MASTER

Assessing the potential of statistical forecasting conducted at the Dow Chemical Company

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Assessing the Potential of Statistical Forecasting

Conducted at the Dow Chemical Company

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Abstract

This master thesis considers the demand forecasting process at Dow Coating Materials, and consecutively aims to provide actionable recommendations to improve the forecast process in Europe. An analysis of four operating regions' forecasting processes showed each region's forecast process has differing elements. It has been found that one specific sub-region is applying statistical forecasting, while other regions traditionally rely on market-intelligence for their demand forecasts. A subsequent forecast performance analysis revealed that the statistical approach leads to the most accurate forecasts compared to other regions, while taking into account variability. As the European region – subject of this research – is shown to be equally variable and has a different demand forecasting process in place, there seems to be an opportunity to improve the forecasting process. By comparing the current marketing-intelligence forecast to a selection of univariate statistical forecast, it has been found that on the lowest level of aggregation, 58.5% of the volume saw an average increase in accuracy of 8.8%. Also, higher aggregation levels yielded higher forecast accuracy. Based on the findings, statistical forecasting is recommended to be implemented, with the condition that it is used as a raw-forecast. Judgmental input is still required in case of variable demand or when significant changes in the demand pattern occur.

Management Summary

This master thesis is conducted at Dow Coating Materials (DCM), part of the Dow Chemical Company. DCM maintains a global and capital intensive supply chain with 41 production facilities producing over 1,400 base-products. An important operating region is formed by Europe, Middle East, Africa and India (EMEAI). DCM sees an opportunity to improve the efficiency of operations in EMEAI by enhancing the current forecasting process. Therefore, this research aims to improve the current European forecasting process by providing actionable recommendations with respect to statistical forecasting.

Opportunity Statement

Over the last decade, the value of total global shipments in the chemical industry has more than doubled (American Chemistry Council Inc., 2015). At the same time, Europe has gradually lost its top position in world chemical sales (i.e. market share has halved) as emerging economies drove – and still drive – a large part of the growth (Marawietz, Gotpagar, Sarathy, & Ratta, 2015). Efficiency in supply chain operations is therefore of crucial importance to remain competitive. Improving the forecasting process is one way to achieve this, as improved accuracy on forecasts can result in “significant monetary savings, greater competitiveness, enhanced channel relationships, and customer satisfaction” (Moon, Mentzer, & Smith, 2003). In collaboration with DCM, the following goal has been set for this research:

“Identify the potential of statistical forecasting for DCM Europe, and provide actionable recommendations to improve the European forecasting process“

Research Design

The research consists of three parts, all contributing to the final recommendations. The first part focuses on mapping the current forecasting processes in each of the operating regions, realized by using questionnaires and subsequent interviews. A second analysis aims to evaluate the performance of the identified forecasting processes using forecast error metrics (calculated based on the most recent ten months). Third, the performance of a statistical forecasting in Europe will be assessed by comparing various statistical forecasts to the current forecast. The results of these analyses will contribute to the final recommendations provided to improve the forecasting process at DCM.

AS-IS analysis

The AS-IS analysis showed that each operating region has a distinctive forecast process in place. The region of Australia, New Zealand, Japan and Korea (ANZJK) is structurally using statistical forecasts, while other regions mainly use market-intelligence forecasts. However, in North America (NAA) a redesign involving statistical forecasting is currently being finalized and implemented. Also, the Latin American region (LAA) is getting ready for a similar redesign process, starting in 2016. Considering the forecast horizon, the EMEAI region uses a one year fixed horizon, while the NAA and APAC regions apply an 18 month *rolling horizon* forecast. Considering statistical forecasting, in each region issues are mainly caused by a lack of education. A big challenge is to embed statistical forecasting in the current regional processes, as it does not only requires a change of the process. Instead it should be supported by the creation of statistical expertise amongst users, and convincing them of the potential of statistical forecasting.

Regional Forecast Performance

The forecast performance analysis reported the forecast errors of each (sub-) region. As variability and external influences are different for each region, the coefficient of variation (CoV) is used to quantify variation and to support the analysis. The performance analysis revealed that the AZNJK sub-region is generating the most accurate forecasts on all levels and lag-forecasts (Table 1). Furthermore, ANZJK also has the highest percentage of volume for which all forecasts are in place (98.6% versus 92.9% for Europe). With Europe being equally variable, a similar performance is expected. The gap in accuracy and forecasted volume shows otherwise, and suggest an opportunity for improvement. Although the amount of data is more manageable in ANZJK, the region is handling it with less resources and can serve as an example for other regions considering the forecasting process. It was also shown that GCSEA, MEATI and the LAA-region are the least accurate regions and that aggregated forecasts have less forecast errors. It was also proved that forecast accuracy increases when more historical data is available.

Table 1: DFU Level Regional sMAPE Results per Lag-forecast

Region	Lag-0	Lag-1	Lag-2	Lag-3	CoV
EUR	45.37%	47.86%	48.81%	52.14%	0.090
MEATI	51.40%	54.73%	57.76%	61.43%	0.106
ANZJK	38.17%	39.32%	40.47%	43.55%	0.090
GCSEA	49.63%	53.29%	55.31%	60.37%	0.143
NAA	47.25%	47.58%	48.19%	50.79%	0.156
LAA	49.96%	51.89%	53.47%	55.60%	0.129

Statistical Forecasting in the European Region

The effects of statistical forecasting in Europe are quantified by comparing various statistical forecasts to the current (lag-1) forecast. Four statistical methods are selected based on their simplicity and conformity with DCM's information system. The methods ensure that seasonality and growth patterns are taken into account. Two years of history are used for 'model learning', while a third year is forecasted and compared to actual sales and current forecasts. The results for 4 different aggregation levels are shown in Table 2, and prove that there is a clear potential for statistical forecasting by revealing an *improved accuracy*. Eventually, the use of statistical forecasting can result in *time-savings for the account-managers, demand planners and managers.* However, to properly function, statistical forecasting requires sufficient historical data to be available and requires relatively 'stable' demand patterns (i.e. no huge, *sudden* changes in level, trend or seasonality). Thus, new product (groups) or infrequently ordered products will be *harder,* but not impossible, to forecast using a statistical model. On lower levels of aggregation this problem occurs more frequently, resulting in a lower average accuracy. Segmentation of products based on predictability and volume, offers a clear insight on which items will most likely be troublesome. For the DFU level, a total 34% of the volume is required as such and will need to be assessed to identify solutions to increase forecast accuracy.

Table 2: Lag-1 and statistical accuracies per aggregation level

Level	# of Items	Lag-1 Acc.	Stat. Acc.
Chemistry	9	92.39	**94.20**
Profit Center	26	88.87	**91.19**
Base-Bulk (selection)*	150	74.87	**82.25**
Base-Bulk (all)	296	77.01	**79.36**
DFU (selection)†	758	58.52	**67.33**
DFU (all)	2495	**56.06**	55.74

* For base-bulk products with a statistical forecast being up to 3% worse than the MI-forecast (58% of total volume)

† For DFU's with a statistical forecast being up to 3% worse compared to the MI-forecast (57% of total volume)

Actionable Recommendations

The AS-IS analysis revealed that DCM Europe currently makes no use of statistical forecasting for demand planning activities. Subsequently, the forecast performance analysis showed that the European region lags behind in terms of forecast accuracy. It was hypothesized that statistical forecasting could positively change the accuracy of forecasts, and this was proven to be a valid statement. Based on all findings, the following recommendations are provided for DCM to realize an improvement in the forecasting process:

1. **Implementation of bottom-up statistical forecasting at a DFU level:** Statistical forecasting should be implemented to build a raw-forecast which is consecutively adapted where needed, as summarized in TBALE X. Implementation should go hand in hand with extensive training, embedding the process across DCM, but also redesigning the forecast evaluation process to fit statistical forecasting. Furthermore, the role of market intelligence should be emphasized by structurally incorporating its input and low-volume, low predictability items should be addressed.
2. **Initiate a top-down forecasting pilot:** As top-down forecasting will yield more accurate forecasts (Table 2), a pilot should be started to assess impact on processes such as packaging and logistics. However, to do so, the right aggregation level should be found prior to starting such a trial.
3. **Improve data-maintenance:** The key-enabler of accurate statistical forecasting is proper data. Therefore, data-maintenance should be a high priority activity in the new process.
4. **Change to a rolling forecast horizon with extended length:** Instead of a fixed one year forecast horizon, statistics can be used to create a rolling 18 or 24 month rolling horizon.
5. **Share experiences and process-learnings globally**
6. **Proceed with roll-out of statistical forecasting in other regions:** The analysis also showed a potential for statistical forecasting in MEATI and LAA. To support future implementation in the MEATI region, a dedicated demand planner for MEATI (instead of EMEAI) should be appointed.

Table 3: Comparison of Current and To-Be situation

Forecast (demand) level	Current Process	Statistical Forecasting
Baseline Demand	Agreed during S&OP demand review	Agreed during S&OP demand review
Planner Adjusted Forecast	***Heavy interaction*** DP and Commercial. (monthly forecast-update file) (+/- 3600)	***Minimal interaction*** by using management by exception
Raw Statistical Forecast	**No statistical forecasting used**	Forecast is built by **statistical models at DFU level** (+/- 3600)

Preface

This master thesis marks the end of my master in Operations Management and Logistics, and the end of my student life in general. It marks the start of a whole new phase in my life in which I will be able to apply all the knowledge the TU/e has brought me in a business environment. I would like to express my gratitude to all who have helped me to reach this point in my life.

First of all, I would like to thank Tom van Woensel for his outstanding guidance and flexibility during this project. Thanks to your connections I was able to do this project, and your valuable input during our weekly WebEx calls gave me new insights and convinced me that I made good progress. Furthermore, I would like to thank Remco Dijkman for his valuable input and his kindness.

I really enjoyed my time at the Dow Chemical Company, and I am grateful to have received the opportunity to fulfil this project at the Supply Chain Department in Terneuzen. I would like to thank all my colleagues and supervisors at Dow. I really enjoyed being surrounded by business experts from all over the world, and the collaboration with the people from the Center of Excellence. Starting with an impressive first day, where I was introduced to the complete leadership team by Eran Hubert, and met my supervisors Josef Mosali and Steve Lima. Especially, I want to thank Stephen Lima – or Steve – for his expert opinion, valuable input, and his cheerful attitude. Furthermore, I want to thank Dobromir Likov for sharing his expertise. Sharing an office with you definitely gave me a head start with my project, and besides, it was a fun time. Besides that, it was great to meet two fellow OML-students doing an internship at Dow. Daniel and Leon, it was great getting to know you guys better during our 'daily-walks'. I wish you all the best for the remainder of your projects.

Last but not least, I would like to thank my parents, sister and girlfriend for their support, not only during this project, but during my whole student-life. Because of your best efforts, I have been able to successfully do all the things I wanted to do. I am happy to have experienced all of this with you.

The last year has been a great experience. My international semester in Vienna has been a wonderful experience, where I got to know a lot of great people from all over the world. When I returned, the gap that I expected to be there, was quickly overcome by the supportive environment I found back home. I hope to keep on meeting such wonderful people in my life and to enrich it with more wonderful experiences. Once again, a big thanks to all of you!

Remi van Riet

April 2016

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4 List of Abbreviations

AE	Acrylic Envelope
ANZJK	Australia, New Zealand, Japan and Korea
APAC	Asia, Pacific and Caribbean region
APO	Advanced Planning and Optimization
App.	Appendix
BSCL	Business Supply Chain Leader
COS	Chance of Success
CVC	Characteristic Value Combination
DASRF	Demand Alignment Supply Request Form
DCM	Dow Coating Materials
DFU	Demand Forecasting Unit
DM	Demand Manager
DPA	Dow Plastic Additives
DPA	Demand Planner
DSP	Demand & Supply Planner
DSR	Diamond Systems Reporting
EMEAI	Europe, Middle East, Africa & India region (India, Bangladesh, Pakistan)
FSS	Forecast Support System
GATP	Global Available to Promise
GBU	Global Business Unit
GBU	Global Business Unit
HW	Holt Winters
LAA	Latin America region
LT	Leadership Team
MAPE	Mean Average Percentage Error
MAPE	Moving Average
MI	Market Intelligence
NAA	North America region
PC	Pro Cast (Forecast X optimization method)
PM	Performance Monomers
S&OP	Sales and Operations Planning
SA	Styrene Acrylics
SD	Sales Director
SE	Simple Exponential Smoothing
sMAPE	Symmetric Mean Average Percentage Error
SN	Seasonal Naïve
UOM	Unit of Measure
VA	Vinyl Acrylics
VWAA	Volume Weighted Average Accuracy
WD+X	Start of the month + Number of weekdays

1 Introduction

The research as described in this report is executed at the Dow Chemical Company, one of the largest players in the chemical industry, and considers the potential of statistical forecasting for the Coatings Materials business group. In this report, sales figures cannot be disclosed due to confidentiality reasons, leading to graphs without y-axis. The main function of these graphs is to display the demand pattern, and therefore y-axis without scale do not harm interpretability. This first section will provide a basic insight in the chemical industry, the Dow Chemical Company and the Coating Materials business unit.

1.1 The Chemical Industry

The chemical industry delivers an incredibly large number of products for a wide variety of applications. Fuel, lubricants, plastics, paints, water-treatment, fertilizer, and pesticides are just a small number of products delivered by this industry. It is said that "*over 96% of all manufactured goods are directly touched by the business of chemistry*" (American Chemistry Counsil Inc., 2016). Over the last decade the value of total global shipments more than doubled, with shipments worth $ 2.375 trillion in 2004 to $ 5.389 trillion in 2014 (American Chemistry Council Inc., 2015). During this period, Europe gradually lost the top position in world chemical sales, as emerging economies drove (and still drive) a large share of the growth (Marawietz, Gotpagar, Sarathy, & Ratta, 2015). Whereas the total sales in Europe did grow continuously, providing 1.2 million jobs in 2014, the global sales grew at a faster pace, resulting in a European market share that has halved in 20 years (35.2% in 1992 to 17.8 in 2012%). **Figure 1** shows the percentage share in global sales for most geographical regions, according to data provided by Cefic (2014). Furthermore, **Figure 2** shows that by 2013 the joint sales of the NAFTA and European Union (EU) were only marginally larger than China's sales.

Figure 1: World Sales Comparison 2003 vs. 2013 **(Cefic, 2014)**

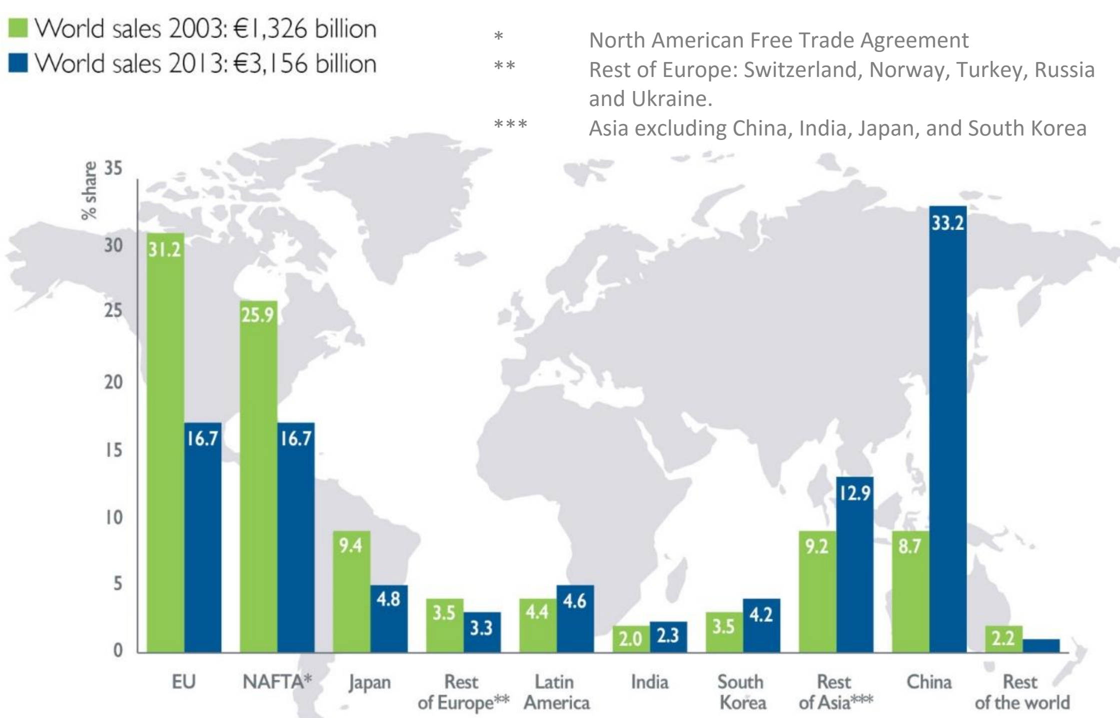
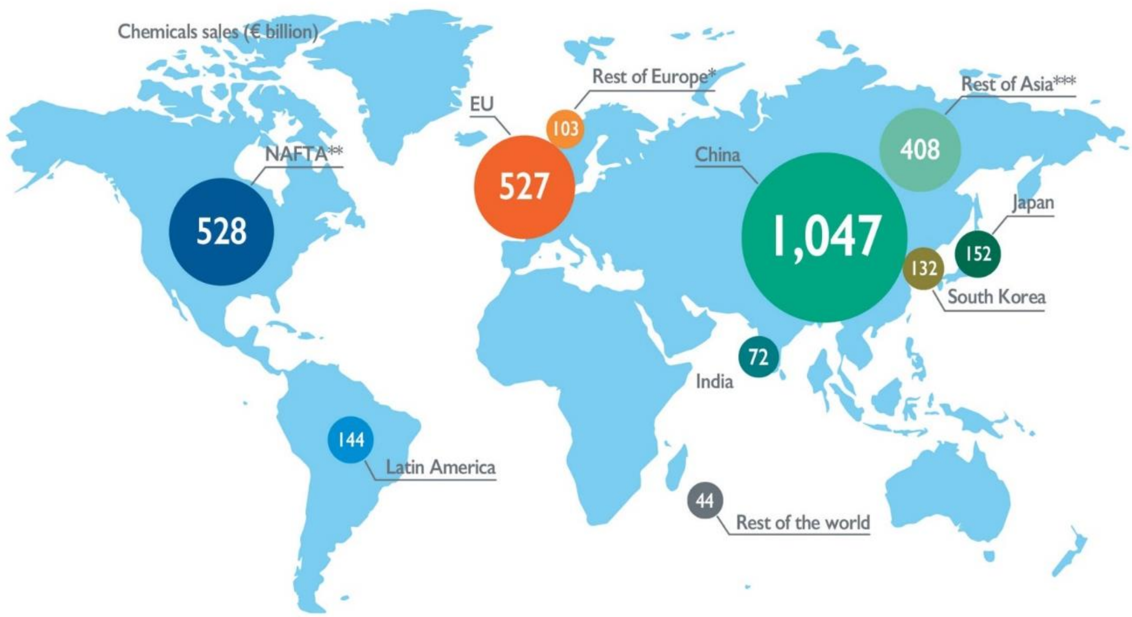


Figure 2: World Chemical Sales in 2013 (per Area)

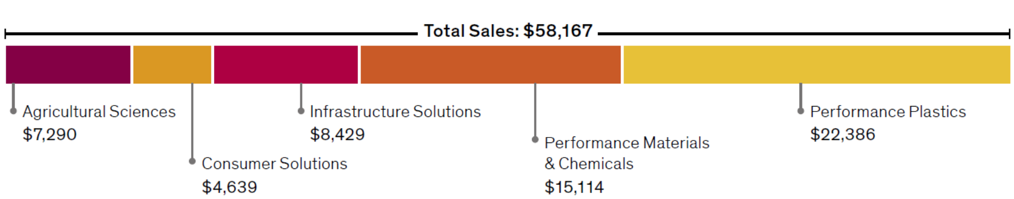


A large part of European sales is accounted for by Petrochemicals (26.6%) and Polymers (21.5%) and jointly form the 'Base-Chemicals'. These commodity chemicals are mass-produced and used as feedstock for the chemical industry itself or used in other industries. During 2013, base-chemical sales represented 61.8% of total sales. Two other major product areas are the 'Consumer-Chemicals' (shampoo, detergents, perfumes), and 'Specialty-Chemicals' (crop protection, inks, dyes) with respectively 11.7% and 26.5% of total sales.

