focus on larger distributors)
- Consumer preferences (for example move towards products with shorter drying times)

Factors internal to the organization are:

- Price changes (regular price changes, price changes due to increased raw material prices)
- Promotions (for example 5+1 litre promotion)
- Advertising
- Chemical changes that change the properties of a product (for example the cover-up project)
- Introduction of substitute products (for example a new clear coat, but also the introduction of a new packaging volume of an existing product)
- New distributors
- Pipeline filling effect (temporary surge in demand to initially place inventory at customers' stock points)

The focus on the incorporation of human judgement in the system forecast has been primarily on the addition of knowledge in the forecast about points not (yet) seen in the historical data. This focus is also reflected in the literature. Typically, we say the system forecast is fine until a break in a trend occurs. This trend break needs to be taken into account when the system forecast is calculated, and the magnitude of the forecast needs to be changed by hand. A typical example is the introduction of legislation banning certain products.

Besides this kind of incorporation of human judgement, we could also look back at past sales and correct them if we have reasons to believe the realised sales are not at a normal level. With the corrected data we can then go back a step and recalculate the system forecast. This last approach is the subject of Section 4.1: “Aggregate correction of the input data”, whereas the first approach is subject of Section 4.2: “Adjustment of the forecasts”. In *Section 4.3: “Forecasting items with limited history and new items”* we discuss forecasting of new product introductions. We once again draw our conclusions on this subject in Section 4.4: “Conclusions”.

4.1 Aggregate correction of the input data

We discuss three effect which we hypothesize to have a big impact on the forecasts of multiple end products in Section 4.1.1: “Correction of yearly historic data for major effects”. We give intuition and to a certain extent try to verify the three possible effects.

In Section 4.1.2: “Aggregate seasonal adjustment based on litre production” we use aggregated production levels in litres to adjust the sales data. We reintroduce seasonal effects, which might be lost in the variation within products at the end product level, but which might show through in these aggregated levels.

We eventually test if changing the sales data in line with these adjustments improves the forecast for our benchmark year, FY 2010.

4.1.1 Correction of yearly historic data for major effects

We look at yearly production data stated in litres (thus a higher aggregation level than what we previously considered) to find any major effects, as this is often used in paint producing companies and as such is readily available. We want to correct for these effects in the damped trend model to achieve better forecasting accuracy. We therefore fit a damped trend line to this data to find multipliers for each year. Using the lowest sum of errors we arrive at the solution as displayed in *“Figure 9: Total production per year in litre * 1000, an adjusted damped trend fitting, and a corrected adjusted damped trend fitting” on page 30*. We use this to correct the original sales data. We refer to that correction as the DA-N method with (α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8) and lowest sum-of-errors correction. We arrive at a level of 4,030,000, a trend 620,000, and a damping factor of 0.95.

*Figure 9: Total production per year in litre * 1000, an adjusted damped trend fitting, and a corrected adjusted damped trend fitting*

Using litres produced as an indicator for major effects prevents issues with pricing levels changing over the years. However, it does require some implications:

- Production levels and sales levels are highly correlated, but are not the same.
- The correction is applied uniformly over all end-items, while there certainly are differences in the degree to which a specific end-item is affected.

We find that the data in the last 5 years is much more erratic than in the first 5 years. Three years in particular deviate from the trend line: 2006, 2007, and 2008. From discussion with the principal, we arrive at two hypotheses for the peak/dip in 2006/2007 (Hypothesis 1 & Hypothesis 2) and one hypothesis for the 2009 dip (Hypothesis 3).

Hypothesis 1: VOC (Volatile Organic Compound) legislation in the European Union came into effect in January 2007. This legislation has banned sales of certain products which exceed a limit in VOC percentage. In anticipation, customers have bought more of these products in 2006 and less in 2007.

Hypothesis 2: The series of VOC compliant clear coats did not meet quality standards compared to competitors. Many customers continue to buy other products in 2007 compared to 2006, but purchase clear coats elsewhere.

Hypothesis 3: The global credit crisis has led to a decrease in demand and lowering of inventories downstream in the distribution chain.

VOC and non-VOC compliant products are spread over all product groups as defined in *"Table 2: Summary of product groups" on page 10*. Only group 7, the water based mixing colours are VOC compliant as a whole. It is therefore not easy to test if much fewer non-VOC items were sold in 2007 than in 2006. However, one would expect that if Hypothesis 1 is true, the decrease in sales would not be visible in the exclusively VOC compliant group. From the data in *"Table 11: Sales of water based mixing colours" on page 31* we see that there is an increase, rather than a decrease in sales of water based mixing colours. Although this does not prove Hypothesis 1, the data gives no indication that it should be rejected either.

FY 2006	FY 2007	FY 2008	FY 2009	FY 2010
[redacted]				

Table 11: Sales of water based mixing colours

Hypothesis 2 implies that the group of clear coats as a whole should account for much of the decrease in sales in 2007 compared to 2006. From *"Table 12: Sales of clear coats"* we see a slight increase from 2006 to 2007. There is however a significant decrease from 2007 to 2008 which continues in 2009 and restores in 2010. We therefore conclude that there is no proof for Hypothesis 2.

FY 2006	FY 2007	FY 2008	FY 2009	FY 2010
[redacted]				

Table 12: Sales of clear coats

Hypothesis 3 is hard to test. We expect the decrease in sales in 2009 to be independent of product group. This indeed seems to be the case. We therefore cannot reject Hypothesis 3.

The events described in Hypothesis 1 and Hypothesis 3 have impacted the trend fitting procedure also. This is why we choose to take 2006, 2007, and 2008 less into account for fitting the trend than the least-squares-method does. This mainly shows in a lesser degree of damping in the trend line. We now find an adjusted corrected damped trend as displayed in *"Figure 9: Total production per year in litre * 1000, an adjusted damped trend fitting, and a corrected adjusted damped trend fitting" on page 30*, with the level set at XXX, the trend at XXX, and the damping factor at XXX.

Using this adjusted trend, we find multipliers for 2006 onwards, as displayed in *"Table 13: Correction multipliers for 2006 onwards"*. We use these multipliers on all demand data (and do not discriminate between quarters in a given year). The resulting forecast we refer to as the DA-N method with (α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8) and adjusted correction.

FY 2006	FY 2007	FY 2008	FY 2009	FY 2010
0,8899	1,1433	1,0290	1,1288	0,9625

Table 13: Correction multipliers for 2006 onwards

4.1.2 Aggregate seasonal adjustment based on litre production

Since we see no benefit in using a trend model on individual item level, we would like to know if there is a general trend in the data. This would mean the general trend as seen on an item level may be obscured by the variability in the data on an item level. To circumvent disturbances by price chances we take a look at the total sales in litres. This is plotted in *"Figure 10: Total sales in 1000 litres per quarter"*.

Figure 10: Total sales in 1000 litres per quarter

Q1	Q2	Q3	Q4
0.9091	0.9887	1.0148	1.0873

Table 14: Seasonal indices per quarter established from total litre sales

We calculate the seasonal indices per quarter using the same data. This is presented in *"Table 14: Seasonal indices per quarter established from total litre sales"*. We see here that there is less production at the first quarter of the financial year and more production at the end of the financial year. We suggest that this may be caused by customers wanting to achieve yearly targets in the final quarter.

Given the fact that the aggregated data does show some seasonality, we try to implement this general seasonality in the overall model. We therefore use the seasonal indices as multipliers, and adjust the historic sales data of each product by these multipliers. We refer to this as the DA-N method with (α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8) and seasonal indices.

4.1.3 Results of the corrections

Forecasting method	MAD/mean FY09	MAD/mean FY10
DA-N method with (α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8) and lowest sum-of-errors correction	55.37%	43.98%
DA-N method with (α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8) and adjusted correction	55.58%	44.00%
DA-N method with (α_{HW} = 0.2, β_{HW} = 0.2, and ϕ = 0.8) and seasonal indices	52.33%	43.91%

Table 15: Summary of the results of the data correction

From *"Table 15: Summary of the results of the data correction" on page 32* we see that the corrections hardly have the desired effect of improving the forecast (compare to *"Table 10: Overview of future demand forecasting performance" on page 24*). We therefore choose to focus our attention to the adjustments of the forecasts themselves, rather than changing the historic sales data.

4.2 Adjustment of the forecasts

The rationale of adjusting a system forecast is the introduction of additional data, which we have referred to as market data. This information is dispersed across the organization. Whereas individual sales managers have more knowledge about their respective regions, the Management Team (MT) has some more general information. In discussion with sales managers, we find that sales managers usually do not have detailed knowledge about individual products, but are able to say something about the main product groups, as presented in *"Table 2: Summary of product groups" on page 10*.

Since the system forecasts itself should be sufficient to track trends in sales and continue them for the next period, it is crucial that we do not adjust the forecast for a similar trend (*Franses & Legerstee, 2009*). To prevent this, we propose to not let sales managers adjust the system forecasts themselves (even for their specific sales area), but instead delegate this task to the sales director. The sales director should be informed by the sales managers about breaks in trends for product categories or for specific products. Since trend breaks in different regions are likely to be different, the sales director should weigh and combine the information and adjust the system forecast where necessary.

To aid the sales director in adjusting the forecast for entire product categories, we propose an adjustment interface as displayed in *Figure 11: Implementation of an adjustment interface*.

[redacted]

Figure 11: Implementation of an adjustment interface

The main product groups have historically been setup as presented in *"Table 2: Summary of product groups" on page 10*. Some main product groups are however very broadly defined, such that we can distinguish subgroups which are not likely to show the same trend breaks. We therefore propose, for forecasting adjustments purposes, to make use of more subgroups as presented in *"Table 16: Proposition of subproductgroups"*.

Product group #		Product Group Name
1		Thinners
2		Primers

Product group #		Product Group Name
	2a	MS Primers
	2b	HS Primers
3		Hardeners
	3a	MS Hardeners
	3b	HS Hardeners
4		Clear Coats
	4a	Scratch Resistant Clear Coat
	4b	HS420 Clear Coat
	4c	MS Clear Coat
	4d	Speed Clear
5		Topcoat (ready made colours)
6		Topcoat (mixing colours except water base)
	6a	500 Series
	6b	2000 Series
	6c	3000 Series
	6d	MI
	6e	IC
	6f	2-tinters
7		900 Series
8		Other Professional

Table 16: Proposition of subproductgroups

4.2.1 Weighing of judgemental data and incorporation in model

How should the adjusted forecasts be dealt with? The literature indicates there is often an optimistic bias involved in forecast adjusting (*Franses & Legerstee (2009), Fildes et al. (2009)*). Simply taking the adjusted forecast for truth is therefore dangerous, even though in the end it verified by management. *Blatberg et al. (1990)* have proposed a heuristic where the system forecast and expert forecast are averaged.

Since the experts in the hierarchical framework have already been presented the system forecast, their forecast and the adjusted forecast are not independent. As *Fildes et al. (2009)* explain, the heuristic in this case will act as a dampening of the adjustment. We therefore would like to keep progress of the bias introduced in the adjusted forecast and then correct for it by finding a multiplier which can be applied to future forecasts. This requires some data for initialization, which we do yet not have. We therefore choose to take the adjusted forecast for granted until more data on the bias is available.

4.3 Forecasting items with limited history and new items

We have already seen Section 3.4: "Results of future demand forecasting" that the variability in the data set is high. One of the difficulties in forecasting is the introduction of new products. In this section we discuss the forecasting of items with limited or no sales history.

Diffusion models, such as those developed by *Bass (1969)* are suggested for use with new product introductions. Unlike exponential smoothing, which depends on historic (time series) sales data, the Bass model allows for forecasting with little data. *So Young Sohn (2006)* refers to it as the classical alternative for ARIMA, exponential smoothing, etc. *Norton and Bass (1987)* have extended the Bass model for use with multiple product generations.

The Bass model does not account for seasonality and is therefore not a very good choice when seasonality shows in the data set. We have already seen in Section 3.2: "Forecast model parameter estimation" that there is little seasonality in our data set, so we do not expect to encounter any problems there.

The Bass diffusion model or the Norton-Bass diffusion model are however not a good choice for forecasting on a SKU-level. *Kahn (2001)* reports: "Diffusion models are best used at the aggregate level — not the individual product item level, and are intended to model emerging technologies/new-to-the-world products, not product improvements." Valspar introduces very little, if any, new-to-the-world products. In many cases, a similar end product already exists (for example, another packaging volume). Interactions between similar products are not incorporated in the Bass model.

The basic Bass model does not account for promotions and advertising although extensions to the Bass model which include promotions and advertising have been proposed (*Lilien et al, 1981*). *Delre et al.* (2007) argue however that these extensions are more descriptive than prescriptive. The Bass model also does not take into account competitors actions and is more focussed on an entire market ("flat screen televisions") than on individual end items at one manufacturer ("De Beer brand one gallon scratch resistant speed clear coat for the US market").

In this report we focus on relatively short term forecasting (less than a year and usually just one-quarter-ahead). Bass' model incorporated the entire product life cycle, which in Valspar's case usually spans many years.

For these reasons we choose not to use the Bass model.

Another issue is the volatility of the data set. *Tanaka (2010)* suggest that there is a high correlation between initial sales and later sales. He proposes to make use of this correlation by forecasting using only very limited sales data. To see whether this might be a feasible approach, we have plotted several newly introduced items in terms of their sales volume in the second and fourth quarter. We have explicitly not taken the first quarter, since that could distort the outcome when for example a product is introduced halfway that quarter. The plot is shown in *"Figure 12: Scatter plot of the sales of new products in the second quarter (horizontal axis) and the fourth quarter (vertical axis)"*. Although we can see some correlation, the relation is not very strong, so we do not advice to use this.

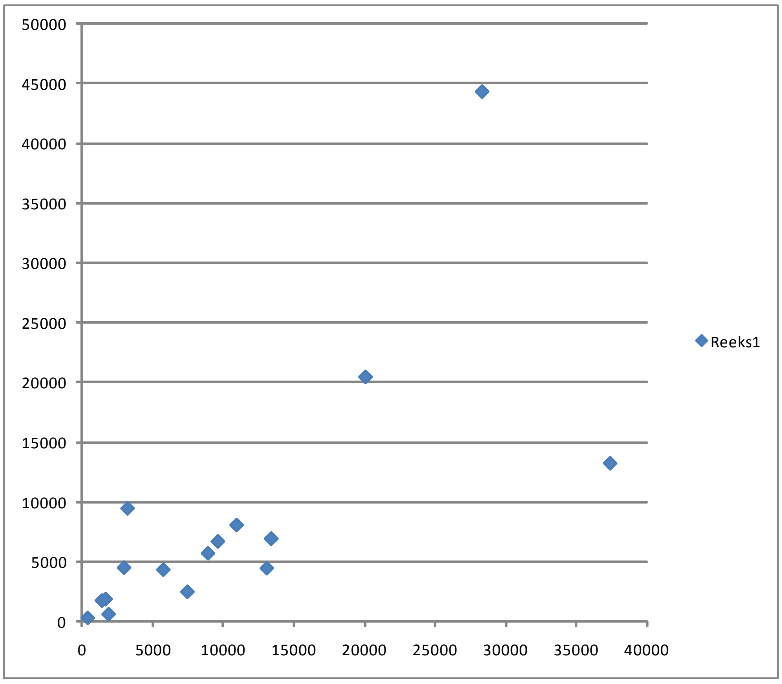


Figure 12: Scatter plot of the sales of new products in the second quarter (horizontal axis) and the fourth quarter (vertical axis)

Most of the new products introduced by Valspar are not very novel: a different container volume, an extension of an existing product, etc. We therefore propose to use forecasting by analogy. Forecasting by analogy makes use of data for existing products and uses them through a judgemental process for forecasting new product introductions. For this approach, we present a flowchart to aid with the forecast for new product introductions. This is discussed in Section 4.3.1: "Flowchart for forecasting items with limited history and new items".