1.2 Dow Chemicals

In 1897, Herbert Henry Dow founded the Dow Chemical Company in Midland, Michigan with an initial success based on the production of bleach and bromide. Nowadays, the corporate strategy is to *"invest in a market-driven portfolio of advantaged and technology-enabled businesses that creates value for our stakeholders and customers"* (Dow, 2015). This results in a wide range of technology-based products and solutions to high-growth sectors such as packaging, electronics, water, coatings and agriculture. Serving customers in 180 countries, the operations are spread globally, and so is Dow's supply chain. Over 6,000 product families are produced at 201 sites in 35 countries worldwide (Dow, 2015). In 2014, Dow reached net sales of over 58 billion dollar (**Figure 3**), and an adjusted EBITDA of 9.3 billion. Compared to 2013, a 1.9% growth in net sales and 11.7% growth in adjusted EBITDA has been realized.

Figure 3: Dow Chemical Sales by Operating Segment (2014)



1.2.1 Dow Coating Materials

Dow has several operating segments, each serve different markets and produce different products. These segments are subsequently divided into numerous Global Business Units (GBU). The division Advanced Materials captures the so called 'Acrylics Envelope', formed by Dow Coating Materials (DCM), Dow Plastic Additives, and Performance Monomers. This research will focus on DCM, which provides innovative technologies that help advance the performance of paints and coatings. With a broad portfolio of binders, dispersants, rheology modifiers and surfactants, the DCM serves 6 distinct markets: architectural, additives, industrial, leather, paper and traffic (Dow, 2015).

With 1,700 employees the production of 1400 different products is realized in the production locations. Monomers are the main feedstock, and are used in the vast majority of the products produced at the 41 DCM facilities, spread over Northern America (9), Europe, Middle East, Africa and India (16), Latin America (3), and Asia the Pacific, Australia and the Caribbean (13). Currently, a big portion of production and trade is realized in the Europe, with Germany and France as biggest markets. The greater part of the products are produced at multiple sites (multi-sourcing) on a make-to-order basis, with a production lead time of on average 7 days. Only the high-volume products are made-to-stock. DCM receives feedstock from external or internal suppliers (monomers) and converts this to products that are supplied to either internal or external customers (Figure 17, Appendix I).

2 Research Design

Subsequent to the concise introduction of the chemical industry and Dow, this section will elaborate on the actual research design. Starting with the problem – or opportunity statement – the subject will be introduced, supported by research questions, the research methodology, scope and deliverables.

2.1 Problem Statement

With its customers and production facilities globally dispersed, Dow Coating Materials developed a global, but capital intensive supply chain, as production facilities in the chemical industry are known to be costly. Section 1.1 showed that traditional chemical markets (Europe and the U.S.) are losing market share. This emphasizes the importance of efficiency – both time- and cost wise – for companies, to keep concurrent supply chains profitable and serve customers within the set customer service levels. One way of doing so, is to improve the demand forecasting performance within the firm. This is a crucial resource to manage supply chains, as tactical and operational decision on production planning, inventory levels, transportation, and scheduling are based on forecasts (Blackburn, Lurz, Priese, Göb, & Darkow, 2015) (Chopra & Meindl, 2013). Improved accuracy on forecasts can result in "significant monetary savings, greater competitiveness, enhanced channel relationships, and customer satisfaction" (Moon, Mentzer, & Smith, Conducting a Sales Forecasting Audit, 2003).

As the operations of DCM are globally dispersed, each global area has its own forecasting process in place. The form of this process is dependent on the local leadership and historical developments, as each area has a local demand manager responsible for the planning activities in that specific region. Taking into account various market and process characteristics, a forecast is made using methods that apply to the specific region. Some areas apply a statistical approach, while others purely focus on market intelligence forecasts. It is estimated that only 30% of the demand planning at DCM world-wide is somehow supported by statistical methods to forecast demand in both long- and short-term.

A challenging, more competitive business environment, together with a need for sustainable developments emphasizes the need for a more structured approach to demand forecasting and the potential benefits. The DCM business also recognizes the strategic alignment of this project: *"DCM aims to have the best in class supply chain setup to serve our customers in the optimal way. We want to create the best customer experience by simplifying the order flow and reducing the 'waste'. In order to optimize the supply chain, the forecast must be as accurate as possible"* (Mosali, 2015).

While there is no sign of degrading (financial) performance – in contrary, net sales and adjusted EBITDA are on the rise – one cannot speak of a clear problem at hand. Nevertheless, there is a clear need to improve business processes from a competitive as well as from a sustainability perspective. Therefore, one can speak of an 'opportunity', instead of a problem, in the form of the forecasting process at DCM. Based on the information provided in earlier sections, the author and Dow Coating Materials have identified the corporate opportunity statement (Mosali, 2015):

The global supply chain of DCM is producing a wide variety of products at various production sites. With long lead times on raw materials and plant capacity constraints, accurate forecasts are of key importance. Currently, each region has a demand manager and an individual forecast process, which progressed naturally for each region. There is an opportunity to improve and streamline the forecasting processes throughout the firm, leading to a strengthened competitive position and better customer service levels.

2.2 Assignment & Research Questions

Based on the opportunity statement and further discussion with DCM, the final assignment is to "*Identify the potential of statistical forecasting, and provide actionable recommendations to improve the European forecasting process*". To structure the approach towards reaching the objective, a number of research questions have been formulated which will be answered individually to arrive at the final conclusion.

The importance of the forecasting process has been recognized by several authors. Danese and Kalchschmidt (2011), state that "a proper forecasting process gives companies the opportunity to better understand market dynamics and customers behaviors, reduce uncertainty on future events, and provide the company's functions with useful analyses and information". Darkow (2014) concludes that more awareness for sustainability, resource scarceness, industry regulations, and global competition further increase the importance of sophisticated planning activities on both the short- and long-term. The first research question focusses on the forecasting process currently in place at the DCM business globally. This analysis should reveal the most commonly used forecasting methods, the available tools to support forecasting practices, but also considers the way in which the forecasting process is embedded in the local business functions. Lastly an important part of this research question can be answered by finding difficulties that currently restrict demand managers in their forecasting role. Therefore, the first research question and sub-questions can be described as follows:

1. *What is the current state of the forecasting process in each of DCM's operating regions?*
    a) At which level of detail are forecast generated?
    b) Which forecasting tool(s) are currently used?
    c) What forecasting methods are most commonly used at DCM?
    d) Which time-horizon is used for forecasting practices and is there a consensus in the usage of a specific time-horizon?
    e) How is the forecasting function embedded in local business functions in different areas?
    f) What difficulties are currently experienced by demand managers?

Subsequently, the performance of each of the identified regional methods will be evaluated. To what extend do forecasts mimic the actual demand, i.e. how accurate are the forecasts produced by the current forecasting mechanism. This enables an insight in how effective each region forecasts its demand, which might lead to important insights for the solution design for the forecasting process in Europe. To evaluate and compare forecasts, a proper error measure has to be found. This measure should be reliable as well as complying with requirements set by decision makers at DCM. To find this measure, the current evaluation criteria can be used as a basis and literature will be consulted.

2. *How are current forecasting methods at DCM performing?*
    a) Which forecast error measure(s) is (are) currently used to evaluate forecasts at DCM?
    b) What error measures are recommended by literature?
    c) At what level is forecast accuracy measured?
    d) How do current forecasting methods perform based on historical data?

The third research question will prove whether or not the European region, which is the focus of this research, has a potential to improve when compared to other regions. The outcomes of the former research question will partly feed the solution design, and will direct the way in which the potential of statistical forecasting will be assessed for the European region. Therefore the third research question is:

3. *Does statistical forecasting improve the forecast accuracy in the European region?*
    a) Would statistical forecasting be beneficial for the whole of Europe?
    b) Is there a difference in demand pattern for different aggregation levels?
    c) Which statistical methods should be used to forecast demand at different levels?
    d) What percentage of sales volume would benefit from statistical forecasting?
    e) How much does the forecast accuracy raises when using statistical forecasting?

After the evaluation of forecast performance in each of the areas and the associated methods, a next step is to identify areas for improvement within the forecast process in the European region. A more integrated and accurate forecast can boost business performance. By assessing scientific literature but also considering the findings of the previous research question, the fourth research question will lead to actionable recommendations for the improvement of the forecasting process at DCM on forecast methods, level and scope. It is crucial that the potential improvements fit to the requirements as imposed by DCM and support the business in making decisions based on future demand. This ensures that relevant and meaningful recommendations are made.

4. *What actionable recommendations can be given to improve the forecasting process at DCM Europe concerning the forecast level and scope?*
    a) Should the demand forecasting process make use of statistical forecasting?
    b) At what level should forecasts be made (i.e. Customer, Chemistry, Country, etc.)?
    c) What are the possible actions that can lead to a better forecasting process?

2.3 Deliverables

To end the project successfully, the following deliverables should be realized:

1. An assessment of the current forecasting process and tools available in DCM's operating regions.
2. A benchmark of regional forecast performances.
3. Actionable recommendations to improve the European forecasting process
4. A (confidential) report of the master thesis project
5. Presentations for DCM's commercial and supply chain teams, and the TU/e.

2.4 Methodology

Van Aken, van der Bij and Berends (2012) propose a general Framework for scientific research: the problem solving cycle. This general approach provides an initial idea of how to approach a problem or opportunity and indicates which phases are of major importance. For most theses, the last two stages (evaluation & Learning and Intervention) are not addressed, as academic work mostly focusses on designing solutions, and let the company decide whether or not the solution is implemented. However, recommendations concerning the implementation of the proposed solution can be given.

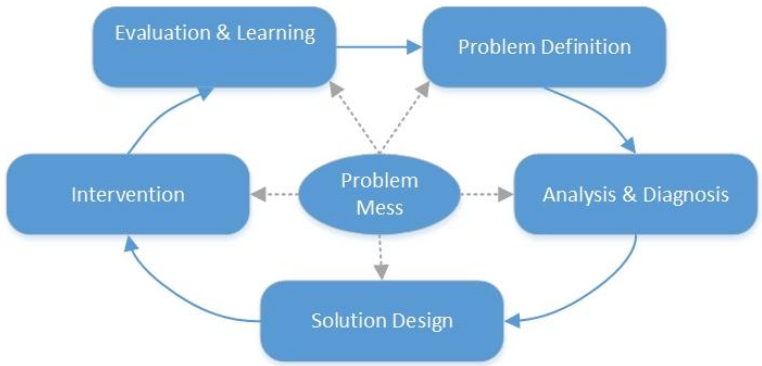


Figure 4: Problem Solving Cycle **(van Aken, van der Bij, & Berends, 2012)**

In the case of this thesis, the first three steps will be considered. The analysis & diagnosis phase will concern the first and second research question with an assessment of different forecasting practices and their relative performance. Based on the findings provided by those research question the problem definition can be slightly adjusted. In a third phase the solution design, or in this case the potential improvements, will be elaborated. In **Figure 5** this process is visualized.

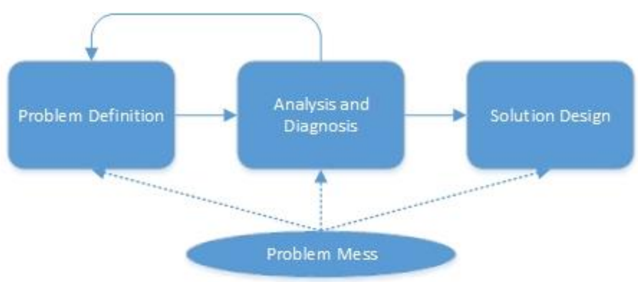


Figure 5: Adjusted Problem Solving Cycle

2.5 Scope

This project is focused on the forecasting process of Dow Coatings Materials. Initially, the As Is investigation of the process and the forecast performance analysis focus on all geographical regions, considering DCM as a whole. Afterwards, the recommendations for the improvement of the forecasting process will have a limited reach, and are only applicable to the European region. However, as will be noted later on, these recommendations can be used as a starting point for improvements in other areas.

3 Demand Forecasting at DCM | As Is Analysis

With 41 production facilities worldwide, DCM covers all continents. As different regions have different needs and processes, operations are split in 4 regions, managed separately. The same holds for the other businesses operating in the Acrylic Envelope (AE). The following areas can be distinguished: 1.) Europe, Middle East, Africa and India (EMEAI), 2.) Asia, Pacific and the Caribbean (APAC), 3.) North America (NAA), and 4.) Latin America (LAA). To assess the current forecasting process in the AE, a questionnaire was sent out to the relevant people in the organization. The results of this questionnaire can be found in Appendix II, and will be discussed within the next sections.

3.1 Business Overview & Reporting Levels

In each of DCM's operating regions, there is a structure of Business Segments, Value Centers and Performance- or Profit-centers which is used for decision making (Appendix III). This structure is supported by the information system (SAP), and allows people to request or add data for a certain part of DCM. In practice, people at different levels of the business use a hierarchy consisting of Chemistry, Profit Center, Performance Center, Base-Bulk and DFU to view sales volumes and financials. People can view data at an aggregate level such as Chemistry for financial reporting or more granular level such as Base bulk or DFU for Supply planners. Business performance is discussed by analyzing metrics at various levels per area and forecasts are evaluated mainly using the forecasting bias. On an operational level, where actual planning and forecasting processes are executed, the planners and demand managers use the more granular level to support individual product planning. Some regions have to manage a larger product portfolio, reaching up to 5.000 separate forecasts. Since Dow is using SAP, they have to deal with the data structure as provided by the SAP. For demand planning objects data is structured at a detailed level, called a CVC. However, as a remainder of the previous planning tool, the 'Demand Forecasting Unit' (DFU) is also used, as elaborated in the following section.

3.1.1 Characteristic Value Combination & Demand Forecasting Unit

Concatenating 8 basic characteristic, a CVC is at the very bottom of the aggregation levels. The base elements of a CVC contain hierarchies that are maintained in SAP. For example, a ship to customer is accompanied by a State/City ship-to and a Region ship-to attribute on a higher level (Appendix IV). CVC's can be created or deleted by planners, but only within their working space. The creation and realignment of CVC's happens frequently as new customers, materials or any other aspects of a CVC change.

With only 3 basic characteristics, a DFU is less detailed. A 27 digit long code identifies the material sold, ship-to customer, and area profit center. This information serves to retrieve information about packaging and logistic needs. Unlike the CVC, a DFU is not an integrated part of the SAP structure and is therefore not contained in any standard SAP transactions. In practice CVC's and DFU's are often interchanged as CVC's are mostly displayed with only the attributes of a DFU. The DFU/CVC level is currently used for forecasting and planning purposes in DCM's supply chain. It is estimated that there are roughly 24,000 CVC's globally, of which 13% is statistically forecasted.

3.2 Advanced Planning and Optimization (APO) tool

Globally, the generic SAP add-on APO is used as a tool to support the forecasting and planning process. This means that compromises have to be made, as it is not individualized to needs of each business. Dow uses thee parts of APO: Demand Planning, Supply Network Planning, and Global Available to Promise (GATP) (Dow, 2012). It follows logically that APO Demand Planning supports the demand planning process at DCM. For the purpose of forecasting, a limited number of forecasting methods is offered, including single exponential smoothing, Holt's method, Holt-Winters method, Seasonal Linear Regression, and Linear Regression. Where applicable, forecast parameters can be set manually, but automatic settings are also available. Furthermore, what-if analysis, Life Cycle Planning and promotion planning are included.

The Supply Network Planning part of the tool allows the user to manage both the material and capacity aspects for their respective supply chain. This tool can aid managers to align their supply plan to the inventory strategy and also manage capacity by managing supply plans for bottleneck resources. Finally, with the GATP module, the supply chain is able to react to customer requests by the knowledge of availability of goods in any area in the world. However, the most frequently used module is Demand Planning, having a potential to increase forecast accuracy and simultaneously decrease efforts spent.

3.3 Analysis of Operating Regions

In this section the forecasting process that is currently in place will be elaborated per region. For the EMEAI and APAC region flow charts are available. For the other regions, processes are currently being changed and process details are still being designed. These flowcharts can be found in Appendix V, where each orange box stands for an action in APO.

3.3.1 Europe, Middle East, Africa, and India

In the EMEAI region, the forecasting process is executed by three persons with a total of 2.33 FTE. The demand planning function is integrated in the Supply Chain organization, and executed by a Demand Manager (DM) and two Demand Planners (DP). The DM in this region is driving forecast accuracy, bias and improvement projects, but also analyzes historical data and participates in the S&OP process, whereas the DP's are concerned with the day to day operations within the demand forecasting process. In this region, the S&OP process is currently being redesigned to be more efficient.

Both the DP as well as the DM go through a weekly and a monthly cycle with the purpose of creating forecasts at a detailed CVC level for about 4,930 unique active CVC's. The weekly cycle functions to process short term changes (0-13 weeks) in the demand forecasts. The usage of bias correction on a weekly basis keeps forecasts up to date in the short run and makes the supply planning more efficient, stable, and reliable. The long term cycle generates reports for the long run, starting three months ahead up to the end of the next calendar year. These forecasts also form an input for the monthly S&OP meeting and for a monthly meeting with the Leadership Team (LT). In the S&OP meetings short and long term highlight in demand are discussed, outliers are analyzed, and revenues are predicted. Both cycles are visualized in Figure 22 and Figure 23. For the monthly cycle, the forecast revisions are validated by the DM, Sales Director and Account Managers. The S&OP team is formed by sales representatives, the Supply Director, DM, and DP's. An important notice is that in both processes, statistical forecasting is not applied to generate or support forecasts. All forecasts are produced based on market intelligence that come from Account Managers who are in close contact with their customers. To manage the current process as efficiently as possible, active CVC's are updated frequently while the less active CVC's are managed by an ad-hoc approach and less frequently updated forecasts.

The involvement of various departments and functions, and the S&OP meeting, classify the forecasting process in the EMEAI region as a cross functional one. This only occurs within the area, as on the global level, there is little or no communication with other regions to discuss worldwide trends or learning experiences. It is important to note that the lack of statistical forecasting is mainly accounted for by the complexity of the APO tool and the absence of theoretical knowledge of statistical forecasting.

3.3.2 Northern America

In 2015 the NAA demand planning process has been redesigned, and changes are currently being implemented incrementally. With a dedicated DM and DP (2 FTE), and several newly defined processes, the planning process is now more structured and is expected to produce better results. As some aspects were still subject to changes, the description of the process will stick to the main characteristics.

Comparable to the EMEAI region, this region has a monthly and weekly cycle and is dealing with around 5800 active CVC's. The weekly cycle is defined by an S&Oe process, which focusses on the short term demand planning (0-13 weeks). A forecast bias review is executed each week by sending out a so called Demand Alignment Supply Request Form (DASRF), and this is subsequently discussed in the S&Oe meetings on Monday to update forecasts and discuss changes with supply. The DASRF is currently not integrated into APO and is a separate excel sheet which – in case supply approves – will be inserted into APO. The monthly cycle is focused on the long term and produces forecast for 3 to 18 months ahead. Eventually this has to evolve to a 24 month look-out. The monthly cycle starts with a demand review, taking place at WD+2 of each month and ends with an S&OP meeting at the end of the month.