4.3.1 Flowchart for forecasting items with limited history and new items

We have adapted the classification of new product portfolio by *Griffin (1997)* and the advice for implementing a new product forecasting system using forecasting by analogy by *Ching-Chin et al. (2010)* for the specifics of the automotive refinish market. Griffins classification deals with the 'newness' of new product introductions. Whereas some products are merely small improvements over existing products, other products might even be new to the world. In Valspars case, even different packaging volumes are considered different products. This requires different forecasting analogies.

As the 'newness' of products increases, forecasting becomes harder and the uncertainty of the forecasts also tends to increase. This is displayed in *"Figure 13: Forecast analogy based on 'newness' of a to-be-introduced product" on page 37*.

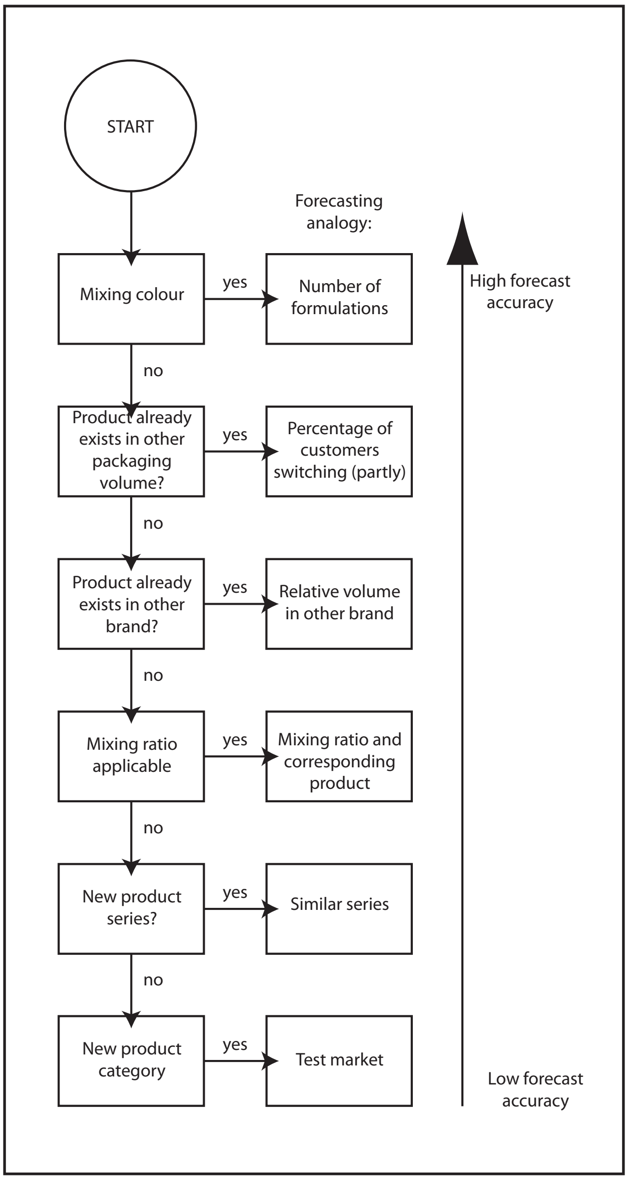


Figure 13: Forecast analogy based on 'newness' of a to-be-introduced product

Mixing colours are always used in a formula to get a specific car colour, much in the same way ingredients are used in a recipe to prepare a dish. Since Valspar supplies the formulations (recipes), it can use the number of formulations which use a certain new mixing colour as a base to estimate the sales turnover. A more accurate approach for forecasting new mixing colours is presented in *Appendix F: "Online Mixing Colour Formulation Tool"*.

When the new introduction consists of merely a new packaging volume, a forecast can be made using the data of the already existing product. One has to estimate the proportion of end users who will switch to the new packaging. Of course, it is highly advisable to also adjust the forecast for the already existing product!

When the product is already available in a different brand, the relative proportion of the product within the different brand can be used to forecast the new introduction. Since product portfolios in different brands seldom match, the accuracy of the forecast will most likely be lower than that of the new-packaging-same-brand scenario.

Mixing ratios are the ratio's in which certain product types need to be mixed with other products before use. Using data from products a new product introduction can be mixed with and the mixing ratio, a forecast can be established.

A complete new product series is much harder to forecast. Data from similar series may be used. Data from a market test and market research may also be used. For new product categories no data from other products can be used and one can only use data from market tests or market research.

Three issues are not displayed in the flowchart. These are changes over time, monitoring, and adjustment of related products. We will now briefly discuss them.

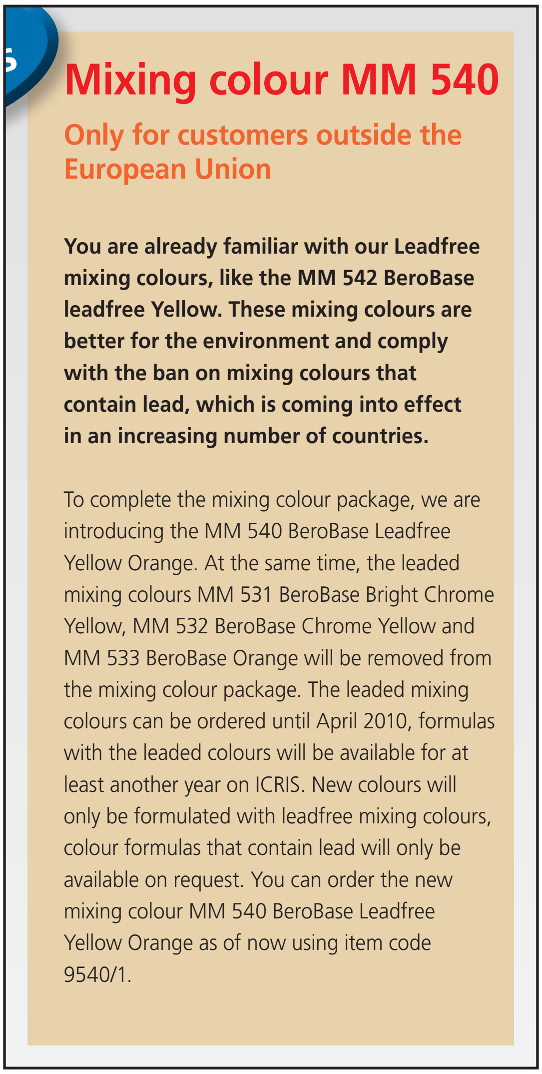
Forecasts for new product introductions should take changes in sales over time specifically into account. A newly introduced product does not reach maturity instantly. Also, the pipeline filling effect should be taken into account. Before the end user can purchase a product, all the distribution channels, as shown in *"Figure 8: Valspars distribution channels. The thickness of the connecting lines indicate the relative volume of products that use that particular link." on page 26*, need to be filled. This usually manifests itself as a peak briefly after the product introduction.

After the initial forecast is made, frequently monitoring sales data as it comes in is imperative. This is not only important for products which end up lower in *"Figure 13: Forecast analogy based on 'newness' of a to-be-introduced product" on page 37* and are thus considered to have a lower forecasts accuracy, but also for products higher up. Many more formulations which use a newly introduced mixing colour might for example be published by the company.

We have already stated that in case of the introduction of a new packaging volume, one has to look carefully at the forecast for the other packaging volumes of that same product. Usually, the sales in total volume of a product does not change after introducing a new packaging volume. Just the mix between the packaging is likely to change. To a somewhat lesser extend this is also the case for product introductions that are not merely a different packaging. The forecaster should therefore always ask himself what the impact on related products might be and appropriately adjust these product forecasts too.

4.3.2 Case: introduction of lead free mixing colours

As an example of a recent product introduction, we discuss the case of the introduction of the De Beer brand MM 540 Berobase Leadfree Yellow mixing colour. This product was introduced to Valspars customers in the February 2010 newsletter and replaces three leaded mixing colours. The article is displayed in *"Figure 14: Excerpt from a De Beer newsletter introducing a new mixing colour (De Beer Newsletter, February 2010)" on page 39*.



Mixing colour MM 540

Only for customers outside the European Union

You are already familiar with our Leadfree mixing colours, like the MM 542 BeroBase leadfree Yellow. These mixing colours are better for the environment and comply with the ban on mixing colours that contain lead, which is coming into effect in an increasing number of countries.

To complete the mixing colour package, we are introducing the MM 540 BeroBase Leadfree Yellow Orange. At the same time, the leaded mixing colours MM 531 BeroBase Bright Chrome Yellow, MM 532 BeroBase Chrome Yellow and MM 533 BeroBase Orange will be removed from the mixing colour package. The leaded mixing colours can be ordered until April 2010, formulas with the leaded colours will be available for at least another year on ICRIS. New colours will only be formulated with leadfree mixing colours, colour formulas that contain lead will only be available on request. You can order the new mixing colour MM 540 BeroBase Leadfree Yellow Orange as of now using item code 9540/1.

Figure 14: Excerpt from a De Beer newsletter introducing a new mixing colour (De Beer Newsletter, February 2010)

Given the information in the newsletter, one would expect the lead free mixing colour to be close to the combined level of the mixing colours it replaces. This is not the case, see *"Figure 15: Overview of the sales of five mixing colours" on page 40*. Since the introduction of the MM 540 mixing colour is quite recent and the sales data therefore is very limited, we have chosen to display the sales data in months rather than quarters. The replacement is not one-to-one: the MM 540 mixing colour replaces the three leaded mixing colours together with the previously introduced MM 542. When we combine the sales of the two lead free mixing colours and also combine the three leaded mixing colours, we can see that from the summer of 2010 on the sales of leadfree mixing colours increases, whereas the sales of lead containing colours approaches zero. This case shows that it is important that with new product introductions not only the new product should be looked at, but also other products which the new products (partly) replaces or complements.

Figure 15: Overview of the sales of five mixing colours

A peculiarity we see is that there is already a considerable amount of sales before the official announcement in the February 2010 news letter. Word-of-mouth can generate sales before the official introduction. This effect should be taken into account. It might even be used as a first indicator of future sales.

From *"Figure 15: Overview of the sales of five mixing colours"* we also see that there is relatively more sales volume in the first months after introduction than in the months directly following it. We consider this part of the pipeline-filling effect.

Figure 16: Overview of the sales of five mixing colours, combined into two groups

4.4 Conclusions

Incorporating human judgement in the forecast in general is shown to improve a forecast based on historic sales data (the system forecast) only. We have seen that there are both factor internal and external to the organization which may require the system forecasts to be adjusted. We have discussed two approaches, one in which we use aggregated sales data and correct the individual product sales data by accounting for disruptions and one in which we propose a framework to process information that is not historic sales data and use it to adjust single products or complete product groups.

We find disruptions — upwards in 2006 and downwards in 2007 and 2009 — in the aggregated sales which are most likely caused by the VOC legislation for the disruptions in 2006 and 2007 and the global credit crisis for 2009. We find that correcting all sales data and redoing the forecast with the corrected sales data does not yield better results than without the correction. We therefore do not recommend this approach.

We have identified sales managers as being closest to the market and as such having the best available information about breaks in trends. However, since sales managers are considered only knowledgeable about their own sales region and since adjusting the system forecast requires know-how of the mechanics of the system forecast, we do not recommend letting sales managers directly adjust the forecast. Instead, the sales director should be informed about possible trend breaks in their sales area, so that he can weigh and add up this information before adjusting the forecast.

We have identified new product introductions as one of the causes for the large variability on end product level. We presented a flowchart to aid with the forecasting of items with no or limited sales data. We have identified regular sales monitoring of the new product, timing of the forecast, and adjustment of related products as important tasks when considering new product forecasting. This was illustrated using a case.

5

Conclusions and recommendations

The research goal is to evaluate the current fit between forecasted sales and achieved sales and to design alternative approaches to achieve better forecasting results by combining forecasts based on historic data (system forecasts) with forecasts based on market know-how (judgemental forecast). In this final chapter, we summarize conclusions and formulate recommendations.

5.1 Conclusions

We have come to the following conclusions:

1. The Mean Absolute Deviation divided by the mean (MAD/mean) is a good measure for monitoring the forecasting quality of individual products and entire product categories.
   - Unlike the more commonly used MAPE measure, the MAD/mean is symmetrical and more suitable for products with low levels of demand.
2. The MAD/mean of the forecast as currently established by the company's Management Team is about 55% for 2008-2010 (lower is better).
   - This percentage is achieved after assigning proportions of the product group forecast to individual products. On higher aggregation levels the MAD/mean improves.
3. Selecting unique exponential smoothing parameters for every product does not yield better results than selecting the same value for the exponential smoothing parameters for all products simultaneously.
   - Select parameters alpha = 0.2, beta = 0.2 and phi = 0.8.
4. The aggregate selection of the damped trend with no seasonality component (DA-N) exponential smoothing model for all products in scope yields a MAD/mean of about 44% for 2010, while the currently established forecast has a MAD/mean of 52% for 2010.
5. Forecasting on a higher aggregation level and then correcting the sales data does not improve the individual product forecasts.
6. Using human judgement to adjust the system forecast is likely to improve the accuracy of the forecast, when used properly.
7. The system forecast by itself is not enough to achieve a MAD/mean of 40%. After adjusting the system forecast by human judgement, this MAD/mean might be reached.

5.2 Recommendations

We have split up the recommendations in ones directly following the conclusions and general recommendations.

5.2.1 Recommendations following the conclusions

1. We recommend to use exponential smoothing for item level forecasts on a quarterly basis, since it has increased forecast accuracy compared to the current forecasting system.
2. A tracking signal may be implemented to notify the forecaster when the forecast shows a bias.
3. The software can be used for developing a system forecast for more paint related products, not just the scope items, and human adjustment could be focussed on important items and/or items with a large deviation between forecast and achieved sales.
4. Forecasts for new product introduction can be made using an appropriate driver based on the 'newness' and type of products involved. Sales of new product introduction can be monitored carefully, preferably on a more intensive basis than once per quarter.
5. Since the variability of the sales is high, we propose that efforts should be made to reduce this variability, for example using coordination with customers.
6. We recommend adjustments to the system forecasts to be tracked, such that feedback can be given on the adjustments (learning effect) and to check whether the process of adjusting the system forecast is necessary in the first place.
7. We suggest the sales director, rather than individual sales managers for their own sales area, should adjust the system forecast. He should weigh and interpreted information about possible trend breaks.