A unique progress that has been made in the NA-region is the structural handling of demand uncertainty. With a process called the 'PLUG-review', uncertain demand is reviewed and classified according to the level of uncertainty. Classification of potential demand is done by the Chance of Success (COS). All demand with a COS of 80% or higher and occurrence within 8 weeks, is put into the PLUG, meaning that it is inserted in APO and is accounted for by supply. The opportunities with a lower COS are considered in the so called Planit+ process, which aims at reserving some spare capacity for these orders. To do so, other measures will be taken, such as adding only half of the demand, or planning for demand further into the future (depending on the COS and the time to occurrence of demand). Besides this PLUG review, a monthly bias and forecast consumption report are used to keep track of progress. In the bias report, occurring at the start of the month, forecasts that are repeatedly coming in biased are considered (top 5+ and 5-) and discussed with relevant account managers and sales managers. The bias report is issued at WD+3, and is therefore not included in the demand review but remains e-mail based. Halfway throughout the month (WD+15), a forecast consumption report is used to see if demand is 'consumed' as forecasted. If the demand consumption falls below a certain threshold, information about possible causes is gathered.

Combining all of these processes in the monthly process, the region produces a consensus forecast which is made by combining information from multiple sources and chronological verification steps.

Currently, forecasts are still generated using market intelligence, and statistical forecasting is not used in a structural way. However, statistical forecasting is gradually introduced using pilots to assess the functionality and to train the stakeholders with using statistical methods. Furthermore, for cross functionality of the process, the same conclusion as for EMEAI can be drawn.

3.3.3 Asia, Pacific, and Caribbean

With a total of over 6.000 CVC's and 3.55 FTE (excluding account managers), the Asia Pacific and Caribbean region has the most resources assigned to demand planning. The process is executed by 7 Demand & Supply Planners (DSP's) with a total of 3.2 FTE, which are supported by a Business Supply Chain Leader (BSCL) and Administrative Assistant (AA) for reporting purposes. Each DSP deals with a sub-region such as Japan & Korea, or China and a specific business segment (Industrial or Architectural).

Within APAC, two sub-regions can be distinguished: Australia, New Zealand, Japan and Korea (ANZJK), and Greater China combined with South East Asia (GCSEA). The first region structurally implemented statistical forecasting, whereas the latter region relies on market intelligence to create forecasts. In ANZJK, the monthly cycle starts with reviewing statistical forecasts, which are made according to a number of forecasting profiles to which CVC's/DFU's are assigned. New DFU's are assigned to profiles, and existing DFU's with significant forecast biases will be adjusted and potentially transferred to a different profile. At WD+3 the so called WD+3 and bias reports are issued. The WD+3 report is an input for the supply planning, while the bias report is sent to account managers which subsequently have 2 days to correct their forecasts or discuss other changes. At WD+8, the final forecast for next month is issued, called the lag-1 forecast or the WD+8 report. After issuing, the change document period starts, lasting until the end of the month. In this period data is prepared for the next monthly cycle and a DFU audit process is executed. This mainly entails the maintenance of DFU's to keep the APO database up to date by avoiding double instances, adding new ones and deleting old ones. Due to the relatively stable demand patterns in this area, statistical univariate models, relying on historical data, are believed to generate reliable predictions. For GCSEA, with a more fluctuating demand and variable economic growth pattern, statistical forecasting is occasionally used, and mostly overridden by market intelligence to develop more realistic predictions. For both market intelligence as well as statistical forecasting, the area is using APO as a tool to forecast and to save the market intelligence data.

3.3.4 Latin America

The Latin America region only has 0.15 FTE in place to manage the forecasting process. The relatively small market size of this area, causes the process to be managed ad-hoc. Due to the absence of account manager forecasts for some key customers, statistical forecasting is used as an ad-hoc solution but is not comprehensive. The majority of demand is still forecasted using market intelligence. Currently, a redesign for the demand forecasting process is started of which details are not yet known.

3.4 Pain Points in the Forecasting Process

In this section the pain points, as identified by participants of the forecasting process, are elaborated. The issues, as pointed out by the participants, were gathered using a questionnaire and subsequent interviews with selected DM's and DP's. The pain points can be divided in three main categories: APO, Diamond Systems Reporting (DSR), and Organization. In Appendix II, the pain point count per category is shown for EMEAI and APAC. Some of the NAA issues are neglected, as they specifically refer to the new process being introduced. Subsequently, these pain points are grouped into sections, which are prioritized by the DCM Demand Managers. According to the findings of the questionnaire and the DM inputs in the following paragraphs the most influential pain points will be elaborated.

3.4.1 Advanced Planning and Optimization tool

As briefly introduced before, the APO tool offers a variety of options to develop univariate forecasts. From an academic perspective this is a rather simple method, however for non-specialists the theory behind this is rather difficult to understand. Besides that, the AP interface is very basic and does not provide an intuitive working environment. As a result, the most frequently mentioned issue is the need for a basic understanding of APO, and learning APO's capabilities. For example, currently there are no clear guidelines on the choice of an appropriate forecasting method for a certain item. Accordingly, choosing the right model and parameters is a difficult practice and is mostly a result of automatic settings. This makes the structural and conscious usage of statistical forecasting a difficult matter.

Besides the lack of knowledge, there are some system issues that cause inefficiencies. Data maintenance consumes a lot of time due to locked CVC's in the system. But also, the timing of the month-end load does not match to the WD+3 timeframe, until which invoices can be submitted. Another issue that is mentioned, is the current processes of incorporating market-intelligence in APO, which has to be done manually and is time consuming. Furthermore APO somewhat limits the choices for demand planners concerning aggregation level. As APO is built upon the usage of CVC level, it requires a considerable extra workload to forecast at an aggregation level that is not in the line of the SAP structure, such as chemistry level or sub-region / country level.

3.4.2 Diamond Systems Reporting

All the data that is stored in the SAP databases can be accessed using Diamond Systems Reporting (DSR); the dedicated resource for transforming data into reports. With a large number of options offered to structure data, users are able to customize reports. However, for some purposes the options are not sufficient. This requires users to manually create their own reports. Users state that the inclusion of certain data is impossible or requires a work-around. Not only does this unnecessarily consumes time, it also causes reporting standards to fade. An often cited problem is the forecast consumption report, which does not shows all required data. For example, consignment warehouse sales, open order numbers, and business plan volumes cannot be included. Also in this area users feel the need to receive training to get familiar with the options the system offers. Not only would this streamline the process, it will also reduce the time spent on potentially needless workarounds. A final issue with DSR stems from the fact that users have to wait to WD+4 to access accurate sales figures, as reports are not refreshed every day.

3.4.3 Organizational Issues

From an organizational point of view, there are some flaws that restrain the forecasting process from functioning more efficiently. Often referred to are the relatively tight deadlines for the monthly S&OP process concerning reports, presentation and the limited time for preparatory analysis to provide meaningful input during the meeting. Furthermore, a number of meetings would benefit from pre-work by other departments to increase the efficiency of that meeting. Examples are financial estimates and project review meetings.

Due to different areas and different sales managers, involved planners feel that requirements are differing per region. This is also related to the roll-out of a new set of standards, referred to as the 'Gold-Standard', which did not cover all areas simultaneously. In general, respondents of the questionnaire seem to agree that there is a lack of communication and coordination between regions. Due to the different businesses within the AE, deadlines for Business Plans and other planning purposes are not synchronized, causing difficulties for supply planning. In the EMEAI region there is a need for departments within the same business unit need to start collaborating to arrive at a single set of numbers that make sense. Another pain point is the lack of sharing lessons learned. Sharing ideas with planners, managers in different areas or businesses can increases the engagement and performance of the respective persons and businesses.

3.5 Provisional Conclusion

The regional AS-IS analysis showed that each region has a distinctive process in place. Where the ANZJK region is extensively using statistical forecasts, the NAA and LAA regions only apply this for a minority of the CVS's, and the EMEAI region relies exclusively on market-intelligence. Considering the forecast horizon, the EMEAI region is working with a one year ahead fixed horizon, while the NA and APAC regions apply an 18 month *rolling horizon* forecast. Even though there are some similarities within the bias review and S&OP process in each region, the timing of these events is not synchronized across areas. However, with the roll-out of the new process in NA, and the planned development of a new S&OP process in the EMEAI region, it is expected that the processes will become more similar for all of the regions.

Issues with statistical forecasting, as mentioned by users, are mainly centered on education. A big challenge is formed by embedding statistical forecasting in the current regional processes. The APAC region already has dedicated process steps concerning statistical forecast, but other regions lack those steps. It can be concluded that not merely the process requires a change, the creation of statistical expertise and convincing users of the potential of statistical forecasting is needed to support the use of and movement towards statistical forecasting.

4 Regional Forecast Performance Analysis

With the global forecasting processes mapped, the forecasting performance for each of the regions can be analyzed. As revealed in the As-Is analysis, the ANZJK sub-region was the only region to apply statistical forecasting in a structured way, whilst other regions still rely on market intelligence (MI) for their forecasts. To be able to quantify the performance, evaluation metrics will be used. These will be discussed first, followed by a discussion of regional results.

4.1 Forecast Error & Metrics

In the business environment, forecasts are made to help decision makers improve their decisions (Granger & Pesaran, 2000). But, as stated by Silver, Pyke and Peterson (1998), "*all that we can say for certain about a forecast of demand is that it will be in error".* The forecast-errors can be measured, and reveal valuable information. Managers can use it to determine whether the forecasting method currently used is predicting the systematic component of demand accurately. When this information is used effectively, it helps organizations – and supply chains as whole – to adapt to changing market conditions and to improve operating performance (Fildes & Beard, 1994) (Gardner, 1990) (Wacker & Lummus, 2002). Also, contingency planning is related to the forecast performance, as it must account for the forecast error which in turn is closely related with production and inventory planning (Chopra & Meindl, 2013). To correct for the forecast error, inventory assets are frequently relied on to maintain service when forecast performance degrades (Armstrong J. , 1988) (Winklhofer, Diamantopoulos, & Witt, 1996).

Various authors have proposed metrics to measure the size of the error, each having unique characteristics. It is however a hard quest to find the right forecast metric(s). Some say that no single measure gives an unambiguous indication of forecast performance (Armstrong & Collopy, 1992) (Mathews & Diamantopoulos, 1994). Others question that statement, and point to some frequently used and easily understood measures (Chatfield C. , 1992) (Makridakis & Hibon, 1995). Furthermore, many metric proposed in literature can be infinite or undefined, and can produce misleading results (Hyndmann & Koehler, 2006). Makridakis and Hibon (1995) tested 14 forecast accuracy metrics, considering two statistical criteria (reliability and discrimination) and two user related criteria (information content and intuitiveness). Table 22 informs about all the error measures considered by Makridakis and Hibon, and concludes on their positive and negative characteristics. Table 26 summarizes the findings of their research (based on Table 23 to Table 25), and Makridakis and Hibon (1995) conclude that the MSE can be recommended for statisticians once something is done to deal with outliers, and that the symmetric MAPE is suggested for non-statisticians. The latter advice is based on the intuitiveness and the lesser influence of outliers, making the sMAPE useful for both comparison of methods as well as decision making. For this research, evaluation metrics will be chosen that appeal to a broad audience. Metrics need to be understandable for unexperienced users and should have an intuitive meaning, leaving metrics with little or no intuitive meaning, such as Theil's-U, Geometric Mean Relative Absolute Error, GMMSE, or Median-RAE, out of scope (Makridakis & Hibon, 1995). Based on this, and the forecast metric analysis, the sMAPE is chosen as forecast accuracy measure used for further analysis. However, other literature suggests that the sMAPE is not as symmetric as suggested, and treats large positive and negative errors differently (1999). To be able to identify large, deviating errors, the sMAPE is not sufficiently discriminating.

Therefore, this research will also make use of the MAPE. This metric is more sensitive to outliers, but has a relative character and supports the analysis by identifying which region has major forecasting errors or many faulty data-entries. This choice is supported by Chatfield (1988), who states that due to variations in the scale of observations, unit dependent accuracy measures such as the MSE or MAE are inappropriate when comparing performance. Finally, since the MAPE does not take into account any weighting factor such as volume or margin, the wMAPE is introduced for this analysis. With this measure the MAPE is combined with it 'impact' considering the volume (i.e. changing a low volume items MAPE from 40 to 30% might have a much lower impact than changing a high volume item from 33% MAPE to 30%).

Furthermore, to assist in analyzing the extent to which over or under forecast errors exist, a non-absolute measure should be used. According to McCarthy, Davis, Golicic, and Mentzer (2006), the percentage error is appropriate for this matter. Its popularity has been prove by a survey indicating that 45% of 480 companies use the PE as a measure, where 75% of them combine this metric with other measures (McCarthy et al., 2006). In a previous study, 11 years earlier, only 3% of respondents used this measure (Mentzer & Kahn, 1995). The chosen metrics will now be elaborated below.

4.1.1 Percentage Error

The percentage error (PE) is one of the simplest metrics around, providing the error expressed as a percentage of the actuals. This makes the metric easy to understand and usable for a broad audience.

$$\text{PE: } \frac{x_t - \hat{x}_{t-1,t}}{x_t} \times 100$$

As this is a relative measurement, the metric is independent of size, and can be used to judge the extent or importance of errors irrespective of the size of the error. It can be used to see whether there is a tendency for over- or under-forecasting as it is not an absolute measure. This is, however, also the biggest downside of this metric. Once averaging or aggregation takes place, negative and positive errors tend to level out, painting a rosy picture of the forecasting performance. 4834

4.1.2 Mean Absolute Percentage Error

The Mean Absolute Percentage Error (MAPE) is a relative measure, and is a general measure within company settings (Fildes & Goodwin, 2007). The following formula is used to calculate the MAPE:

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

Because of the relative character of this metric, it can be averaged across series and forecasting horizons and can be used to compare more than one forecasting method (Makridakis & Hibon, 1995). Furthermore Armstrong and Collopy (1992) rate this metric as a fairly good metric in their study of different forecast accuracy metrics, and Makridakis and Hibon (1995) evaluate this metric as informative and intuitive, as well as with a medium reliability and high discrimination. However, Armstrong (1985) pointed to an asymmetry in the MAPE, having a bias favoring under-forecast errors. Makridakis (1993) extends this argument by stating that equal over-forecast errors result in a greater (M)APE than under-forecast errors (i.e. if x_2=100 and $\hat{x}_{1,2}$=50, then the MAPE is 50%, but if x_2=50and $\hat{x}_{1,2}$=100, then the MAPE is 100%). This is due to the limitless range of the MAPE [0,∞), so negative errors can have an infinite error, which makes the MAPE very sensitive to outliers (Makridakis & Hibon, 1995). The MAPE also has the disadvantage that it is undefined when actuals are 0 (Armstrong S. J., 1985), and is unable to distinguish important high volume or high margin products from the less important ones.

4.1.3 Symmetric Mean Absolute Percentage Error

In reaction to their findings, Armstrong (1985) and Makridakis (1993) developed an adjusted version of the MAPE which did not had the symmetry problem outlined above: the symmetric MAPE or the Smoothed APE (O'Connor, Remus, & Griggs, 1997). The advantage of this measure is that it is less prone to small values in the denominator (Makridakis S. , 1993) compared to the MAPE. Furthermore it also considers accuracy as a relative measure and is widely used and understood (Armstrong & Collopy, 1992).

$$\text{sMAPE: } \left[\frac{2}{n}\sum_{t=1}^{n}\left|\frac{x_t - \hat{x}_{t-1,t}}{x_t + \hat{x}_{t-1,t}}\right|\right] \times 100$$

However, research by Goodwin and Lawton (1999) shows that this metric also has an asymmetric character, as it treats positive and negative errors differently, especially in series with large absolute errors. A graphical illustration of this is provided in (Appendix VI). Also, in some cases this absolute measure can show negative values (Hyndman & Koehler, 2006). Furthermore, just like the MAPE, this metric does not takes into account any weight factors such as volume, importance, or margin.

4.1.4 Weighted Mean Absolute Percentage Error

By weighting the MAPE with a certain factor, such as volume, margin – or any other criteria set by the user – the limitation for MAPE and sMAPE can be overcome.

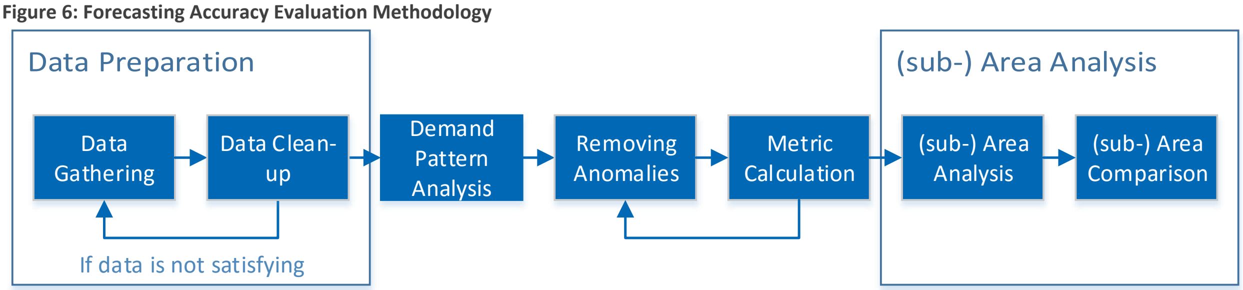
$$\text{Weighted MAPE: } \left[\frac{Y_x}{\sum Y}\cdot\sum_{t=1}^{n}\left|\frac{x_t - \hat{x}_{t-1,t}}{x_t}\right|\right] \times 100$$

This metric can give a clear sight on what products or parts of the business to focus on, however, this metric should be used with caution. For example, when weighted on volume, the MAPE will become small for low volume products, automatically shifting attention to larger volume products or segments. However, the low volume products might have a higher margin or bigger impact on customer satisfaction. Therefore one should be aware of the market and product characteristics when interpreting this metric.

4.2 Evaluation Methodology

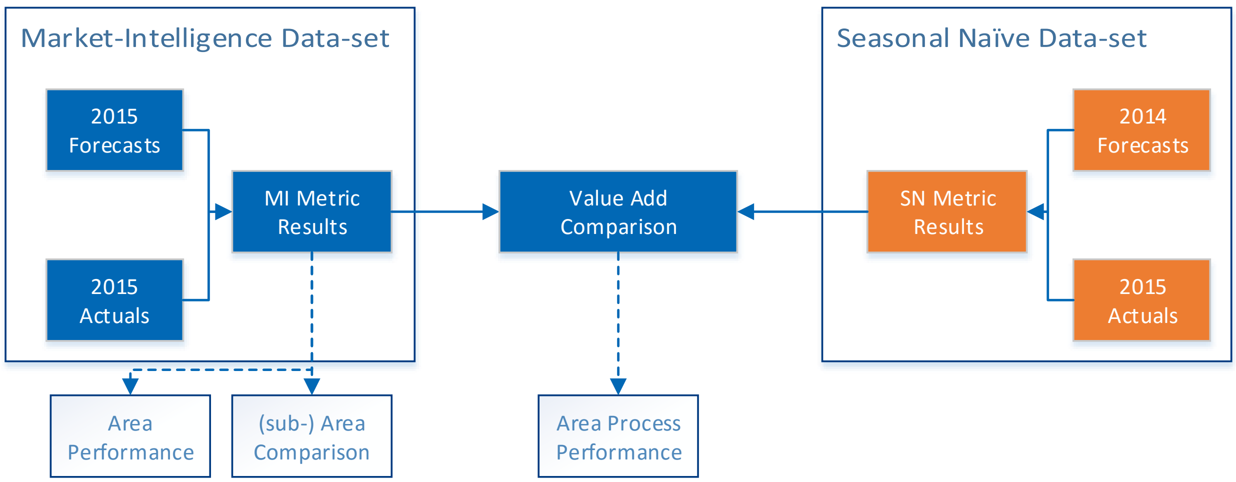
To execute the analysis, a structured approach with subsequent steps will be used (see Figure 6). For each region the same methodology will be used, with the goal of calculating metrics with data that has been selected on the same criteria. Metrics will be calculated on the following levels: Chemistry, Profit-Center, Base-Bulk, and DFU.