5.2.2 General recommendations

8. We propose to decrease the number of slow moving items where alternatives are available: not only are there fewer items to keep track off, the demand for the alternative item will be higher and likely more stable, since individual order do not offset the demand pattern too much.
9. Consider making use of integrated forecasting systems based on exponential smoothing in (future) ERP systems to be used by Valspar (such as Oracle 11i), to increase automatization of the system forecast.
10. We propose a limit, based for example on order size, on Deliver From Stock items (orders exceeding this limit should be considered Make To Order) in order to smooth demand for stock keeping units. At least, abnormal orders should be tagged as such for easier filtering.
11. We propose to make use of the fact that the end user needs information from Valspar for every formulation to gather data of mixing colours usage, for example by introducing an online formulation database or by logging the offline data (with the end users consent). See *Appendix F: Online Mixing Colour Formulation Tool*.
12. More information is better: we suggest that people involved in the forecasting process become informed as much as possible on changes which may affect future sales. Especially through sales offices and technicians Valspar can come closer to the end user.

Many of the above mentioned recommendations at least temporary increase workload, but are helpful for Valspar to meet its ambitions with respect to increased service levels, cost reduction, and expansion of its business. Information which needs to be gathered to improve forecasting accuracy at the same time may lead to valuable knowledge about the needs of its customers and end users.

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A

Appendix A: Causes of the core problem

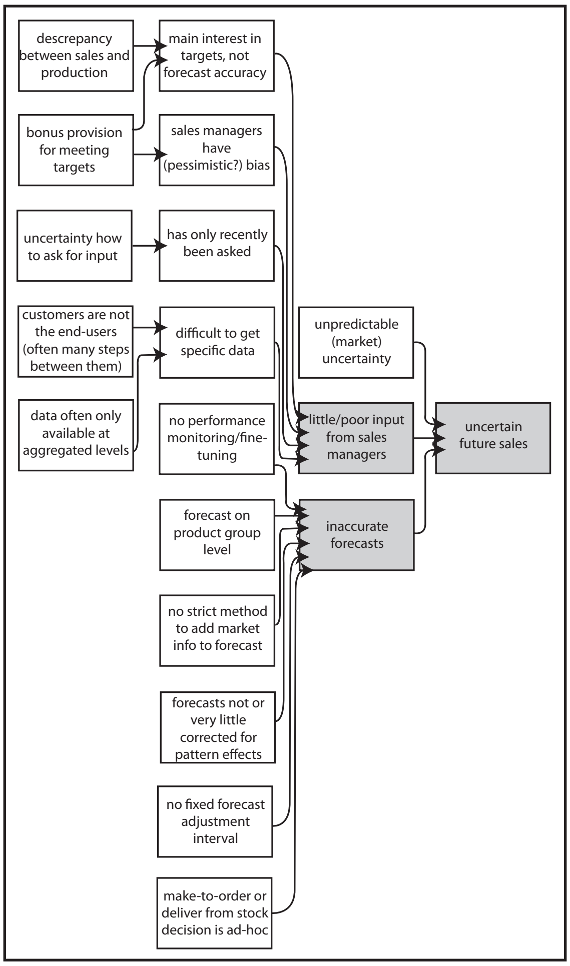
We have uncovered three direct causes of the core problem: unpredictable (market) uncertainty, little and poor input from sales managers, and inaccurate forecasts. What the weather is for ice cream sales, market uncertainty is for the core problem: although it might have great impact, one cannot reasonably influence it. We therefore focus on the other two causes in this research.

Inaccurate forecasting has historic reasons. Within the company, it was never thought of as something that needed to be done at more than a very rough level. This means forecasting is done at a product group level rather than on an individual product level. Furthermore, no guidelines or rules exist on how to implement market information in the forecast. Indeed, no guidelines exist on a frequent interval for forecasting. Seasonality is considered, but again only at an aggregated level.

Ad-hoc MTO versus MTS decisions further complicate things. A large but similar order for an SKU at one point in time might be delivered from stock, while at another time it is made to order. The first case may disrupt normal variance such that the safety stock should formally be much larger, while in the second case it does not influence the safety stocks.

The market input which is lacking or poor is also caused by multiple factors. This info should normally come from sales managers, because they are most directly connected to the customers and the market. Sales managers at present only provide forecasts in financial terms. They are most likely to have a pessimistic bias, because their bonus provision is to a large extend based on meeting this forecast. This focus on targets may influence the forecast accuracy.

At the same time, sales managers have only recently been asked to provide forecasts, while some regions do not supply a forecast at all. Even for sales managers the data required for accurate forecasting is not readily available. Their customers are often importers. In turn, importers often have resellers as customers. These resellers are the ones in direct contact with the end-users: body shops with car refinishing facilities. All these steps limit the flow of information from the market to Valspar, such that often only data on an aggregated level is easily available.


descrepancy between sales and production
main interest in targets, not forecast accuracy
bonus provision for meeting targets
sales managers have (pessimistic?) bias
uncertainty how to ask for input
has only recently been asked
customers are not the end-users (often many steps between them)
difficult to get specific data
unpredictable (market) uncertainty
data often only available at aggregated levels
no performance monitoring/fine-tuning
little/poor input from sales managers
uncertain future sales
forecast on product group level
inaccurate forecasts
no strict method to add market info to forecast
forecasts not or very little corrected for pattern effects
no fixed forecast adjustment interval
make-to-order or deliver from stock decision is ad-hoc

B

Appendix B: VBA code

```
Function TrendForecast(InitSales As Range, NewSales As Range, Op-
tional alpha As Variant, Optional beta As Variant, Optional phi As
Variant) As Variant
    '--- Version ---
    'TrendForecast v1.0

    '--- About this function
    'This function forecasts using a damped linear trend
    'exponential smoothing model.
    'As input it takes the first range selected (InitSales) and
    'initialises the forecast. Then, it updates this forecast
    'using newer values as defined in the NewSales range. It
    'returns a one-period ahead forecast.

    'This updated version is meant to also provide forecasts
    'for the periods it uses to initialize.

    '--- Usage of this function ---
    'The function requires two ranges, one for initalization and
    'one for updating. Optionally, you can provide values for
    'alpha, beta and phi. When these values are not given, it
    'defaults to alpha = 0.2, beta = 0.2 and phi = 8.


    'definitions
    Dim xt As Double
    Dim txt As Double
    Dim a0 As Double
    Dim b0 As Double
    Dim a As Double
    Dim preva As Double
```

```
    Dim prevb As Double

    'set missing parameters to default
    If IsMissing(alpha) Then alpha = 0.2
    If IsMissing(beta) Then beta = 0.2
    If IsMissing(phi) Then phi = 0.8

    'determine xt
    xt = 0
    For i = 1 To InitSales.Cells.Count
        xt = xt + InitSales.Cells(1, i).Value
    Next

    'determine txt
    txt = 0
    For i = 1 To InitSales.Cells.Count
        txt = txt + (-1 * ((InitSales.Cells.Count - i) * InitSales.
Cells(1, i).Value))
    Next

    'determine a0
    a0 = ((6 / (InitSales.Cells.Count * (InitSales.Cells.Count +
1))) * txt) + ((2 * (2 * InitSales.Cells.Count - 1)) / (InitSales.
Cells.Count * (InitSales.Cells.Count + 1)) * xt)

    'determine b0
    b0 = (12 / (InitSales.Cells.Count * (InitSales.Cells.Count ^ 2 -
1))) * txt + (6 / (InitSales.Cells.Count * (InitSales.Cells.Count +
1))) * xt

    'set current a and b at a0 and b0, respectively
    a = a0 - b0 * (InitSales.Cells.Count + 1)
    b = b0

    'update at with new values
    For i = 1 To NewSales.Cells.Count
        preva = a
        prevb = b

        a = alpha * NewSales.Cells(1, i).Value + (1 - alpha) * (pre-
va + phi * prevb)
        b = beta * (a - preva) + (1 - beta) * phi * prevb
    Next

    'output
    TrendForecast = a + phi * b '& " DEBUG -- " & " a: " & a & " b:
" & b
End Function
```

```
Sub ParameterSolver()
`
` ParameterSolver
` This script invokes the Excel Solver for every row of data (i.e.
for every product)

For i = 4 To 1479
    'reset the Solver parameters
    OplosserOpnieuw

    'make sure all parameters are non-negative
    OplosserToevoegen Celverw:="$Y" & i, Relatie:=3, Formu-
letekst:="0"
    OplosserToevoegen Celverw:="$Z" & i, Relatie:=3, Formu-
letekst:="0"
    OplosserToevoegen Celverw:="$AA" & i, Relatie:=3, Formu-
letekst:="0"

    'make sure all parameters are < 1
    'since Excel ignores the constraint when the upper limit of 1 is
directly,
    'we choose to make a reference to a cell (C10) with that value
    OplosserToevoegen Celverw:="$Y" & i, Relatie:=1,
Formuletekst:="$C$10"
    OplosserToevoegen Celverw:="$Z" & i, Relatie:=1,
Formuletekst:="$C$10"
    OplosserToevoegen Celverw:="$AA" & i, Relatie:=1,
Formuletekst:="$C$10"

    'Minimize to total absolute deviation for 2008 and 2009
    OplosserOk CelBepalen:="$AR" & i, MaxMinWaarde:=2,
WaardeVan:="0", DoorVerandering:="$Y$" & i & ":$AA" & i

    'Do not show the dialog box
    OplosserOplossen GebrEinde:=True

    'refresh the sheet
    Calculate
Next
End Sub
```

```
Sub FindLowest()
For i = 1 To 1477
If Worksheets("Scope Items").Cells(i + 3, 52) = 0 Then i = i + 1
Worksheets("Grid Search").Cells(3, 14) = i
Application.Calculate

IamTheLowest = 9E+50
LowAddr = ""
LowRow = "4"
LowColumn = "2"
alpha = ""
beta = ""
phi = ""

Dim k As Integer

For Each c In Range("B4:L14,B19:L29,B34:L44,B49:L59,B64:L74,B79:L89,
B94:L104")
    cv = c.Value
    ca = c.Address
    cr = c.Row
    cc = c.Column
    If cv < IamTheLowest And cv <> 0 Then
        IamTheLowest = cv
        LowAddr = ca
        LowRow = cr
        LowColumn = cc
    End If
Next

'determine alpha, beta and phi
For j = 1 To 11
    If (LowRow = j + 3) Or (LowRow = j + 18) Or (LowRow = j + 33) Or
(LowRow = j + 48) Or (LowRow = j + 63) Or (LowRow = j + 78) Or (Low-
Row = j + 93) Then
        alpha = (j - 1) * 0.05
    End If
Next

beta = (LowColumn - 2) * 0.05
k = (LowRow - 3) \ 15
phi = 1 - (k * 0.05)

Worksheets("Scope items").Cells(Worksheets("Grid Search").Cells(3,
14).Value + 2, 53) = alpha
Worksheets("Scope items").Cells(Worksheets("Grid Search").Cells(3,
14).Value + 2, 54) = beta
Worksheets("Scope items").Cells(Worksheets("Grid Search").Cells(3,
14).Value + 2, 55) = phi
Next
End Sub
```

C

Appendix C: Reducing the bull-whip effect

Typical measures to reduce the bullwhip effect by reducing uncertainty, variability and lead time are (*Mason-Jones, 2000*):

- Vendor Managed Inventory (VMI)
- Just In Time replenishment (JIT)
- Strategic partnership
- Information sharing
- Smooth the flow of products
  - Coordinate with retailers to spread deliveries evenly
  - Reduce minimum batch sizes
  - Smaller and more frequent replenishments
- Eliminate pathological incentives
  - Every day low price policy
  - Restrict returns and order cancellations
  - Order allocation based on past sales instead of current size in case of shortage

D

Appendix D: Example of the graphical representation of the Grid Search results

phi 1

alpha\beta	0,00	0,05	0,10	0,15	0,20	0,25	0,30	0,35	0,40	0,45	0,50
0,00	6140,3971	6140,3971	6140,397	6140,397	6140,397	6140,397	6140,397	6140,397	6140,397	6140,397	6140,397
0,05	6236,5965	6267,3148	6297,483	6327,104	6356,179	6384,711	6412,703	6440,157	6467,074	6493,458	6520,176
0,10	6391,4851	6460,6749	6527,952	6593,336	6656,846	6718,5	6778,318	6836,32	6892,526	6946,954	6999,626
0,15	6599,8473	6688,9915	6774,242	6855,664	6933,323	7007,285	7077,618	7144,387	7207,662	7267,51	7323,999
0,20	6774,5165	6876,5347	6972,337	7062,077	7145,913	7224,001	7296,499	7363,568	7435,806	7549,026	7654,904
0,25	6922,2714	7031,8327	7132,739	7225,289	7309,785	7386,529	7455,827	7517,982	7624,656	7726,268	7817,952
0,30	7048,8084	7162,0987	7264,368	7356,122	7437,869	7510,118	7573,376	7628,151	7698,84	7781,275	7851,542
0,35	7158,7485	7273,2251	7374,539	7463,467	7540,785	7607,265	7663,677	7710,783	7749,337	7780,087	7803,769
0,40	7255,6625	7369,8043	7468,974	7554,28	7626,823	7687,692	7737,963	7778,694	7810,928	7835,685	7853,961
0,45	7342,1146	7455,1739	7551,85	7633,635	7701,998	7758,386	7804,211	7840,856	7869,662	7891,931	7908,921
0,50	7419,7218	7531,4841	7625,874	7704,804	7770,144	7823,716	7867,283	7902,548	7931,145	7954,637	7974,511

phi 0,95

alpha\beta	0,00	0,05	0,10	0,15	0,20	0,25	0,30	0,35	0,40	0,45	0,50
0,00	5485,1795	5485,1795	5485,18	5485,18	5485,18	5485,18	5485,18	5485,18	5485,18	5485,18	5485,18
0,05	5419,8554	5464,968	5509,35	5553,004	5595,938	5638,153	5679,657	5720,452	5760,544	5799,938	5838,637
0,10	5591,2593	5665,3629	5736,851	5805,76	5872,123	5935,977	5997,356	6056,295	6112,827	6166,988	6218,812
0,15	5697,9658	5788,2505	5873,299	5953,225	6028,14	6098,153	6163,375	6243,576	6338,545	6429,103	6515,356
0,20	5752,5237	5891,0473	6030,948	6162,955	6287,314	6404,268	6514,059	6616,924	6713,097	6802,81	6886,292
0,25	5994,7052	6154,4275	6302,946	6440,714	6568,182	6685,788	6793,966	6893,144	6983,739	7066,164	7140,823
0,30	6209,9928	6375,9568	6527,787	6666,215	6791,957	6905,715	7008,174	7100,008	7181,872	7254,409	7318,245
0,35	6395,9565	6564,411	6716,1	6852,099	6973,455	7081,188	7176,289	7259,725	7332,431	7395,317	7449,263
0,40	6558,2326	6726,7635	6876,306	7008,338	7124,29	7225,544	7313,439	7389,264	7454,261	7509,625	7556,506
0,45	6701,1091	6868,3134	7014,776	7142,421	7253,1	7348,59	7430,591	7500,732	7560,564	7611,566	7655,141
0,50	6827,6387	6992,8254	7135,999	7259,561	7365,801	7456,897	7534,913	7601,805	7659,413	7709,469	7753,594