Figure 6: Forecasting Accuracy Evaluation Methodology



Each step shown in Figure 6 will be elaborated separately in the following sections. As will be shown in the *Demand Pattern Analysis,* each region has a different demand profile. While variability and external influences are different for each region, it is unfair to compare metrics side by side, as the variability can naturally influence the size of percentage errors. To overcome this problem, two sets of forecasts will be evaluated for each region. One set will include the actual market intelligence forecasts and sales for January to October 2015, referred to as 'MI' (except for ANZJK where this is a statistical forecast, 'SF'). A second dataset consists of 2014 forecasts – or a seasonal naïve forecast (i.e. using last year's data for each data point) – referred to as the 'SN' forecast. A schematic overview can be seen in Figure 7.

Figure 7: Structure of data-sets for the Region-Analysis



For both data-sets all metrics are calculated and consecutively compared, resulting in a 'value add comparison' which informs decision makers about the improvement in forecasting accuracy of the current forecasting process versus a very simple statistical forecast. This difference reveals similar information as gained by calculating the Geometric Mean or Relative Median (Makridakis S. , 1993). The 2015 metric results will be used to quantify the accuracy of current regional forecasts. Finally, regions can be compared to a limited extend, when the variability of the regional sales are taken into account. When looking at the variability of the demand patterns of each regions, similar patterns should have similar performance. If there is a gap in performance, decision makers can consider this as an indication that the forecasting process in the respective region might be more efficient and robust.

4.3 Data Preparation

The performance analysis is based on 2015 data. Due to time constraints and the availability of data, the 10 most recent months have been used at the time of conducting this analysis (January to October). The data contains monthly forecasts and actual sales. Monthly forecasts are chosen, as this is the frequency at which DCM's forecasts are renewed. The data for different aggregation levels is gathered, showing four forecasts a month. The lag-0 forecast is the forecast for a certain month made in that specific month, while the lag-3 forecast is the forecast made three months ahead of the month being forecasted. Lag-0 to Lag-3 forecasts are all included, providing 4 data-points a month. As this data results from both automatic and manual input, subsequent data-cleaning is done, as described in the next section.

4.3.1 Cleaning the Dataset

The raw data, as retrieved from the diamond systems reporting tool contains all demand data for each of the regions. As the data is manually inserted, there is a chance for data entries to be incomplete or to contain unrealistic content. To get a proper and reliable dataset for the demand pattern analysis, data will be deleted in the following cases:

1. *No assigned chemistry*: this will complicate the aggregation from DFU level to chemistry level.
2. *No assigned – or invalid – sub-region*: demand not belonging to the (sub)-region in question (should not be of any influence on the results of that region).
3. *Negative total demand*: All instances where the total demand is negative will be deleted. These instances are considered as exceptional and should not influence results.
4. *No demand*: All instances with no demand will make the analysis lumpier to execute.

For each area multiple instances were encountered that had no correct assignment of region (e.g. a region in another continent). Furthermore, for three areas, around 50 DFU's had no assigned chemistry, and thus these two groups of DFU's have been deleted. For EMEAI, APAC, LAA, and NAA this was respectively 0.029, 0.0, 0.069 and 0.015 % of the total demand. Lastly, all DFU's with no demand during 10 months are deleted. The final number of active DFU's per region can be found in Table 4.

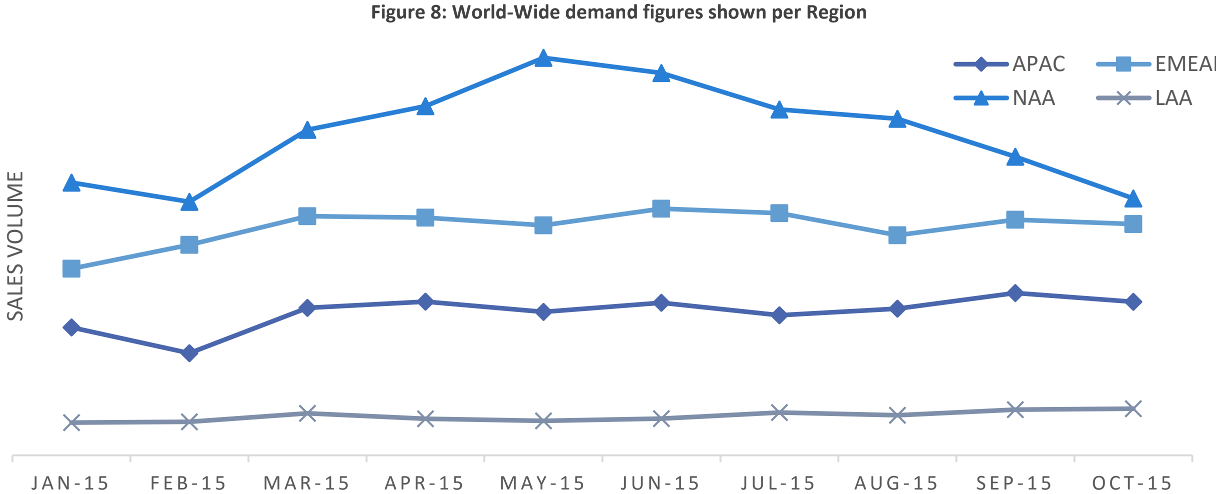
Table 4: Data-set size after and before cleaning

Area	Initial Size	Invalid Region	No Chemistry	No Demand	Size after screening	Sub-Areas
EMEAI	**5,838**	6	51	1,339	**4,442**	E: 2,564 MEATI: 1,878
APAC	**5,611**	7	55	1,606	**3,943**	ANZ: 493 JKR: 483 GC: 2,043 SEA: 924
LAA	**3,508**	-	50	1,762	**1,696**	-
NAA	**4,543**		16	487	**4,040**	-

4.4 Demand Pattern Analysis

Based on the cleaned datasets an initial analysis of the data can be given. To get a basic understanding of the dataset, this section will elaborate on total sales figures for each of the areas and according sub-areas. Figure 8 visualizes the total sales figures for all four operating areas.

Figure 8: World-Wide demand figures shown per Region



4.4.1 North America

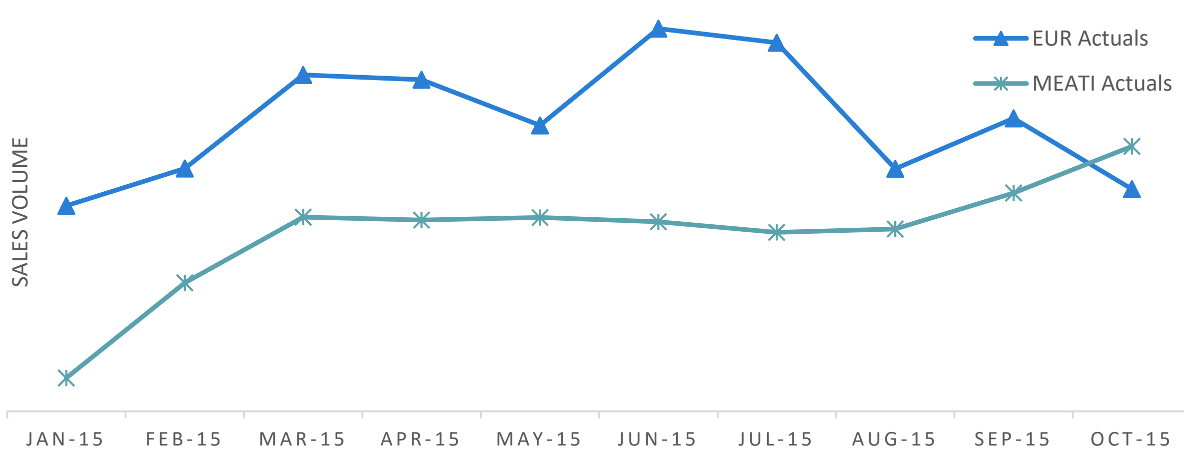
As shown in Figure 8, NAA is the area with most sales volume but also the most variability throughout the year. The seasonality, with a peak in May, is mainly caused by products in the Acrylics chemistry, which account for 51.9% of total sales, followed by vinyl acrylics (21.2%) and OP with 12.2% (for all chemistries see Appendix VIII). Stretching over 10 months, the Acrylic chemistry is maintaining 1145 DFU's with an average of 783 actively forecasted DFU's per month, whereas Vinyl Acrylics offers less DFU's with only 150 maintained and an average of 99 managed DFU's per month. Looking at the order frequency, about 22% of DFU's is ordered each month, representing 71.4% of the total demand. Another 21.0% of volume is generated by products ordered in at least 7 out of 10 months (Figure 29, Appendix VIII). The biggest part of the volume is therefore ordered frequently, which is beneficial in case statistical forecasting is to be implemented.

4.4.2 Europe, Middle East, Africa, and India

Based on information provided by the regional DM, this region is split in two sub regions: Europe, and MEATI, short for Middle East, Africa, Turkey and India (Appendix VII). The region had most sales generated by three chemistries: Styrene Acrylics (30.3 %), Acrylics (29.6%), and OP (26.4%). For each sub-area, these chemistries have a relatively fluctuating demand (Appendix VIII provides a graphical overview). Looking at the sales volumes per sub-region (Figure 9), the European demand pattern looks more seasonal compared to the MEATI region. Also, the MEATI region seems to gain volume by the end of the year, while Europe has a seasonal low during that period. As the MEATI region increased sales with 69% within 10 months, it can be assumed that this region is experiencing growth. However, based on only 10 months, this statement should be confirmed when new data is available.

Based on 10 months of data, order frequencies can be analyzed. In Europe, 81.8% of volume is caused by orders placed with a frequency of 10 to 7 out of 10, whilst in the MEATI region, this is 64.8%. Figure 32 and Figure 35 (Appendix VIII) show that in Europe, there are more DFU's with an order frequency of 1 out of 10 Months (14.3 vs. 6.6%). However, in Europe this only causes a low percentage of total sales (1.6% vs. 4.11% for MEATI). In short, MEATI has a lower amount of DFU's that are ordered infrequently, although, they represent a larger share of the volume.

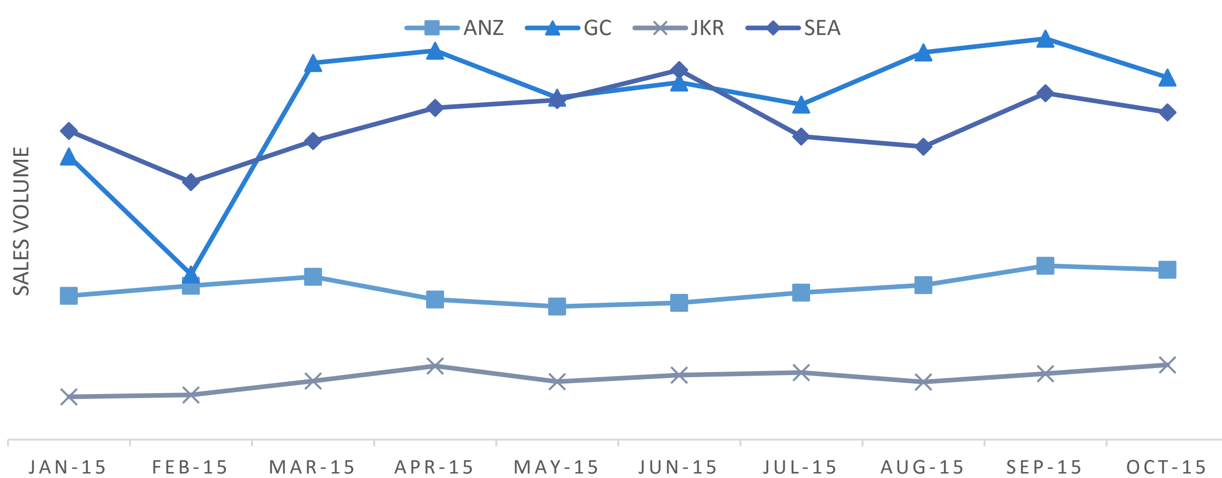
Figure 9: Actual Sales per Sub-Area in EMEAI



4.4.3 Asia, Pacific & the Caribbean

As was mentioned in section 3.3.3, a part of the APAC region structurally uses statistical forecasting, without the forecast *always* being overridden by market-intelligence. This sub-area is ANZJK, and has a lower – but more stable – demand. A visualization of the demand in each sub-region clearly shows this volatility and the relative stable demand trend in ANZ and JKR (Figure 10). The immatureness of the growth region can also be seen in the growth of number of actively forecasted DFU's, with a growth percentage of 25% and 17% for respectively GC and SEA. Compared to 10 % and 4 % for ANZ and JKR, this is significantly higher.

Figure 10: Actual Sales per Sub-Area in APAC



Similar to other regions, Acrylics is a major chemistry in both sub-regions, followed by OP. The chemistry demand profiles for both regions (Appendix VIII) lead to the same conclusion: the ANZJK area is more stable when compared to GCSEA. Furthermore, an important observation can be made by using Figure 38 and Figure 41 (Appendix VIII). In AZNJK, 78.6% of demand is caused by monthly orders (10 out of 10 months have demand), while another 16.0% is ordered with frequencies of 7-9 out of 10. Compared to GCSEA, where only 51.3% of volume is ordered each month, the demand occurs more frequently in ANZJK. Together with the stability of demand, this high order frequency gives good reasons to support the decision of applying statistical forecasting in the region.

4.4.4 Latin America

With the lowest average sales per month, the Latin America region is the smallest out of four regions with respect to sales volume. Similar to NAA, in this region there is no need to identify sub-areas as the forecasting process is exactly the same across the whole region. Looking at the demand patterns emerging from the chemistry sales (Figure 42, Appendix VIII), there seems to be growth in several industries. The demand is peakier, due to the lower volume, but nonetheless, it's not extremely variable. A more objective view can be provided by calculating the coefficient of variation (CoV), which is a measure of dispersion for different variables being independent of size. Table 5 reports the CoV values for each (sub) region, per chemistry. Here we see that LAA is more variable than the very stable ANZJK region, but does not has the most variation on several chemistries. Looking at the volume, aggregated to (sub-) region, LAA is less variable than NAA, and GCSEA, but more variable than Europe, MEATI and ANZJK.

Table 5: Coefficient of Variation for (sub-) areas per Chemistry and in Total

Chemistry	NAA	EUROPE	MEATI	LAA	GCSEA	ANZJK
Acrylics	**0.241**	0.183	0.153	0.152	0.132	0.095
Dispersants	0.100	0.138	0.162	0.149	0.216	**0.218**
Hase/Ase	0.088	0.110	0.188	0.142	**0.227**	0.105
Heur	0.090	0.125	**0.288**	0.139	0.198	0.081
Op	0.051	0.047	0.131	**0.230**	0.169	0.091
Other	0.446	0.247	**0.458**	0.216	0.264	-
Paraloids Solid	0.218	0.220	**0.774**	0.211	0.550	0.644
Paraloids Solution	0.182	**0.446**	-	0.299	-	-
Styrene Acrylics	0.165	0.130	0.138	0.139	0.160	**0.319**
Vinyl Acrylics	0.118	**1.110**	0.183	0.424	0.383	0.251
Total CoV per Area	**0.156**	0.090	0.106	0.129	0.143	0.090

4.5 Anomalies in Remaining Data

The demand analysis provided an insight in the trends of sales volumes per regional chemistry. To do so, only the sales volume was used. In the next sections, a comparison of forecasts versus actuals will be made, to calculate the forecast health metrics, as defined in section 4.1. As most metrics cannot be calculated when there are no sales in a specific month, the exceptionally low volume DFU's should be avoided. Furthermore, DM's and DP's stated that low volume and ad-hoc demand is mostly not forecasted at all, or forecasts are not maintained once a value has been inserted. Therefore, only DFU's with a 10 month total demand of 5 MT or more are included for metric calculations. Thus, also DFU's with a negative total sales volume are deleted.

The MAPE can also be greatly affected when the forecast is much bigger than the actual value (Makridakis & Hibon, 1995). Some actual sales of 0.01 kilograms have been recorded, combined with a forecast of 0.8 MT this yields a forecast error of 79,999%. To avoid skewing of the results due to extremely large values, it was chosen to delete all *monthly* instances that have an actual value of $0 < x_t < 10$. In Table 6 the final sizes of datasets for each of the regions is shown.

Table 6: Number of DFU's left after removing anomalies

Area	Initial Size	After Screening	Sub-Areas	< 5,000	Final Size	Sub-Areas
EMEAI	5,838	4442	E: 2564 MEATI: 1878	1649	**2793**	E: 1608 MEATI: 1185
APAC	5611		ANZ: 493 JKR: 483 GC: 2043 SEA: 924	1835	**2108**	ANZ: 229 JKR: 199 GC: 1056 SEA: 624
LAA	3508	1696	-	780	**916**	-
NAA	4543	4040	-	1806	**2234**	-

4.6 Regional Forecasting Performance

Sections 4.6.1 to 4.6.4 will discuss the results of the forecast performance analysis for each of the regions. As elaborated in the methodology section, forecast metrics will be reported for both the market intelligence (MI) forecasts, as well as for the seasonal naïve forecast (SN), which are 2014's actual sales values used as a forecast. If the MI-forecast has less error than the SN-forecast, this means that the market-intelligence is able to improve the seasonal naïve forecast. In other words, there is a 'value-add' for the MI-forecast when compared to the SN-forecast. In the analysis this difference (the value add, is indicated by delta (Δ) and is shown in percentage points. During the forecast performance analysis the Paraloids Solution chemistry will be omitted, as this chemistry accounts for little or no volume at all. Furthermore, the 'Other' chemistry captures miscellaneous products and has a varying nature, making it hard to give a sound conclusion based on this individual chemistry. Performance will be evaluated using three different aggregation levels: DFU, Base Bulk, and Chemistry level. The PE is not aggregated, due to the canceling of errors, however on the DFU-level the PE is used to see towards which side the error flips, be it a positive or negative error.

While interpreting the results below, one should keep in mind that it takes a significant amount of resources to create forecasts based on market intelligence. So the fact that MI forecasts are a few percentage points better should not directly lead to the decision to justify a reliance on MI forecasts only, as this is a very costly procedure. This decision is way more complicated and cannot be made merely on the findings of this evaluation. Therefore, the outcomes will serve as an input for the next deliverable.

4.6.1 North America Area

In each of the geographical regions forecasts are created at a DFU level, which is expected to yield high errors due to the variability. The metrics results, as shown in Table 7, confirms this at first sight. Due to many high error values, the MAPE is considerably higher and less constant than the sMAPE. The unlimited upper boundary of the MAPE can be misleading, as the 10 month average can raise seriously by a few (negative) outliers. The sMAPE provides more stable results, giving a more general oversight (i.e. extreme values do not influence the metric and are therefore not noticed). This stability comes at the price of an asymmetry, which should be kept in mind.

Table 7: NAA – DFU Level Metric Results for Lag 0-3 on MI & SN Forecasts

DFU LEVEL	MAPE (%)			sMAPE (%)			PE (%)			
	MI	SN	Δ	MI	SN	Δ	MI	Neg. Err	SN	Neg. Err
NAA-Lag 0	94.37	117.45	**-23.08**	47.25	51.52	**-4.27**	-54.77	43.63	-74.22	43.38
NAA-Lag 1	98.19	119.98	**-21.79**	47.58	51.67	**-4.09**	-58.06	43.08	-75.99	42.36
NAA-Lag 2	95.72	115.68	**-19.96**	48.19	52.16	**-3.97**	-54.67	42.29	-70.86	41.22
NAA-Lag 3	106.10	107.98	**-1.88**	50.79	52.57	**-1.78**	-67.28	45.54	-62.21	40.30

The North American forecast process provides MI-forecasts that have a better accuracy than the SN-forecasts, with the remark that lag-3 forecasts are far more inaccurate. Table 29 (Appendix IX) shows the results on a base-bulk level, and also reveals that there is less value add on the lag-3 forecast. The MAPE values on the BB-level converge to the sMAPE values, as aggregation levels out large forecast errors. Furthermore, the general trend shows that forecasts become more accurate once the actual month lies closer (i.e. more historical data is available). The percentage error shows that there is a tendency to over-forecast at the DFU level. These two findings can be generalized for all regions

Looking at the performance of individual chemistries (Table 30, Appendix IX), it can be seen that high volume chemistries are the most accurate. With 52% of volume, Acrylics is the most voluminous chemistry, while having a relatively high (s)MAPE values. The strong seasonality could be causing this. An interesting finding relates to Styrene Acrylics. This chemistry would be forecasted more accurate with a SN-forecast in place, as indicated by both of the forecast accuracy metrics.