phi 0,90

alpha\beta	0,00	0,05	0,10	0,15	0,20	0,25	0,30	0,35	0,40	0,45	0,50
0,00	8161,8481	8161,8481	8161,848	8161,848	8161,848	8161,848	8161,848	8161,848	8161,848	8161,848	8161,848
0,05	7070,9175	6959,8353	6849,842	6740,932	6633,097	6526,333	6420,632	6315,988	6212,396	6109,848	6008,338
0,10	6152,9306	5958,8822	5768,759	5652,68	5610,574	5633,354	5653,756	5684,525	5752,77	5818,444	5881,587
0,15	5410,4197	5428,177	5529,334	5624,959	5715,182	5800,132	5879,936	5954,718	6024,603	6089,714	6150,169
0,20	5443,0595	5557,9827	5664,085	5761,653	5850,968	5932,309	6005,947	6072,151	6135,071	6245,508	6349,199
0,25	5510,3583	5625,0108	5727,645	5840,01	5992,501	6134,338	6266	6387,957	6500,666	6604,576	6700,123
0,30	5600,4314	5795,0088	5974,351	6139,269	6290,549	6428,956	6555,234	6670,106	6774,272	6868,413	6953,191
0,35	5846,9773	6044,2621	6223,583	6386,108	6532,967	6665,251	6784,013	6890,269	6984,997	7069,142	7143,612
0,40	6060,7676	6257,8696	6434,726	6592,916	6733,956	6859,299	6970,339	7068,407	7154,778	7230,67	7297,241
0,45	6247,6233	6442,8068	6615,961	6769,112	6904,191	7023,033	7127,382	7218,892	7299,128	7369,569	7431,61
0,50	6411,8659	6604,2096	6773,241	6921,452	7051,196	7164,691	7264,022	7351,146	7427,891	7495,967	7556,96

phi 0,85

alpha\beta	0,00	0,05	0,10	0,15	0,20	0,25	0,30	0,35	0,40	0,45	0,50
0,00	10507,269	10507,269	10507,27	10507,27	10507,27	10507,27	10507,27	10507,27	10507,27	10507,27	10507,27
0,05	9149,9736	9028,5857	8908,331	8789,202	8671,193	8554,296	8438,505	8323,813	8210,213	8097,698	7986,262
0,10	8003,7674	7792,2218	7584,729	7381,238	7181,699	6986,062	6794,278	6606,299	6422,076	6241,561	6114,033
0,15	7038,8885	6762,73	6494,708	6234,667	5982,453	5798,908	5791,671	5795,523	5848,048	5919,75	5986,854
0,20	6228,9756	5908,8307	5601,567	5605,933	5702,031	5790,303	5871,018	5944,443	6010,838	6070,459	6123,554
0,25	5550,7938	5496,8643	5605,912	5703,747	5790,864	5867,745	5934,862	5992,673	6101,099	6217,401	6325,385
0,30	5432,655	5546,815	5646,444	5736,231	5899,74	6050,551	6189,387	6316,948	6433,912	6540,935	6638,65
0,35	5456,5831	5665,067	5855,954	6030,38	6189,435	6334,17	6465,598	6584,69	6692,381	6789,567	6877,109
0,40	5710,7761	5918,4952	6106,489	6276,273	6429,296	6566,942	6690,535	6801,333	6900,537	6989,29	7068,677
0,45	5931,6919	6136,8006	6320,549	6484,862	6631,565	6762,386	6878,963	6982,841	7075,478	7158,247	7232,439
0,50	6124,7721	6326,2839	6505,288	6664,128	6805,005	6929,988	7041,012	7139,887	7228,3	7307,819	7379,899

phi 0,80

alpha\beta	0,00	0,05	0,10	0,15	0,20	0,25	0,30	0,35	0,40	0,45	0,50
0,00	12423,341	12423,341	12423,34	12423,34	12423,34	12423,34	12423,34	12423,34	12423,34	12423,34	12423,34
0,05	10834,141	10708,719	10584,4	10461,19	10339,07	10218,03	10098,07	9979,189	9861,372	9744,615	9628,911
0,10	9490,49	9272,536	9058,515	8848,379	8642,078	8439,566	8240,795	8045,717	7854,286	7666,457	7482,182
0,15	8357,3066	8073,5167	7797,578	7529,34	7268,656	7015,381	6769,372	6530,486	6298,586	6115,961	6065,044
0,20	7403,6958	7075,4634	6759,589	6455,751	6163,636	5882,933	5842,001	5861,475	5929,95	5992,11	6048,185
0,25	6602,5724	6246,7815	5908,054	5662,453	5733,693	5811,433	5880,144	5940,243	5992,139	6036,227	6072,894
0,30	5930,311	5638,7148	5611,851	5696,943	5770,137	5832,108	5890,958	6023,679	6146,448	6259,858	6364,484
0,35	5585,9742	5536,584	5621,061	5757,745	5919,648	6068,235	6204,415	6329,063	6443,017	6547,082	6642,028
0,40	5513,0331	5674,4438	5862,553	6033,878	6189,715	6331,303	6459,819	6576,387	6682,075	6777,898	6864,82
0,45	5715,3104	5918,3109	6101,771	6267,4	6416,818	6551,557	6673,063	6782,702	6881,76	6971,445	7052,894
0,50	5930,249	6129,0508	6307,366	6467,26	6610,669	6739,409	6855,177	6959,558	7054,027	7139,955	7218,61

phi 0,75

alpha\beta	0,00	0,05	0,10	0,15	0,20	0,25	0,30	0,35	0,40	0,45	0,50
0,00	13993,696	13993,696	13993,7	13993,7	13993,7	13993,7	13993,7	13993,7	13993,7	13993,7	13993,7
0,05	12202,114	12077,294	11953,51	11830,75	11709,01	11588,29	11468,57	11349,86	11232,15	11115,43	10999,69
0,10	10687,25	10471,006	10258,42	10049,44	9844,024	9642,134	9443,724	9248,752	9057,176	8868,952	8684,041
0,15	9409,0852	9128,3408	8854,854	8588,489	8329,114	8076,599	7830,814	7591,632	7358,927	7132,576	6912,456
0,20	8332,5329	8008,7161	7696,265	7394,892	7104,316	6824,26	6554,453	6294,628	6055,634	6025,261	5993,064
0,25	7426,9611	7076,8625	6742,379	6423,007	6118,253	5881,001	5850,919	5909,684	5961,128	6005,595	6043,419
0,30	6665,7538	6302,2851	5958,552	5763,221	5761,813	5821,115	5871,065	5912,207	5945,064	6015,644	6122,673
0,35	6025,9062	5742,9306	5681,954	5697,772	5751,021	5852,165	5987,508	6112,482	6227,804	6334,166	6432,229
0,40	5684,8685	5619,0169	5680,763	5846,918	5999,332	6139,058	6267,102	6384,419	6491,918	6590,465	6680,878
0,45	5694,9718	5763,1378	5939,246	6099,663	6245,757	6378,824	6500,086	6610,697	6711,744	6804,25	6889,173
0,50	5866,6819	5989,8778	6160,649	6315,285	6455,412	6582,551	6698,128	6803,47	6899,816	6988,316	7070,034