Table 31 and Table 32 (Appendix IX) relate the accuracy to order frequency and volume. Based on these results it can be concluded that frequently ordered DFU's are better forecastable and have a better accuracy with market-intelligence than with a SN-forecast. Furthermore, it is shown that for items with the same order frequency (10 out of 10 months), the products with high volume have a more accurate forecast compared to the lower volume items[3]. More explicit, the top 25 had an sMAPE value of 25.98% while the bottom 25 showed a value of 41.46%. It can also be concluded that for 1.26% of volume there is not a single (lag) forecast in place during 10 months, causing 3.01% of the total absolute error for lag-1 forecasts (Table 33).

4.6.2 EMEAI

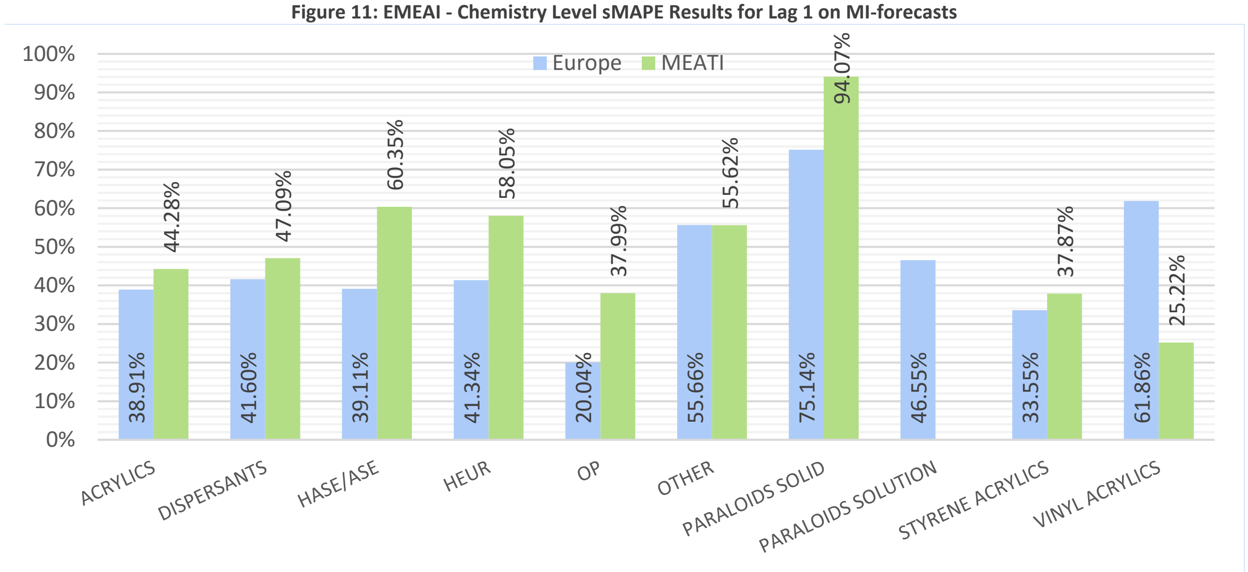
Based on recommendations by company representatives – and on basis of data – the EMEAI region is split in two sub-regions. The DFU level data (Table 34, Appendix IX) show that indeed the European region is more accurate compared to the MEATI-region on all lag-forecasts and shows added value for the market-intelligence forecast compared to the SN-forecast (minimum of 3.76% added-value). For example, the lag-1 forecast in Europe shows a difference of 25.55% (MAPE) and 6.87% (sMAPE) compared to the MEATI region. Extending the comparison between those regions, it can be concluded that Europe has lower PE values, while both sub-regions have a similar percentage of negative errors. This means that either Europe has larger positive errors (causing canceling of the negative errors), or more likely, smaller negative errors.

For the MEATI region, the sMAPE and MAPE contradict each other with respect to added value. While the MAPE has no excessively high monthly values, figures are quite high for MI-forecasts and show that SN forecasts would perform up to 10.49% (lag-3) better. Detailed data shows that the MI forecasts have a higher average of the top 5 MAPE values (Table 35, Appendix IX). As the sMAPE is less influenced by these values, in this instance the MAPE can be considered as most reliable, *and thus SN forecasts could play an important role in forecast improvement on a DFU level in the MEATI sub-region.* This is supported by the base-bulk level results.

Again, the BB-level results show that MAPE and sMAPE values are now similar (Table 36, Appendix IX), and mostly agree with the conclusions stated above. For Europe, MAPE values are now worse than the MEATI values, due to a number of BB-products with high errors (over 8,000%). The chemistry level results (Figure 11), show that on most chemistries Europe is the more accurate sub-region[4].

[3] This finding is supported by data in all the regions and can therefore be generalized.
[4] Table 37 and Table 38 (Appendix IX) report on the detailed figures.

Figure 11: EMEAI - Chemistry Level sMAPE Results for Lag 1 on MI-forecasts



Based on Table 39, Table 40, and Table 41 (Appendix IX), the following conclusions regarding order frequencies and forecasted volume can be drawn:

- Europe has lower sMAPE values for all DFU's with 2 to 10 Months of demand, while the MEATI has more DFU's which are ordered infrequently (Table 39 and Table 40, Appendix IX).
- In Europe, 3.21% of the volume is missing a forecast, causing 6.26% of the total absolute error (lag-1). In the MEATI sub-region this is 7.99% of the volume, having a share of 11.19% in the total absolute error on the lag-1 forecasts.

4.6.3 APAC

Similar to the EMEAI region, the APAC region is split in two: GCSEA and ANZJK. The latter area uses statistical forecasting and is therefore an important subject in this analysis. Figure 12 and Figure 13 visualize results for DFU and BB levels, based on Table 42 and Table 44 (Appendix IX).

Figure 12: APAC – DFU Level results for MAPE and sMAPE (MI)

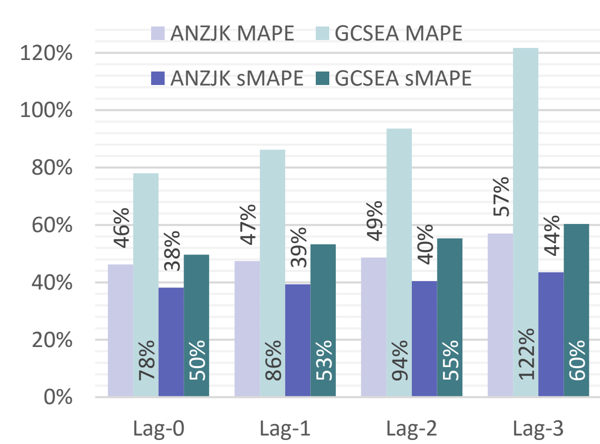
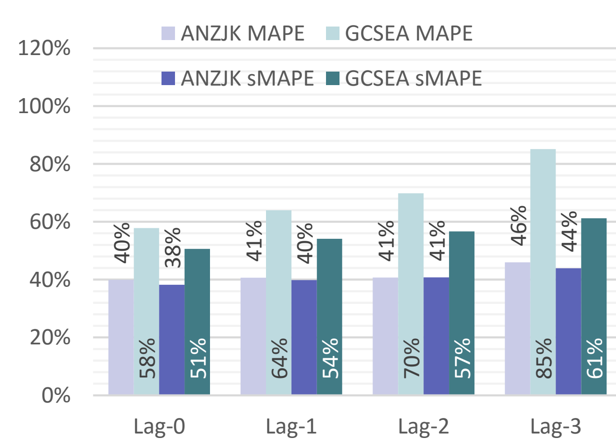


Figure 13: APAC – BB Level results for MAPE and sMAPE (MI)



As for the other regions, it can be concluded that forecasts get more accurate when shifting from lag-3 to lag-2, -1, and -0. An important conclusion here is that the ANZJK sub-region is providing forecasts that are far more accurate, supported by the BB-level results (Table 44). Besides, the average of the top 5 highest MAPE values is significantly smaller with 465% versus 2101% (Table 43, Appendix IX), indicating that there are less extreme values in this area. The PE-metric also shows that ANZJK is the more accurate sub-region (assuming that the cancellation of negative and positive errors is similar in both regions). Considering the added value of a MI-forecast (or the statistical forecast in case of ANZJK), both the sMAPE and MAPE show that that both regions benefit from the adjusted forecast when compared to a SN-forecast. The base-bulk level results support the DFU-level findings on the added value of the *new* statistical forecast for ANZJK. For the GCSEA region the MAPE and sMAPE values do show added value. The MAPE is however influenced by a few base-bulk products with high error (over 4,800%), raising its value.

Looking at the chemistry-level results (Table 45 and Table 46, Appendix IX), once more it can be concluded that the ANZJK sub-region is generating more accurate forecasts. As for GCSEA the MAPE and sMAPE contradict each other concerning the value add of the MI-forecast. The MAPE pleads for the use of a SN-forecast, while the sMAPE concludes the opposite. The volatile nature of the area causes naturally high errors, which suggests that the MAPE results might be more reliable as they are influenced more by the higher errors.

Based on additional data that considers the order frequencies and forecast volume (Table 47 to Table 49, Appendix IX), it can be stated that in both sub-regions the forecast performance increases when order frequencies are higher, with ANZJK being the most accurate. Looking at order frequencies, especially for frequent demand there is a big difference, which makes sense for a process with statistical forecasting in place. Lastly, in ANZJK only 0.74% of volume is not forecasted, compared to 5.77% of volume in GCSEA. This translates in 2.01% and 8.56% of the total absolute error on the lag-1 forecast for respective areas.

4.6.4 LAA

For the final region of this analysis, the DFU and base-bulk level results in Table 8 and Table 9 support the conclusion that forecasts get more accurate when more historical data is available (i.e. lag-1 is more accurate than lag-3). On a DFU level, both metrics seem to agree on the added-value of a MI forecast, except for the lag-3 forecast, which is influenced by outliers (up to 3900% error in April). Therefore the sMAPE gives a more reliable view. The figures for the base-bulk level show different results, concluding that a SN- forecast is beneficial on lag 1 to 3 according to the MAPE, while the sMAPE indicates added value for a MI-forecast. As there are no extreme values in both series, the MAPE should give the most realistic viewpoint here. *Therefore, the BB level analysis shows that statistical forecasting should be considered as a valuable alternative to the current practice.*

Table 8: LAA – DFU Level Metric Results for Lag 0-3 on MI & SN Forecasts

DFU LEVEL	MAPE			sMAPE			PE			
LAA	MI	SN	Δ	MI	SN	Δ	MI	% Neg.	SN	% Neg.
LAA-Lag 0	66.60%	78.53%	-11.93%	49.96%	56.05%	-6.09%	-27.99%	43.52	32.86%	42.21
LAA-Lag 1	69.27%	72.15%	-2.88%	51.89%	56.82%	-4.93%	-28.94%	43.93	26.07%	43.53
LAA-Lag 2	72.65%	79.04%	-6.38%	53.47%	57.76%	-4.28%	-31.09%	43.80	30.64%	41.43
LAA-Lag 3	82.12%	75.60%	6.52%	55.60%	58.41%	-2.81%	-42.09%	47.42	23.10%	38.89

Table 9: LAA– Base Bulk Level Metric Results for Lag 0-3 on MI & SN Forecasts

PBL LEVEL	MAPE			sMAPE		
LAA	MI	SN	Δ	MI	SN	Δ
LAA-Lag 0	48.45%	50.65%	-2.19%	51.28%	57.27%	-5.99%
LAA-Lag 1	49.48%	48.71%	0.77%	53.01%	57.81%	-4.80%
LAA-Lag 2	51.80%	44.31%	7.48%	54.31%	58.80%	-4.49%
LAA-Lag 3	58.43%	42.38%	16.06%	56.50%	59.65%	-3.15%

With respect to value add, the same contradiction is seen on the chemistry level: the MAPE shows a clear preference for the SN-forecast, while the sMAPE shows value add for MI-forecasts on high volume chemistries (Table 50, Appendix IX). On the other hand, for some chemistries both metrics do agree that a SN-forecast performs better. Similar to the base-bulk level, the higher level of aggregations results in less extreme values. This gives MAPE results more credibility, providing a sound argument for the consideration of statistical forecasting to improve the forecasting process in LAA.

Based on Table 51 it can be concluded that in general forecasts get more accurate when orders are more frequent. It also holds that for SN forecasts, accuracies are lower (in most cases). This indicates once again that statistical forecasting might be of great use in this region. Finally, 12.50% of the total volume has no forecast during all 10 months. This causes 15.21% of the forecast error on lag-1 (Table 52, Appendix IX)

4.6.5 Discussion of Regional Results

Based on the individual analysis of regions, the following general conclusions can be drawn:

- The DFU and base-bulk level analysis show that forecast accuracy increases as the lag between forecast and actual becomes smaller. The lag-3 forecast is the least accurate, and adds the least value compared to a SN forecast, in some cases the MI-forecast adds no value at all.
- Based on the PE, it can be concluded that there is a general tendency to over-forecast. More precise, the over-forecast errors tend to be larger than the under-forecast errors.
- Across all regions (except MEATI) Opaque Polymers are best forecastable, while Styrene Acrylics is amongst the two worst performing chemistries in all regions but the European region.

An important insight is gained by the sub-regional forecast performance. In the EMEAI region, Europe clearly has the best forecast accuracy, while in APAC the lead is taken by the ANZJK region. The latter region has the lowest forecast errors of all regions. Furthermore, in some specific instances, the Seasonal Naïve forecast already proved to be better than the forecasting process currently in place. In Europe this was concluded for the lag-3 forecasts on a DFU and PB level, but also for the Dispersants, Paraloids Solid and Vinyl Acrylics chemistries (lag-1) forecast. For NAA this was only concluded for the Styrene Acrylics chemistry, while for GCSEA for as well Styrene Acrylics, Acrylics and HASE/ASE a seasonal naïve forecast proved to be of better use. For LAA it was concluded that statistical forecasting could offer a valuable addition to the current forecasting process, as the DFU and BB analyses suggested the use of a SN-forecast instead of a MI-forecast. The same conclusion holds for the MEATI region.

4.7 Inter Area Comparison

After the evaluation of individual (sub-) areas, now an inter area comparison can be made. However, this comparison should be interpret with caution, as each of the areas has a naturally higher or lower forecast accuracy due to the different demand patterns. The coefficient of variation (CoV) will therefore be used to classify the amount of variance in the demand. However, the CoV also sees seasonality as variability, which can often be well predicted. Therefore, the CoV is not ideal – and since there is not enough data to deseasonalize the time-series – at least it provides some measure of variability. The sales volume is not taken into account, as the MAPE and sMAPE are relative measures and are not influenced by the size of the demand. Comparisons will be made on DFU-, Base-Bulk, and Chemistry-level. DFU Level Comparison

Table 10 and Table 11 show the 10-month average MAPE and sMAPE results for each region together with the respective coefficient of variation. Furthermore, Table 10 shows the percentage share of volume that has 0, 1, 2, 3 or 4 lag-forecasts in place for at least 1 month.

Table 10: Regional Comparison of Forecast Values and the related volume at DFU level

	Percentage Share of Total Volume					
# Lag-Forecasts	**EUROPE**	**MEATI**	**ANZJK**	**GCSEA**	**NAA**	**LAA**
0 FCST Values	3.21%	7.99%	0.74%	5.77%	1.26%	12.50%
1 FCST Value	1.75%	2.49%	0.22%	1.50%	0.32%	2.48%
2 FCST Values	0.73%	2.12%	0.03%	0.69%	0.19%	1.53%
3 FCST Values	1.39%	3.48%	0.41%	1.29%	0.36%	1.43%
4 FCST Values	92.92%	83.92%	98.59%	90.75%	97.88%	82.06%

Table 11: DFU Level Regional MAPE Results per Lag

	Lag-0	Lag-1	Lag-2	Lag-3	CoV
EUR	52.26%	55.75%	56.78%	68.40%	0.090
MEATI	79.09%	81.30%	80.66%	87.96%	0.106
ANZJK	46.25%	47.41%	48.67%	57.04%	0.090
GCSEA	78.03%	86.24%	93.59%	121.67%	0.143
NAA	94.37%	98.19%	95.72%	106.10%	0.156
LAA	66.60%	69.27%	72.65%	82.12%	0.129

Table 12: DFU Level Regional sMAPE Results per Lag

	Lag-0	Lag-1	Lag-2	Lag-3	CoV
EUR	45.37%	47.86%	48.81%	52.14%	0.090
MEATI	51.40%	54.73%	57.76%	61.43%	0.106
ANZJK	38.17%	39.32%	40.47%	43.55%	0.090
GCSEA	49.63%	53.29%	55.31%	60.37%	0.143
NAA	47.25%	47.58%	48.19%	50.79%	0.156
LAA	49.96%	51.89%	53.47%	55.60%	0.129

When combining the lower two tables, it can be concluded that the ANZJK sub-region has the lowest forecast error, but also the lowest CoV. Remarkably, the European region has the same CoV value but higher forecast errors, with a minimal and maximal difference of respectively 6.01% and 8.11% for the MAPE, and 7.20% and 8.59% for the sMAPE. If it is assumed that both CoV values are equally affected by a stable seasonality pattern, forecast errors should be similar. Since Europe has less accurate forecasts compared to ANZJK, this suggests that the process in ANZJK is performing better. Looking at Table 10, ANZJK also has the highest percentage of volume for which all lag-forecasts are in place (98.59%). Although ANZJK has less DFU's to manage, proper data management lies at the basis of statistical forecasting, as companies have to gather proper information to feed the forecasting process (Zotteri & Kalchschmidt, 2007). Therefore, this high percentage could be caused by the appliance of statistical forecasts. Besides the above stated, the following can be observed:

- It is hard to conclude on the NAA performance, as there is a big difference in results for the MAPE and sMAPE. According to the MAPE, NAA has the highest errors, while the sMAPE shows a rather good performance. Comparisons on BB or Chemistry level should give a clearer sight on this.
- According to the sMAPE, MEATI is the area with least accurate forecasts in place, whilst the CoV value is rather low. The MAPE does shows high values, but still NAA and GCSEA are less accurate. As MAPE figures are still quite high (compared to for example LAA), it is safe to conclude that this region is struggling more than other regions to provide accurate forecasts.
- The MEATI, GCSEA and LAA (sub-) regions have less than 91% of their volume being forecasted, with 83.92%, 90.75%, and 82.06% respectively. Proper data-management is important here, and forms a clear area for improvement.

4.7.1 Base-Bulk Comparison

On the BB-level MAPE values are more stable due to the reduced effect of extreme values(Table 13 and Table 14). Again, it can be concluded that the ANZJK region forecasts most accurately, and Europe has a higher average error (MAPE values for Lag-1 to Lag-3 are influenced by outliers, see section 4.6.2). The same holds for the GCSEA MAPE values, which are also influenced by a few outliers.

Table 13: PB Level Regional MAPE Results per Lag

	Lag-0	Lag-1	Lag-2	Lag-3	CoV
EUR	42.00%	43.74%	44.67%	58.46%	0.090
MEATI	43.70%	43.17%	42.85%	45.90%	0.106
ANZJK	39.96%	40.67%	40.73%	45.97%	0.090
GCSEA	57.85%	63.96%	69.85%	85.12%	0.143
NAA	47.80%	46.59%	47.12%	53.82%	0.156
LAA	48.45%	49.48%	51.80%	58.43%	0.129

Table 14: PB Level Regional sMAPE Results per Lag

	Lag-0	Lag-1	Lag-2	Lag-3	CoV
EUR	43.83%	46.31%	47.10%	51.16%	0.090
MEATI	48.02%	51.79%	55.03%	58.52%	0.106
ANZJK	38.23%	39.82%	40.79%	43.93%	0.090
GCSEA	50.60%	54.10%	56.69%	61.22%	0.143
NAA	47.09%	47.10%	47.94%	50.69%	0.156
LAA	51.28%	53.01%	54.31%	56.50%	0.129

Based on the sMAPE, LAA has the least accurate lag-0 forecast, but performs better than MEATI on lag-2 and 3. Furthermore, a reduction in MAPE values for NAA can be observed, caused by aggregation effects, resulting in a mediocre performance according to both metrics.

4.7.2 Chemistry Level Comparison

Using the CoV and MAPE values per area per chemistry (Table 53 & Table 54, Appendix X) and the sMAPE values shown in Table 15, a better insight in chemistry performance is provided. In the former paragraphs, NAA showed the highest total CoV value, Table 53 reveals that his caused by merely two chemistries ('Other' and Acrylics). Extending the comparison of Europe to ANZJK, it can be concluded that in general the MAPE and sMAPE agree that ANZJK is the most accurate region. As can be derived from Table 15, the MEATI region shows relatively high sMAPE values, while the MAPE is more positive. The opposite holds for GCSEA. In any case, the MEATI and GCSEA regions do not perform as well as the other regions, although it must be noted that they have to deal with more variance in their demand. LAA, which has less variability according to the CoV, still shows high to mediocre MAPE and sMAPE values.

Table 15: Chemistry Level Comparison of sMAPE results per Area for lag 1 forecasts

	EUROPE	MEATI	ANZJK	GCSEA	NAA	LAA
ACRYLICS	38.91%	44.28%	33.02%	40.36%	35.15%	51.74%
DISPERSANTS	41.60%	47.09%	35.85%	55.23%	36.02%	45.76%
HASE/ASE	39.11%	60.35%	30.95%	43.17%	31.92%	39.45%
HEUR	41.34%	58.05%	30.64%	44.97%	31.38%	39.96%
OP	20.04%	37.99%	19.49%	37.32%	27.33%	33.80%
OTHER	55.66%	55.62%		45.61%	42.03%	47.15%
PARALOIDS SOLID	75.14%	94.07%	79.37%	51.19%	71.11%	64.39%
PARALOIDS SOLUTION	46.55%	-	-	-	46.81%	52.43%
STYRENE ACRYLICS	33.55%	37.87%	44.43%	49.17%	45.27%	46.55%
VINYL ACRYLICS	61.86%	25.22%	31.52%	54.73%	19.30%	45.64%

4.7.3 Discussion of Results

Although the CoV does gives an indication of variability, the influence of seasonality can be strong making it difficult to make a sound comparison. However, the performance analysis did reveal that the AZNJK sub-region is generating the most accurate forecasts. This is supported by the analyses on the different levels. With Europe being equally variable as ANZJK, the performance should be similar. With gap in accuracy between the two, there seems to be an opportunity for improvement for the European region. Since ANZJK also has the highest percentage of volume being forecasted on all lag-forecasts, the data maintenance in this region seems very effective and could serve as an exemplar for other regions. It should be mentioned that the amount of data is more manageable here, but the region also has fewer resources available. The analysis also brought forward that GCSEA, LAA and the MEATI region can be classified as the least accurate regions. Although, it has to be noted that the Styrene and Vinyl Acrylics chemistries are accurately forecasted in the MEATI region. Besides that, the results show that the more aggregate the forecast, the lower the (s)MAPE values.

5 The Potential of Statistical Forecasting in Europe

The As Is analysis and the forecast analysis have given a clear indication that DCM Europe should start to apply statistical forecasting in their demand planning process. The NAA is currently implementing its new process, while the LAA region is currently starting with a redesign of the planning process. Both areas plan to gradually introduce statistical forecasting in their processes. The forecast performance analysis showed that the forecasting process in ANZJK – which uses statistics to create raw forecasts – is able to provide the most accurate forecasts, and that Europe lags behind while having a similar variability (following the CoV). These are clear indications that DCM Europe should be considering statistical forecasting as a valuable option to increase forecast performance. To assess the potential of statistical forecasts for Europe, the following two hypothesis (derived from former sections) will be tested:

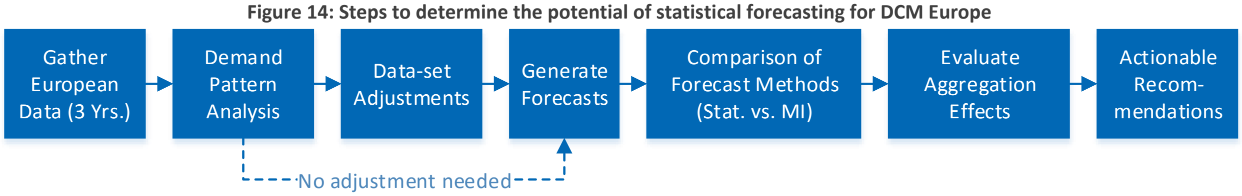
1) *By applying statistical forecasting, the European region can improve its forecast accuracy*
2) *The higher the level of aggregation, the higher the forecast accuracy will be*

To do so, the European demand profiles will be revisited and discussed in more detail. In the next sections the comparison between different forecast methods and the current MI-forecasts will be made to conclude on the added value of statistical forecasting in Europe.

5.1 Methodology

To structurally compare the two different forecasts – i.e. market-Intelligence versus statistical forecasting – the approach that is visualized in Figure 14 will be used.

Figure 14: Steps to determine the potential of statistical forecasting for DCM Europe



The performance comparison for both forecasts will be done at several aggregation levels (high to low):

1. Chemistry (9 entries)
2. Profit Center (16 entries)
3. Base Bulk (300 entries)
4. Demand Forecasting Unit (2495 entries)

On each of the levels, statistical forecasts will be created according to the methods as indicated in section 5.4.1. Consecutively, the most accurate statistical method will be compared against the original forecast. To do so, the dataset – pulled from the Enterprise Central Component – has to contain 3 years of data on all specified levels (2013-2015). Two out of three years serve to feed the model with historical data whilst 2015 data is used as a hold-out to evaluate the performance of the various forecasts methods. The hold-out period is chosen according to the seasonality pattern in the data, which repeats itself yearly.

Several forecasting methods are compared using an absolute error measure, capturing the *total* deviation from the actual 2015 data. When drilling down from the Chemistry level, there tend to be quite some intermittent demand data, preventing a proper calculation of a MAPE type of metric. Therefore the total

Absolute Percentage Error (APE) will be used to compare methods, as this metric looks at total error and sales. This metric will only result in error when the sum of actuals is equal to zero. Furthermore, from this point on, the accuracy of a certain method will be calculated using the following formulas:

$$APE = \frac{\sum_{i=1}^{n} |x_t - \hat{x}_{t-\tau,t}|}{\sum_{i=1}^{n} |x_t|}$$

$$Accuracy = MAX[0, (1 - APE)]$$

5.2 European Demand Profile Analysis

To fully understand how the European demand profiles look for each of the levels indicated above, a more thorough demand pattern analysis is executed. Knowledge of the underlying demand generation process is a prerequisite to fully understand the potential of statistical forecasting, and furthermore, to identify the right level of aggregation (if decided to). The main operating areas in Europe are Central Eastern and Western Europe (CEE/WER), and Greater Russia. These areas will be assed in the analysis.

5.2.1 CEE/WER and Greater Russia

Figure 44 and Figure 45 (Appendix XI) show differing seasonal patterns for each of the European sub-areas. In CEE/WER the high-season starts directly in January and lasts until August, where there is a strong seasonal influence caused by holidays. Demand rises afterwards to end with a seasonal low in November-December, caused by holidays and maintenance stops. In 2013 demand is more stable and flatter due to price changes applied in that year. Compared to 2013, the CEE/WER volume has grown by 21.07% (2014) and 41.35% (2015). In Greater Russia the seasonal-low is longer, and lasts from October to February. The demand is peaky here, with one clear high-volume month: August. There was quite some growth with 62.26% and 103.40% for respectively 2014 and 2015 (versus 2013). Furthermore, business representatives reported that contract business generated most sales in Greater Russia, which is completely different compared to the way Europe conducts business. The contracts cause large volumes at big customers, but limit the sales of smaller volumes. The next sections will conclude on the influence of this.

5.2.2 Chemistry level

When comparing demand profiles on a chemistry level, there is a clear difference in trend, level and seasonality for both regions. Where Europe has a relatively stable volume and similar seasonal patterns for most chemistries, the demand in Greater Russia is dominated by a single chemistry with 76.06% of volume in 2015, Styrene Acrylics. In Europe, 85.28% of 2015's volume is generated by three chemistries: Acrylics (28.19%), OP (28.59%), and Styrene Acrylics (28.49%). The same demand patterns as for the total volume can be recognized in both areas. The low volume chemistries (Figure 47 and Figure 49, Appendix XI) show a clear difference in level and seasonality patterns for CEE/WER and Greater Russia sub-regions.

The demand patterns of SA and VA in CEE/WER show some peculiarities. SA has a sudden and major increase of volume in May 2014, with 470% compared to last year's sales. The Vinyl Acrylics volume also suddenly rises in September 2015, with 1123% when compared to September 2014 or 2485% when compared to September 2013. These deviating patterns should be kept in mind when applying statistical forecasting, as they will require a special treatment or adjusted history to enable statistical forecasting to work properly.

5.2.3 Profit Center level

Where CEE/WER has 28 specified profit centers, Greater Russia has 16. In Greater Russia, SA Architectural generates 65.81% of sales and has a strong influence on the regions total sales figures. In CEE/WER the 3 profit centers with highest sales generate 58.88%, indicating that sales are less focused on one PC. For both areas it holds that, similar to the chemistry level, each profit center has a unique demand pattern. Some are stable, pleading for a constant forecast method, while others have a clear seasonal sales pattern with or without trend) pointing to a Holt-Winters type of forecast (Figure 50 to Figure 53, Appendix XI). In accordance with the chemistry level analysis, in CEE/WER SA Architectural shows a significant increase in volume in May 2014. In Russia, only SA architectural is causing a large sales volume. Other PC have intermittent demand with low (truck-size) volumes, which will most likely be troublesome to forecast statistically. In CEE/WER a number of new profit centers emerge with sales starting in May 2014[5], and low volume PC's with intermittent demand[6]. For the intermittent, low volume PC's, statistical forecasting will likely yield a low accuracy due to the low demand. For the new PC's, the lack of sufficient historical data will most likely cause statistical forecasting to be troublesome.

5.2.4 Base Bulk level & Customer Analysis

The base-bulk level has a higher number of instances (327 for CEE/WER, 90 for Greater Russia) and shows more distinct demand patterns. Compared to the former discussed levels, intermittent demand and other exceptions are more frequent here. Again it can be concluded that Greater Russia has less spread in volume compared over different BB-products compared to CEE/WER, as the top product causes 79.10% of sales compared to 17.04% for CEE/WER's top product. Base-bulk products show more variation in patterns due to new product introductions, substitution (Figure 54, Appendix XI), or quick growth. Numerous products with deviating patterns can be found. Some of these will be traced by statistical methods, while others happen out of the blue and will require additional attention to be captured by a statistical forecast. Therefore it can be expected that on this level the forecasts will be less accurate and for a larger percentage of volume a feasible statistical method will not be found. Especially in Greater Russia this could be the case, as many products are characterized by low volumes and peaky, different intermittent sales patterns. Constant statistical models could be used to set a level forecast (Simple Exponential Smoothing or Moving Average), but the low and peaky demand could imply difficulties for such an approach.

Considering the sales per customer, again it can be concluded that Russia sells most volume to a small group of customers, while in CEE/WER this is more spread out. Customer profiles in Russia are unstable, with intermittent periods of demand followed by periods of high volume. This again implies that statistical forecasting will only yield a high accuracy for a small number of products or customer sales predictions.

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[5] Architectural General, DCM-Cellosize, CMC, MC, Methyl Cellulo, Speciality Alko and SB Architectural

[6] Architectural, Hase industrial, Heur industrial, PCM Construction, and POD

5.2.5 Demand Pattern Analysis Conclusion

The demand pattern analysis showed that Greater Russia has a demand pattern that is clearly distinct from the CEE/WER sub-region. With a different seasonality, a different level (sales volume), but most importantly a difference in conducting sales (with Russia employing contract sales). Besides that, Greater Russia is mainly driven by Styrene Acrylics, whilst in CEE/WER volume is generated by a larger variety of products and customers. Due to the difference in volume, but mainly due to the difference in conducting trade, Greater Russia is seen as a region that differs from CEE/WER. Greater Russia might be suitable for statistical forecasts, but most likely a different approach should be used here. This finding has been discussed with sales representatives and demand managers, which have confirmed this difference in operations and volumes. *Based on this finding it has been decided to separate the Greater Russia region from further analysis.*

5.3 Data Adjustments

As concluded in the former section, Greater Russia will be left out of scope for further analysis. With that knowledge, the DFU data for the CEE/WER region can be cleansed. With a total number of 3615 DFU's it is unfeasible to assess each DFU's demand profile, instead the number of months having demand in a certain year will be used to determine whether a DFU should or should not be incorporated in any further analysis. It was found that of 3615 DFU's, 1120 DFU's have demand occurring only in 2013, 2014 or in both years. As these 1120 DFU's are assumed to be end of life products, and have no demand occurring in 2015. They are left out of scope as they do not generate any volume in 2015, and do not any value to the analysis. This leaves us with a dataset that incorporates 2495 DFU's for CEE/WER.

Within this selection of DFU's there are only 68 DFU's that have volume occurring each month (during 2013, 2014, and 2015). These are responsible for 24.48% of the 2015 volume and are most likely feasible for statistical forecasting. However, for 31.50% of volume – or 475 DFU's – there is limited history available as they have demand only in 2014 and 2015. And 596 DFU's have demand only in 2015, assumed to be new products. In total, 62.10% of volume is caused by DFU's that have at least one month, in which volume is generated, in each year.

5.4 Generating Statistical Forecasts

For all of the levels described previously (Chemistry, Profit Center, Base-Bulk and DFU), forecasts are generated according to the methods as described in section 5.4.1. As for the DFU level this is a large amount of data to cope with (12,475 forecasts solely on the DFU level), a tool (Forecast X) is used to generate the forecasts.

5.4.1 Forecasting Methods

Research indicates that for specific forecasting problems – considering the complexity and uncertainty – there is no one best way to design a forecasting approach (Zotteri & Kalchschmidt, 2007). Companies often implement a tailored forecasting strategy that is consistent with the firms resources in terms of forecast techniques, information availability, human resources, information systems, and the managerial processes (Zotteri, Kalchschmidt, & Caniato, 2005) (Zotteri & Kalchschmidt, 2007) (Hughes, 2001).

Selecting and adopting a certain (number of) forecasting method(s) is part of the forecasting strategy. For the adoption of forecasting methods a similar conclusion can be drawn: merely adopting a forecasting technique is not sufficient to reach a sound forecast accuracy, it should be linked to the management and organization of the forecasting process (Armstrong S. J., 2001) (Mentzer & Bienstock, 1998) (Moon, Mentzer, & Smith, 2003). In the case of DCM, there are two main limiting factors that constrain the selection of forecasting models:

1) Lack of awareness and knowledge of statistical forecasting. Also identified by Hughes (2001).
2) Limitations of the APO tool (only a selection of methods is available).

Considering the first limitation, it is key that all functions involved in the forecasting process are aware of the capabilities and functionality of statistical forecasting. Users should know what the statistical model – underlying a certain method – does, and how the forecast can be manipulated to incorporate the latest demand characteristics. Secondly, the capabilities of APO need to be taken into account, as developing new forecast models in the tool will take a considerable amount of time. Table 55 (Appendix XI) elaborates on the available forecast methods, of which seasonal, trend and constant models form the main methods. As follows from the demand pattern analysis, there is a strong seasonality for many regions and individual items. Therefore the seasonal Holt-Winters method will be included. Furthermore, based on experiences from DCM in the ANZJK region, a number of simple methods are also included. Experience learned that these methods often perform as well as, or better than complicated methods. This converges with the findings of Chatfield (1998), suggesting that there exists little overall difference when comparing numerous forecasting methods. Several forecasting competitions that compared many forecasting methods, concluded that simpler methods are not necessarily outperformed by complex or sophisticated statistical models. Goodwin (2002) supports this and states that complex statistical models may be non-transparent and outcomes may attract skepticism. Based on this, the seasonal naïve and moving average methods are chosen to use in the analysis. For the moving average, a 12-month moving average is used to be able to capture a the full – yearly – seasonality. Following Gijbels, Pope and Wand (Gijbels, Pope, & Wand, 1999), the most commonly used model in sales forecasting is Simple Exponential Smoothing (SES). With the advantages of being non-parametric based on a simple algebraic formula, enabling quick updating of the local level estimation of sales data. Therefore, this method is also included. Lastly, the forecasting tool used to generate the forecasts offers the possibility to deploy an algorithm that selects the best forecasting method automatically. Due to the existence of local minima this might not always result in the best method being selected. Experiences from the ANZJK region support this statement. Nonetheless, the optimization method is being used to assess whether there are other methods performing better than the current selected methods, summarized in Table 16.

Table 16: Forecasting Methods selected to generate Statistical Forecasts

Methods used	Abbreviation	APO terminology
Seasonal Naïve	SN	History
12 Month Moving Average	MA	Constant Models
Simple Exponential Smoothing ($\boldsymbol{\alpha = 0.3}$)	SES	Constant Models
Holt-Winters method (triple Exponential Smoothing)	HW	Seasonal Trend Model
Forecast X Optimization (procast)	PC	Automatic Model Sel.

5.5 Statistical Forecast Accuracy in Europe (CEE/WER)

In the following sections the forecast accuracy for different levels of aggregation will be discussed. For each instance on each level, a statistical forecast will be made. Consecutively, the accuracy of this forecast will be compared to the MI-forecast, which is currently being used. As mentioned by Silver, Pyke and Peterson (1998), one should consider the total costs of using a certain procedure:

$$E(total\ costs\ of\ procedure) = E(\ procedure\ operating\ costs\ ) + E(cost\ of\ resulting\ forecast\ error)$$

It is expected that using a statistical method will significantly reduce operating costs, as currently each account manager spends 1 hour a month on solely creating forecasts. To account for this, a threshold of 3% forecast accuracy is set. This means that a statistical forecast which is up to 3% less accurate, can still be beneficial to generate an initial raw forecast. To compare accuracies, the following paragraphs will mention the volume weighted average accuracy referred to as VWAA.

5.5.1 Chemistry Level

As mentioned in the demand pattern analysis, the SA and VA chemistries have a distinct demand pattern and are expected to have a low statistical accuracy. In Table 57 (Appendix XII), accuracies for the best performing statistical method are shown for each chemistry, and compared to the current lag-1 forecast performance. This table confirms that SA and VA have a statistical forecast accuracy – 77% and 24% respectively – lower than the MI lag-1 forecast (18.60 and 33.52% difference respectively). Therefore, the expectations are confirmed, and there is no value-add compared to the lag-1. These two chemistries are perfect examples to show the required input from market-intelligence in case of particularities.

Six out of nine chemistries have an improved (or identical) accuracy, whist Acrylics has a statistical forecast being 1.99% less accurate compared to the MI-forecast. The statistical methods used are:

- Holt-Winters (Acrylics, HASE/ASE, HEUR, OP)
- Simple Exponential Smoothing (Dispersants)
- Moving Average (Paraloids Solid, Paraloids Solutions)

Based on the demand patterns for each of these chemistries the applicability of these methods can be verified. Where Acrylics, HASE/ASE, HEUR, and OP are showing a strong seasonality, Dispersants shows a rather flat and constant pattern. For the two Paraloids chemistries the peaks and troughs are inconsistent and therefore a Moving Average approach is justified to incorporate trend but keep the forecast relatively constant. When comparing the statistical accuracy to the current lag-3 forecasts (Table 58, Appendix XII), the improvements in accuracy are even higher, with a respective minimal and maximum improvement of 7.19% and 31.09% (neglecting SA and VA).