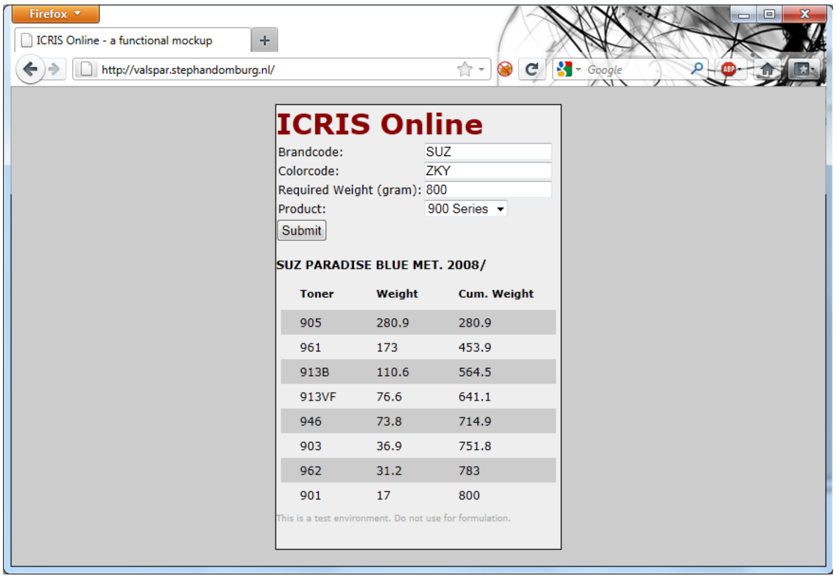
phi	0,70										
alpha\beta	0,00	0,05	0,10	0,15	0,20	0,25	0,30	0,35	0,40	0,45	0,50
0,00	15285,746	15285,746	15285,75	15285,75	15285,75	15285,75	15285,75	15285,75	15285,75	15285,75	15285,75
0,05	13317,075	13196,212	13076,28	12957,28	12839,2	12722,03	12605,78	12490,43	12375,99	12262,44	12149,78
0,10	11653,351	11444,622	11239,18	11036,97	10837,98	10642,15	10449,45	10259,85	10073,31	9889,792	9709,259
0,15	10249,973	9979,818	9716,15	9458,855	9207,817	8962,925	8724,068	8491,136	8264,021	8042,617	7826,819
0,20	9067,9757	8757,301	8456,739	8166,044	7884,975	7613,297	7350,776	7097,184	6852,298	6615,898	6387,769
0,25	8073,4581	7738,5341	7417,438	7109,743	6815,028	6532,884	6262,913	6043,773	5941,813	5984,597	6021,607
0,30	7237,0594	6890,3046	6560,945	6248,318	5970,304	5860,912	5870,279	5909,009	5940,603	5965,479	5984,045
0,35	6533,4783	6184,1442	5879,529	5808,23	5766,747	5805,042	5834,676	5926,44	6039,601	6144,884	6242,835
0,40	5941,0348	5785,3301	5725,296	5701,072	5845,973	5979,93	6103,767	6218,268	6324,179	6422,209	6513,034
0,45	5722,7447	5757,862	5823,292	5968,677	6107,503	6235,132	6352,559	6460,723	6560,511	6652,755	6738,241
0,50	5867,4556	5938,3425	6050,963	6196,381	6329,441	6451,37	6563,319	6666,362	6761,502	6849,669	6931,73

F

Appendix E: Online Mixing Colour Formulation Tool

Our scope contains many mixing colours or 'toners'. Mixing colours come in different series. These series contain about 40 different colours which should be mixed together using a formulation. This formulation depends on the brand and colour of a car. For example, the Paradise Blue Pearl Metallic colour from car maker Suzuki can be made using eight mixing colours.

Valspar provides its end users with the formulations using a piece of software that is linked to database that is stored on the customers computer locally. This database is frequently updated. Since the formulations that are requested can give great insight in the sales and trends of mixing colours, we propose offering an online system to end users, which allows Valspar to keep track of the number of formulations requested and the amounts of mixing colours involved in those requests. We have made a working prototype, as shown below. The php code for this prototype is given in this appendix.



```
<html>
<head>
<title>ICRIS Online - a functional mockup</title>
<link rel="stylesheet" type="text/css" href="style.css" />
</head>
<body>
<div id="outer">
<div id="container">
<div id="inner">
<h2>ICRIS Online</h2>
<?php
//read values from user
$brandcode = $_POST["brandcodeField"];
$colorcode = $_POST["colorcodeField"];
$reqgram = $_POST["reqgramField"];
$series = $_POST["seriesDropdown"];
?>
<form method="post" action="<?php echo $PHP_SELF;?>">
<table border="0">
<tr>
  <td><p>Brandcode:</p></td>
  <td><input type="text" name="brandcodeField" value="<?php echo
$brandcode;?>"/></td>
</tr>
<tr>
  <td><p>Colorcode:</p></td>
  <td><input type="text" name="colorcodeField" value="<?php echo
$colorcode;?>"/></td>
</tr>
<tr>
  <td><p>Required Weight (gram):</p></td>
  <td><input type="text" name="reqgramField" value="<?php echo $req-
gram;?>"/></td>
</tr>
<tr>
  <td><p>Product:</p></td>
  <td><SELECT NAME="seriesDropdown">
  <OPTION VALUE="7">900 Series
  <OPTION VALUE="3">500 Series
  <OPTION VALUE="36">2000 Series
  </td>
  </SELECT>
</tr>
</table>
<input type="submit" value="Submit" name="submitbutton" />
</form>

<?php
//database parameters and connect
$username="********";
$password="********";
```

```
$database="********";

mysql_connect(localhost,$username,$password);
@mysql_select_db($database) or die( "Unable to select database");

//query to find the year
$query="SELECT Year FROM `Color` WHERE (Brandcode = '$brandcode' AND
Colorcode = '$colorcode') ORDER BY ColorID LIMIT 1";
$result=mysql_query($query);
$brandname=mysql_fetch_row($result);
//query to find the color name
$query="SELECT Name FROM `Color` WHERE (Brandcode = '$brandcode' AND
Colorcode = '$colorcode') ORDER BY ColorID LIMIT 1";
$result=mysql_query($query);
$colorname=mysql_fetch_row($result);
echo "<p><br><b>$brandcode $colorname[0] $brandname[0]<br></p></b>";

//query to find the weights and paints from brandcode and colorcode
$query="SELECT Code,Weight FROM Recipeline WHERE (ColorID=(SELECT
ColorID FROM `Color` WHERE (Brandcode = '$brandcode' AND Colorcode =
'$colorcode') ORDER BY ColorID LIMIT 1) AND quality='$series') ORDER
BY Weight DESC";
$result=mysql_query($query);

//read each line from the result
$finalresult=mysql_fetch_row($result);
$weights[]=$finalresult[1];
$color[]=$finalresult[0];

while($finalresult[0] != NULL){
      $weightsum += $finalresult[1];
      $color[]=$finalresult[0];
      $weights[]=$finalresult[1];
      $finalresult=mysql_fetch_row($result);
}

if($weightsum != 0){
      $factor =  $reqgram / $weightsum;
}

//headers
echo "<table id=\"hor-zebra\" summary=\"Mixing Colours\">
    <thead>
      <tr>
            <th scope=\"col\"><b>Toner</b></th>
             <th scope=\"col\"><b>Weight</b></th>
             <th scope=\"col\"><b>Cum. Weight</b></th>
         </tr>
    </thead>
          <tbody>";
```

```
$i = 1;
$newweightsum = 0;
while($weights[$i] != NULL){
      $weights[$i] = $weights[$i] * $factor;
      $newweightsum += $weights[$i];
      $decweight = round($weights[$i],1);
      $deccumweight = round($newweightsum,1);
      if($i&1==1)
            echo    "<tr class=\"odd\">";
      echo  "<td><p>$color[$i]</p></td>
                  <td><p>$decweight</p></td>
                  <td><p>$deccumweight</p></td>
         </tr>";
      $i++;
}
echo "    </tbody>
</table>";
echo "<p1>This is a test environment. Do not use for formulation.</
p1>"
?>
</div>
</div>
</div>
</body>
</html>
```