5.5.2 Profit Center Level

The profit center level shows more variation in forecast accuracy. As mentioned in section 5.2.3, there are multiple profit centers with low volume or with intermittent demand. Furthermore there are a number of new profit centers with demand starting halfway 2014. Table 59 (Appendix XII) verifies a basic hypothesis: *low volume profit centers have a low statistical as well as lag-1 MI forecast accuracy*. For some of the seemingly troublesome profit centers (i.e. low volume or intermittent demand) there is a relatively accurate statistical technique which can be applied. For example Architectural General, DCM Cellosize, CMC, or MC all have a relatively high statistical accuracy when using a SE or MA method while being low-volume BB products. Data for the lag-3 forecast accuracies can be found in Table 60 (Appendix XII).

An important finding here is that for all high volume profit centers (i.e. > 1% share in 2015 volume), there is a statistical forecast that adds value and is relatively accurate (>79%). Note that for AA Architectural the statistical forecast is 3% worse but still has a 94% accuracy. And again the SA and VA Architectural PC's have a low accuracy due to the sudden increase in volume in 2014 and 2015 respectively. The lower volume profit centers – and VA and SA architectural – would have required MI adjustments (or, as referred to in literature, judgmental adjustments) to result in a more accurate forecast.

5.5.3 Base Bulk Level

As mentioned in former sections, the base-bulk products tend to have a more variable and infrequent demand pattern. Out of 327 base-bulk products included in this analysis, 31 had no demand in 2015, leaving no room for accuracy calculations. Therefore, 296 base-bulk products have been assessed.

Of 296 BB-products, 150 products have a statistical accuracy which is better than the market-intelligence forecast. This corresponds to 58.08 % of the yearly volume. Taking into account the base-bulk products that are within the threshold of 3% accuracy, this percentage raises to 76.76% with 175 base-bulk products. For this set of products, the average statistical accuracy (volume weighted) is 82.29% versus 77.01% for the lag-1 MI forecast (for lag-3 this is 81.89% vs. 69.24%). For 46 BB's Holt-Winters is the preferred method, while 55 BB's have a MA (12 months) method. 36 and 34 products are assigned to SE smoothing and a SN method respectively. This means that for the greater part, rather simplistic methods yield the best results. Table 61 shows – for each base-bulk product with a 0.80% share of the total volume – a comparison of statistical forecast accuracy versus the lag-1 MI accuracy. In case there is value add, the accompanying statistical methods is reported. For lag-3 this is shown in Table 62 (Appendix XII).

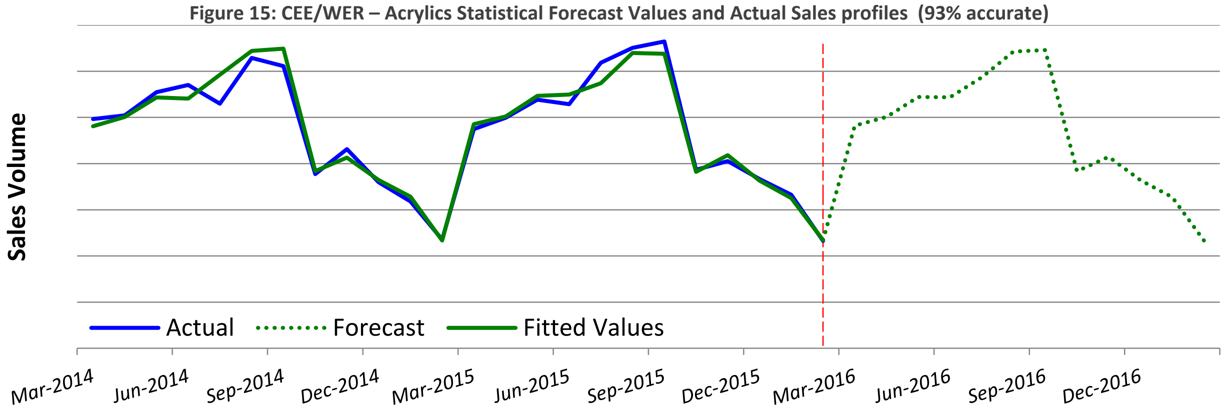
5.5.4 Demand Forecasting Unit Level

In section 5.3, DFU's have been analyzed using the order frequency and volume instead of an individual demand pattern analysis. Looking at monthly demand figures, DFU's are quite volatile in nature and there are numerous periods with zero-demand. This results in a fairly large percentage of DFU's that have a bad statistical forecast accuracy. The results show that from the total of 2495 records, there are 714 DFU's (40.29% of volume) which have a forecast that is better than current market intelligence forecast. Taking into account the 3 percent threshold value, this number raises to 758 DFU's with a 56.73% share in the yearly volume (VWAA of 67.33% for stat. vs. 58.52% for lag-1). A third of these DFU's has a SN method assigned, while another 21% and 25% have a SE smoothing or MA (12 month) method assigned. Thus, a large part of DFU's has a relatively simple method assigned. When comparing to the lag-3 market intelligence forecasts, 847 DFU's (68.46% of volume) have a statistical above or within the 3% threshold having a VWAA of 55.73% for the statistical forecasts versus a 47.57% lag-3 forecast accuracy. An overview of all DFU's with a share in yearly volume greater or equal to 0.70% is provided in Table 63 (Lag-1) and Table 64 (Lag-3) in Appendix XII.

5.6 Applicability of Statistical Methods

As elaborated in section 5.4.1, different forecasting methods have been chosen to generate a variety of forecasts, each taking into account different demand characteristics. Looking at the results, particular methods are assigned to items with a certain characteristic. When looking at the chemistry level, the chemistries with a clear seasonal demand patterns (Acrylics, HASE/ASE, HEUR, and OP) are most accurately forecasted using a Holt Winters method. This results in forecasts that take into account level, trend and seasonality. Figure 15 (and Figure 55 to Figure 57) visualizes such a forecast. As DCM has many seasonal products in its assortment, this is the most frequently used method in this analysis. More stable chemistries such as Dispersants, Paraloids Solid, and Paraloids Solutions are assigned to a constant model, as expected. The resulting forecasts are fixed level forecasts in the case of SES, and slightly fluctuating lines for the moving average method (visualization of forecasts in Appendix XII, Figure 55 to Figure 60).

Figure 15: CEE/WER – Acrylics Statistical Forecast Values and Actual Sales profiles (93% accurate)



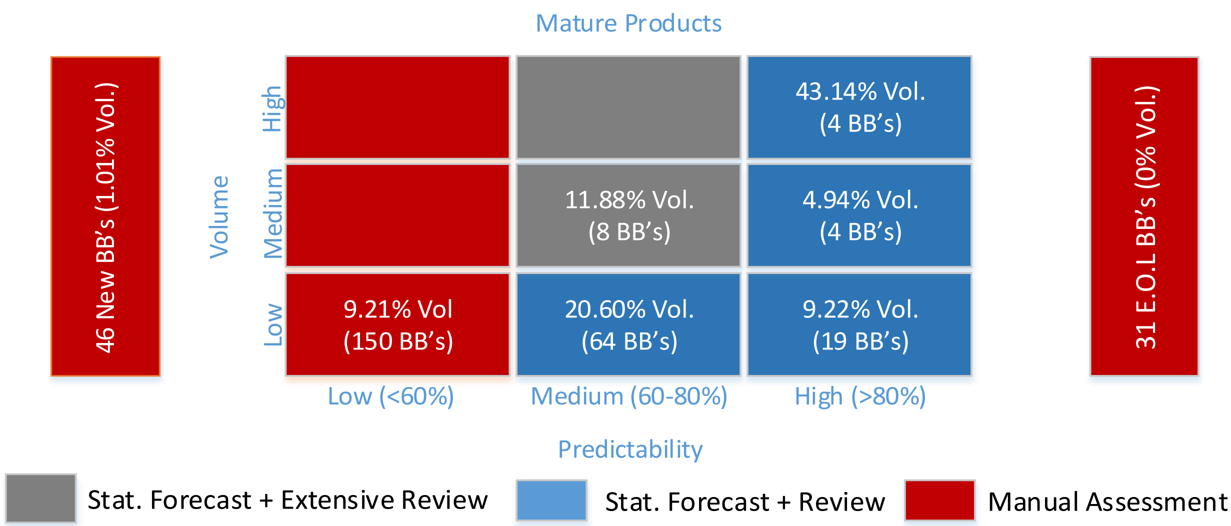
5.7 Segmentation

Currently forecasts at DCM are made at the very detailed DFU level: a combination of global customer, area profit-center, and a packaged material. With over 2600 DFU's active, it is a huge workload to keep track of all DFU's and process changes that are provided by account managers. Furthermore, all forecasts are treated similarly. When implementing statistical forecasts, some items will structurally need additional judgmental inputs, while others require less attention. Segmenting items subject to forecasting – on a certain relevant level – can support the demand planning team to focus efforts on the right problems. To provide some guidance in focus areas, a segmentation of BB products and DFU's is made based on their predictability and volume. The segmentation scheme used to tackle this issue is adapted from EYEON (2015), and is shown in Figure 61 (Appendix XIII). Horizontally, accuracy – as defined in section 5.1 – is used to indicate the ability to predict a certain base-bulk product. Vertically, DFU's are segmented according to their impact based on the 2015 volume. The segmentation recommends that statistical forecasting should be used for all instances with a high predictability (>80%), regardless of the volume. When the predictability is medium (60-80%), statistical forecasts can still be used. For medium and high volumes, the statistical forecasts should be monitored closely to act timely and incorporate Market-Intelligence as soon as possible. Low volume instances with a medium predictability are of less concern, as the lower volume causes minor impact on inventory build-up or shortages. Low predictable products should be manually assessed – no matter the volume – due to the often changing patterns that occur.

5.7.1 Base Bulk Segmentation

Figure 16 shows the segmentation scheme for base-bulk products. The top-right segment reveals that 43.14% of the volume is caused by just 4 BB-products. In total, 57.29% of volume (27 BB-products) has a statistical accuracy higher than 80%. These products have a VWAA of 91.70% compared to 89.25% for the market-intelligence forecasts. Statistics can also be applied to the middle column, forming a subset of 72 BB products with accuracies ranging from 60 to 80%. The VWAA is higher for statistical forecasts (71.82% versus 69.90%) as only 11 BB's within this group do not benefit from a particular statistical method.

Figure 16: CEE/WER - Base-Bulk segmentation matrix



The group of 8 BB products having a medium predictability and volume should be forecasted using statistics, but under close monitoring as there is quite a lot of volume on stake here. A last segment groups 150 BB's, representing 9.21% of the volume. All products situated in this quadrant require an individual assessment. Some of them will be better of using statistical forecasting, while others are just not forecastable at all due to heavy fluctuations and/or *random* intermittent demand patterns. Currently, 120 BB's (0.89% of volume) have a 0% market-intelligence accuracy already. 57 of these BB-products do benefit from a statistical method. With a 5.85% share in volume and a VWAA of 46.72% versus 38.06% for the lag-1 MI forecasts, there is a benefit to gain here although accuracies are lower than 60%. A discussion is required to assess what actions should be taken with respect to these 150 base-bulk products. This also holds for the new products (29) and end of life products (31). Manual imputation of historical data could aid new product forecasting, and actively managing demand for lower volume BB-products can aid the improvement of forecast accuracy for this group.

5.7.2 DFU Segmentation

Similar to the base-bulk level, a small number of DFU's account for a big share of volume. Of the 2495 DFU's represented in Figure 62 (Appendix XIII), 50 represent 20.26% demand and are highly predictable. With a VWAA of 88.75% for statistical forecasts versus an 86.10% accuracy for MI-forecasts, the recommendation to statistically forecast these DFU's is supported. Whilst these 50 DFU's have a fairly good accuracy, 167 DFU's report a statistical forecast accuracy of 60-80%, accounting for 37.02% of volume. For this second group, accuracies might look mediocre, however, the VWAA for this group is 70.24% for the statistical methods and 68.75% for lag-1. Out of 167 DFU's, 7 DFU's (11.30% of volume), are recommended to have active monitoring in place. As these DFU's have a relatively high volume but mediocre predictability, market-intelligence support is crucial here to minimize the forecast error and problems associated with that error. The bottom left segment in Figure 62 shows that 1678 DFU's (35.44% of volume) have a forecast accuracy lower than 60% and a volume share of less than 1%. Similar to the BB level, it is advised to assess each item in this segment individually to find a suitable forecast approach.

To provide more insight in the bottom-left segment, an initial exploration using demand frequency is done. Figure 63 (Appendix XIV) visualizes the results. The 1678 DFU's are divided in three categories with different order frequencies (1-4, 5-8, 9-12). For each category, there are a number of DFU's which have a higher statistical forecast accuracy compared to the MI-forecast. Overall, forecasts for 570 DFU's are better using statistics, which translates in to 16.83% of the volume. This leaves 1108 DFU's that have a MI-forecast which is currently better, and 856 of these DFU's are only ordered 1-4 times per year. Knowing that, all 1678 DFU's can be assessed (piece by piece) to see what can be done to improve forecast accuracy. Better demand management, with for example customer arrangements or volume discounts, can be used to create a more stable, higher volume demand profile, suitable for statistical forecasting.

5.8 Discussion of Results

The results, as presented in the former sections, prove that there is a clear potential for statistical forecasting. It will benefit the company in the form of *improved accuracy*, however, sufficient historical data needs to be available and demand should be 'stable' (i.e. no *sudden* changes in level/trend or seasonality). Eventually, the use of statistical forecasting will result in *time-savings for the account-managers, demand planners and managers.* Therefore, hypothesis 1 can be confirmed. However, there will always be items – no matter the level – which cannot be accurately forecasted using the statistical methods considered in this analysis. Furthermore, the analysis shows that the lower the level of aggregation, the greater the part of volume that will suffer from a bad raw statistical forecast and the lower the general accuracy will be. This confirms hypothesis 2. An overview of average accuracies on all levels is provided in Table 17. The segmentation provided a clear insight on which DFU's to address. On the DFU level, in total 34% of the volume requires a closer look which identifies the causes of low accuracy and subsequent actions to be taken. Another conclusion to be drawn is that rather simplistic methods, such as SE smoothing, MA, or SN, often are the most accurate. This supports the findings in literature, as suggested by Chatfield (1998) and Goodwin (2002).

Table 17: CEE/WER - Accuracy Results per Aggregation Level for Lag-1 as well as Statistical Forecasts

Level	Instances	Lag-1 Acc.	Stat. Acc.	Remarks
Chemistry	9	92.39	**94.20**	Excluding SA+VA
Profit Center	26	88.87	**91.19**	Excluding SA+VA
Base-Bulk	150	74.87	**82.25**	For BB's with FVA ≥ -3.0% (150 BB's, 58% Vol.)
	296	77.01	**79.36**	All BB's
DFU	758	58.52	**67.33**	For DFU's with FVA ≥ -3.0% (758 DFU's, 57% Vol.)
	2495	**56.06**	55.74	All DFU's

6 Redesigning the Forecasting Process | Actionable Recommendations

The previous analyses all contributed to reach the goal of this research. The AS-IS analysis showed that DCM does not use any statistical forecasting in the EMEAI region for demand planning activities, while other regions do so or are planning on doing so. Subsequently, the forecast performance analysis revealed that, compared to similar regions, the European region lags behind in terms of forecast accuracy. Consecutively, it was hypothesized that statistical forecasting could positively change the accuracy of forecasts in Europe. As proven in section 5, this is a valid statement.

This final section will provide actionable recommendations that aim to improve the European forecasting process with a focus on statistical forecasting. The recommendations are derived from the results as shown in each of the analyses and will also refer to findings in literature.

6.1 Implementing Statistical Forecasts at DFU Level (Bottom-Up)

As pointed out by Taylor and Thomas (1982), highly accurate statistical forecast methods are of no use when decision makers have doubts on the credibility of the forecast output and choose to ignore them. Ultimately, decision making is supported by forecasts which are chosen by human beings (Goodwin P. , 2002). Therefore, at the very basis of implementing statistical forecasting, lies a culture change that acknowledges statistical forecasting. Throughout the demand planning function, it should be understood what forecasting is, and what it is not (Moon, Mentzer, Smith, & Garver, 1998). Since the current forecasting process does not entails any statistical forecasting activities – not even as a supporting tool – the implementation will require a big change in both culture, as well as in the process itself.

The difference between the new and old process must be understood by its users. In the redesigned process, statistical forecasting will provide a valuable raw forecast, from which users can build a planner adjusted forecast, and finally arrive at a baseline demand (Table 65, Appendix XV). The statistical forecast must *not* be seen as a mere output of the process, rather it should be regarded as an input. The raw statistical forecast can be seen as the lag-3 forecast, being less accurate, but taking away the efforts of creating a forecast while providing a basis to improve the other lag-forecasts. It helps to transform the active management of over 3600 DFU's to a situation using management by exceptions. Even with very sophisticated tools in place, statistical forecasts can never provide overriding output for demand planning. Therefore it is of key importance that: *The role and objective of statistical forecasting is clear to all forecast stakeholders* (Oliver Wight, 2015) (Chopra & Meindl, 2013). *The basics of statistical forecasting must be introduced by extensive training; awareness of which aspects can be captured by statistical forecasting, how forecast health measures can be interpret, and which actions have to be taken – at the right time – to correct statistical forecasts, are of crucial importance.*

The implementation should be supported by the company as whole (Chopra & Meindl, 2013), including sales and marketing. They will serve as an important information source to improve statistical forecasts. *Therefore the forecasting process should be embedded across the organization, ensuring the input of information from multiple sources.* Monthly S&OP, and weekly S&Oe meetings are perfectly suitable to reach such a cooperative environment.

After providing training and gaining company wide support for the implementation, the process, tools and people have to be aligned (Oliver Wight, 2015). In this specific case, the company is new to statistical forecasting and should be cautious not to lose itself in the change. *Extending the current DFU-forecasting strategy with a statistical bottom-up basis, will limit the change for the people working with forecasts.* This gives stakeholders the opportunity to get acquainted with the new method, and a keeps them closely involved in the process.

6.1.1 Redesign the Forecast Evaluation Process

Related to the previous paragraph, a recommendation is to further develop the bias-review process that is currently in place. At present, DCM evaluates forecasts using the bias-review (section 3.3.1). In this review, the forecasts which have systematic deviation from actuals are filtered out by looking at the forecasts that have a bias for 5 or 6 subsequent months. The demand planner or manager sets a certain volume threshold to regulate which items will be selected to investigate. This approach sets actions only if a forecast has a high bias for multiple periods. However, the bias review does only use one metric: forecast-bias. As this is a scale dependent measure, it is inappropriate to compare across time-series and identify the relative performance of forecasts per item, region, or product group (Goodwin & Lawton, 1999). Furthermore, when aggregation takes place, the negative and positive biases can level out, possibly resulting in a faulty high level overview.

Forecast-bias is mostly used to estimate consistent over- or under-forecasts or if demand has deviated significantly compared to historical norms (Chopra & Meindl, 2013). If one finds an error well beyond historical estimates, this might indicate that either the current forecasting method is no longer applicable, or that demand has fundamentally changed. Furthermore, if all of the firm's forecasts (for a certain group of items) tend to consistently over- or underestimate demand, this is another signal to change forecasting methods. Incorporating the comparison against historical high errors, and the oversight of negative and positive errors gives more insight into the performance of the forecasting process currently used at DCM.

Ideally, the new bias-review will incorporate measures that extend the evaluation capabilities of the current process based on forecast-bias. Using a relative measure size dependency can be avoided. However, multiple authors state that interpretability of relative measures can be difficult and should be taken into account when using these metrics (Armstrong & Collopy, 1992) (Chatfield C. , 1992). Comparing forecast performance can lead to an organization in which learning is stimulated to a larger extend. By comparing groups with different underlying forecast process characteristics, best practices might surface. The forecast analysis executed in this research is an example of such a comparison, and used the MAPE and sMAPE to do so. It proved the MAPE's sensitivity to outliers, where low volume DFU's frequently turned out to be troublesome. In particular, this issue is encountered on a low level of aggregation. The symmetric MAPE is less sensitive to outliers, but this measure treats positive and negative errors differently (Goodwin & Lawton, 1999). The reduced sensitivity to outliers also implies that extreme values will be harder to identify, which will be easier using the MAPE. As the MAPE is already being introduced to the management at DCM, incorporating this measure as the scale-independent measure is advised. This should go hand in hand with a proper knowledge of managing outliers or trimming procedures to reduce the effect of outliers on the MAPE. For example, the MAPE could be imposed with an upper limit, or the median average percentage error could be used to compare time-series (Goodwin & Lawton, 1999).

Taking into account all of the above, the forecast evaluation process could be strengthened by incorporating historical forecast-biases in the evaluation. This enables the identification of historically high forecast-biases and the structural over- or under-forecast errors. Furthermore, adding the MAPE as a forecast evaluation metric enables the comparison of forecast health at different levels. This can give valuable information in well-performing forecast procedures and according best-practices. By combining just two forecast metrics, diverse information is available while keeping the number of metrics to a minimum. This converges with advice given in in academic literature, as well as it simplifies the information flow to managerial levels by keeping the number of KPI's low. Cooperation with other regions, especially the ANZJK region, a renewed forecast evaluation process can be designed focused on statistical forecasting while incorporating learnings from those other regions.

6.1.2 Structurally Incorporate Market-Intelligence input

The implementation of statistical forecast should go hand in hand with setting-up a process to incorporate judgmental (i.e. market-intelligence based) adjustments of forecasts. The importance of incorporating judgmental adjustments has been described by many. Evidence from the economic forecasting literature shows that forecasts can be made more accurate when expert judgmental input is used to take into account the effects of special events (marketing efforts, tax-laws) and changed variables not incorporated in the statistical model (Donihue, 1993) (McNees, 1990) (Sanders & Ritzman, 2001). However, when only time-series information is available to both statistics and the judgmental forecaster, several studies suggest that statistical methods will yield the most accurate forecast (Goodwin & Filders, 1999) (Lim & O'Connor, 1995). Goodwin (2002), shows that behavioral objections to statistical forecasting can be mitigated by providing managers and other users to provide their inputs. However, judgmental input is also often provided unnecessarily when managers have no extra information to bring to the forecast (Sanders & Ritzman, 2001) (Lim & O'Connor, 1995). Some studies provide evidence that this is caused by forecasters seeing patterns in the noise associated with random fluctuations in the time-series (Harvey, 1995). Unnecessary judgmental adjustments are also related to 'illusion of control' effect, where forecasters have a need to retouch the forecast to gain greater confidence in their forecasts (Kottemann, Davis, & Remus, 1994). A study by Fildes, Goodwin and Lawrence (2006) shows that three key problems with judgmental forecasts exist: 1.) excessive trust of managers in their own judgments and unwillingness to trust a model sufficiently in forecasting the regular pattern, 2.) managerial judgment is influenced by randomness, 3.) managers have a poor understanding of appropriate level of confidence in the system.

A Forecasting Support System (FSS), such as APO in the case of DCM, can be used to incorporate such adjustments, as it embodies a database, various forecasting methods and the interventions made by the system users (Fildes, Goodwin, & Lawrence, 2006). A study by Goodwin (2002) shows that when a forecaster has to explicitly make a request to adjust the raw statistical forecast, significant reductions in the amount of harmful adjustments is achieved without reducing the tendency to submit appropriate adjustments. Further reduction can be gained when forecasters have to explicitly state a reason (Goodwin

P. , 2000). Besides the increase of manipulation efforts, manipulation confidence – by warning users when their adjustments exceed the size of any previous adjustments for that series (Fildes et al, 2006) – is another way to find balance between statistics and judgmental forecasts. Furthermore, having an interactive FFS, allowing users to fine-tune forecasts will foster a sense of ownership. And finaly, the same authors suggest that gaining overall acceptability is an important aspect. Acceptability can be gained by ease of use. Another key factor here is the demonstrability of results (Fildes et al, 2006). Comparing forecast accuracies with and without adjustments can strongly influence the acceptability.

A few of these aspects are already incorporated in APO, such as the ability to fine-tune forecasts by setting parameter values, and the visualization of forecasts which creates ease of use. *However, as statistical forecasting is a new concept for DCM, the overrides of judgmental forecasting should be monitored closely. Keeping forecasters and managers informed about the impact of their judgmental adjustments on accuracy is crucial to gain their trust on statistical forecasting.* Initially, this tasks could be executed by the demand manager or planner, which functions as a central focus point for judgmental adjustments coming from (account) managers. As Goodwin (2002) proposed, explicitly making a request for adjustment will decrease harmful adjustments. Of course, the management of this process, which incorporates judgmental input, should avoid that forecasters stop making adjustments at all.

6.1.3 Smoothen the Implementation in APO

The actual implementation of a bottom-up approach to statistical forecasting in APO will require a significant amount of work. APO lets users select a certain forecasting method with according parameter settings. These settings can be saved, by which a forecasting profile is created. Following this procedure, the implementation on a DFU level requires assigning a certain forecasting profile to all individual records. However, there is an option to assign a profile to a BB (or higher aggregation level item), which automatically assigns the same profile to all underlying instances. A general observation for this research is that a statistical method assigned to an item at a higher level, does not has to fit all the underlying data. For example, a BB-product can have a MA method, while some underlying DFU's have a HW forecast in place. To make quick and short-term implementation feasible, this difference could be neglected, and the BB profiles could be used to assign profiles. Here, the company faces a trade-off between ease of implementation and a loss of accuracy, caused by the desired detailed level of forecasting.

As was shown in earlier sections, SA and VA are having deviating patterns. To avoid sketching a somber picture, all SA and VA base-bulk products are omitted in a part of the following analysis. Table 18 provides the VWAA for two different approaches: 1.) the BB-method, which assigns the method preferred for the BB to all underlying DFU's, and 2.) the DFU method, which simply assigns the preferred method to all DFU's. The results show that, when excluding SA and VA, the volume weighted average lowers from 60.98% (DFU methods) to 53.71% (BB methods) compared to 57.19% accuracy currently.

Table 18: Comparison of Accuracies for Base-Bulk and DFU methods of assigning Forecast Profiles

	Average (%)			**Volume Weighted Average (%)**		
	Current	**DFU Method**	**BB Method**	**Current**	**DFU Method**	**BB Method**
Incl. SA+VA	10.00	14.67	10.54	56.42	57.41	48.80
Excl. SA+VA	9.65	14.81	10.77	57.19	60.98	53.71

6.1.4 Address Low-Volume Low-Predictability items

The segmentation in section 5.7.2 pointed to a group of DFU's with low volume and low predictability which has to be addressed manually. This group contains DFU's having a bad statistical accuracy, and most of them have a low MI-forecast accuracy too. First of all, it is important that the existence of these low accuracy DFU's is recognized. Only after showing that, measures can be taken to address these items. Cooperation with stakeholders of those low accuracy forecasts will result in more insight into the difficulties and troublesome aspects of specific (sets of) forecast(s). Once these are indicated, actions can be taken to structurally improve the accuracy of these forecasts. For some of them, there will be no remedy, as the demand is truly random. However, for others a remedy can be sought in aggregating demand for a number of customers or actively managing demand by offering price reductions for orders in a certain period.

6.2 Initiate a Top-Down Forecasting Pilot

In principle there are two main streams of forecasting practices: top-down (TD) and bottom-up (BU). According to Lapide (1998) and Schwarzkopf (1988), the TD approach forecasts the aggregate total, and subsequently disaggregates this aggregate data into individual items again, mostly based on a historical percentage of an item within the product hierarchy. For a bottom-up forecast, first the forecasts for individual items are prepared, where after these forecasts are aggregated to the level of interest for the analysis (Jain, 1995) (Lapide, 1998). As suggested by Lapide (1998), a TD approach makes most sense when all of the individual items follow a similar trend (i.e. growth, decrease or remain stable), whereas if sales patterns of underlying items are very different or have a negative correlation, a BU strategy would be preferable. Additionally, Gelly (1999) shows that the TD approach is more adequate if individual items have a more predictable sales pattern throughout time. Forecasting a higher level item would yield a more precise estimate for that level, but when aggregation down, forecasts tend to become less accurate when the underlying structure is not stable.

If a business chooses to apply a TD approach, an important decision relates to the right level of aggregation. Following Zotteri and Kalchschmidt (2007a), the level of aggregation of a forecasting problem can be defined by three dimensions:

1. *The market:* Demand can be forecasted at different levels. Single store forecasts are however harder to create than forecasts on a country level.
2. *The product:* As is proven in previous sections, forecasting a DFU with high accuracy is hard. Forecasting a product group often causes less difficulties.
3. *The time-frame:* A forecast is created for a certain 'time-bucket', indicating the amount of time considered (months, weeks, days), and spreads a certain forecast horizon (i.e. number of time-buckets forecasted). For DCM, time buckets are months and the horizon is set to 12 months.

The smaller the market, the more detailed the product, and the shorter the time-bucket, the more detailed the forecasting problem will get (Zotteri & Kalchschmidt, 2007a). As pointed out by Dekker, van Donselaar and Ouwehand (2004), growing assortments and shorter product life cycles result in many products with too little data per product to generate reliable forecasts. Top-down forecasts are shown to have an improvement potential here (Dekker, van Donselaar, & Ouwehand, 2004). Several studies report the potential of product-aggregation compared to classical methods, when basic forecasting and clustering techniques are used to generate the top-down forecast (Dalhart , 1974) (Withycombe, 1989) (Bunn & Vassilopoulos, 1993) (Bunn & Vassilopoulos, 1999).

In short, the above stated reveals that TD forecasts have a potential to be more accurate, and are suitable for products groups for which underlying products have a similar trend in growth (van Donselaar, 2003). Furthermore, it will also reduce the number of forecast profiles that have to be assigned. Instead, percentage shares in the group's total volume are calculated based on historical data. Therefore, on a long term, this approach will yield the best results for suitable product groups. For DCM, the path forward should include an exploration of TD forecasting. And t*o explore TD forecasting, a TD-pilot should be started, using product groups that support such a TD practice by having a set of stable underlying products with similar growth patterns.*

6.2.1 Determine the right Aggregation Level

An important decision that comes with applying a TD approach, is to determine the level of aggregation. Zotteri and Kalchschmidt (2007a) suggest that the forecast aggregation level should be equal to the level of the decision making process. In a previous article they report that companies often use different levels of aggregation to support different decision making processes (Zotteri, Kalchschmidt, & Caniato, 2005); rather detailed forecasts are needed to decide on safety stock levels on product level, while budgeting total production costs requires aggregate forecasts. The current process at DCM requires DFU level forecasts to estimate packaging needs (i.e. drums, bags, custom packaging) for the central packaging facilities, logistic requirements, and to keep track of individual customer needs. Furthermore, some customer-product variants differ slightly from the original base-bulk product, due to minor, but quick modifications to the bulk product. This detailed level of monitoring causes high a high workload for account managers and forecasters.

On the supply side, production decisions are made on a base-bulk level. Currently, the BB forecasts are aggregated from a DFU forecast level. But, as follows from sections 5.5.3 and 5.5.4, and as indicated by Chopra and Meindl (2013), aggregation from a low (DFU) level results in less accurate aggregate forecasts. By implementing more aggregate level forecasts (i.e. material-sold or BB level) accuracies will rise, and by using a TD approach the disaggregation to DFU level still enables logistic and packaging departments to plan accordingly. This potentially lowers inventories and increases service levels due to more precise inventory and production planning. *DCM should start analyzing which aggregation level still provides sufficient detail to maintain the required customer service level and keeps logistic and packaging departments informed.* Departments should be closely involved to report on the effects of a TD approach on their operations, as they must be able to provide the same service as they currently do.

6.3 Improve Data-Maintenance

One of the key enablers of statistical forecasting is the availability of sufficient and reliable historical data. Hughes (2001) shows that in the past, one of the reasons for a lack of data was poor record keeping. In section 0, it was shown that the many regions have more than 8% of their volume not being forecasted at all, with Europe lacking forecasts for 7.18% the volume. As the NAA and ANZJK regions are able to achieve higher numbers (97.88 and 98.59% respectively), there certainly is a potential for improvement here, especially since it's an enabler of accurate statistical forecasts. Faulty or missing data entries can lead to significant deviations in forecasts – and as was encountered in the regional forecast performance analysis – this can lead to significant errors. *Therefore, after the top-down statistical forecasts are in place, the importance of proper data-maintenance should be recognized and spread along users*. Besides the former described effect, the use of a decent information base reduces the uncertainty on future events. This might prove to be helpful when deciding on (aggregate) planning of production (Danese & Kalchschmidt, 2011).

6.4 Change to a Rolling Forecast Horizon with Extended Length

Currently, the European forecasting process considers a fixed forecasting horizon of 12 months. This long-term forecast is generated by using account manager input and intensive communication. The fixed character of this look-out is based on the amount of efforts put in to the generation of the forecast. When using statistical forecasting, a baseline forecast – based on objective historical data – for the long term is provided by APO. This shifts workload from human resources to computing capacity, resulting in more time for discussion sessions and the input of market intelligence. Making use of statistical forecasting enables more frequent and less time consuming renewals of long-term forecasts, or in other words, a rolling-horizon forecast can be maintained.

Depending on the level of aggregation, a longer forecast horizon is feasible. One can expect that a 24 month look-out on DFU level is questionable, as product replacements occur and customers can switch sourcing strategies. In 2001, Hughes (2001) already mentioned that 18 month old data is outdated, as product and environment changes happen increasingly fast. However, on an aggregate chemistry level, a 24-month forecast does makes sense. *Depending on the stability of a certain level, the forecast horizon can be extended using statistics.*

6.5 Share Experiences and Processes Learnings Globally

A conclusion that can be drawn from this research is that regions are dealing with different demand generating processes, and that different forecast processes are used to generate forecasts. ANZJK can be acknowledged for their expertise on statistical forecasting, while NAA is experimenting with a whole new approach to demand planning. Sharing experiences and best-practices is key to a learning organization in which improvement is stimulated. To reach this state, *inter-region communication should be stimulated*.

6.6 Proceed with roll-out of statistical forecasting to other regions

As has been shown in section 4.6.2, there is a clear indication that statistical forecasting in the MEATI region will yield better forecast accuracy. Surely, similar to CEE/WER, this will not be the case for all DFU's or Base-Bulk products. It will however start the movement towards a more statistical focused process. Therefore, after gaining the experience of implementing the top-down forecasts in Europe, and ideally, after experimenting with the TD approach, a similar process can be started in the MEATI region. The same holds for the GCSEA and LAA-region. Although in LAA currently a redesign process is being started, the recommendations provided here can be useful.

6.6.1 Employ a regional demand planner for MEATI region

Advancing on the implementation of statistical forecasting in the MEATI region – but also as a general improvement to the current process – a regional demand planner for the MEATI region should be appointed. As we have seen from the demand pattern analysis, demand patterns differ compared to Europe, and besides that, the region is experiencing growth and deals with more volatile demand. To deal with all the differing circumstances in the various EMEAI sub-regions is a heavy – if not impossible – workload when trying to incorporate all regional effects into the forecasts. Therefore, employing a regional demand planner in the MEATI region will offer support for the implementation of statistical forecasting, which also requires additional human resources during implementation.

7 Conclusion

This section provides the conclusion of this research and gives a summarized answer to the research questions as stated in section 2.2. Limitations and future research opportunities are also discussed.

7.1 Overall Conclusion

The objective of this research was to assess the potential of statistical forecasting, focused on the European region. To do so, the current forecasting process was analyzed, followed by a performance analysis of forecasts in all operating areas. These analyses gave strong support for the potential of statistical forecasting in Europe, but also in LAA and MEATI. Therefore, statistical forecasting was put to the test for the European region by comparing it to the market-intelligence forecasts as generated by the current demand forecasting process. This comparison concludes that on average, statistical forecasting provides a better accuracy than the market-intelligence forecast, and that a higher aggregation level yields a higher accuracy. On the DFU level, statistical forecasting for a selected group of DFU's (representing 56.73% of volume), results in the improvement of accuracy from 58.52% to 67.33%. Combining this with judgmental input from various departments, forecasts are expected to yield an even higher accuracy. Therefore, this research concludes with the recommendation to implement statistical forecasting, with the condition that statistical forecasting is used as a raw-forecast. Meaning the statistical forecast serves as a basis, and is adapted based on judgmental input for those items that have a more variable nature, or in case big changes in demand patterns or volumes are expected. Various types of forecast methods proved to be applicable, as each item has a different demand profile, requiring a different forecast method. The implementation will therefore require using a variety of forecast methods which have to be assigned to the items that have characteristics corresponding to the forecast methods characteristics. As DCM has many seasonal products, the Holt-Winters method yielded the best results for most items since it explicitly considers the seasonal pattern of the product being forecasted.

In section 2.2 the research questions have been defined, on which the answers are summarized below:

1. *What is the current state of the forecasting process in each of DCM's operating regions?*
   DCM is divided in four geographical regions, all having separate demand planning processes in place. In all regions forecasts are managed by the supply chain department and are generated on a DFU level – the lowest possible aggregation level – using APO. Most regions still use market intelligence to forecast their products, however, the ANZJK sub-region uses statistical forecasts.

The NAA region is currently implementing a new demand planning process, involving statistical forecasting. Forecast horizons vary from a fixed 12-month to an 18-month rolling horizon. A questionnaire revealed issues related to APO and issues considering the timing of various forecast process steps. Considering statistical forecasting the main concerns relate to a lack of knowledge.

2. *How are current forecasting methods at DCM performing?*
   In the analysis, carried out in this research, the forecast error (MAPE and sMAPE) for geographical (sub-) regions was used to assess the performance. Currently, mainly the forecast bias is used at all forecast levels, which is not useful to compare across time-series. For each area there are different conclusions. In general, accuracy increases moving from lag-3 to lag-0 forecasts. Looking purely at error percentages (lag-1), ANZJK is the best performing region, followed by NAA and Europe. The MEATI region comes last, preceded by GCSEA and LAA respectively. As Europe and ANZJK share the same CoV, it is expected for the regions to have a similar forecast error. As there is a gap in performance, it appears to be possible to increase forecasting performance in Europe.

3. *Does statistical forecasting improve the forecast accuracy in the European region?*
   Demand patterns for Greater Russia and CEE/WER are very distinctive. Big differences in peak volumes, seasonal patterns, growth, and the Russian contract business clearly separate the regions. Furthermore, demand patterns are stable on a high level, and tend to become more variable with a lower level of aggregation. In Russia, already on a Profit Center level, demand tends to become intermittent and instable. Therefore, it is concluded that currently only the CEE/WER is assessed for the implementation of statistical forecasting. In CEE/WER there is not one single statistical model that fits all; multiple parameter settings and methods are used. In total, 56.73% of volume has is more accurate than, or up to 3% worse than the market-intelligence forecast. This leads to an average accuracy improvement of 8.81%.

4. *What actionable recommendations can be given to improve the forecasting process at DCM Europe concerning the forecast level and scope?*
   Eventually, it can be concluded that statistical forecasting raises accuracy for the European region and takes away the workload of creating forecasts manually, shifting that to merely adjusting where needed (i.e. management by exceptions). Based on these findings, statistical forecasting should be implemented. However, to prevent reluctance to change, it should be implemented with caution to avoid getting lost in the change. Initially, statistical forecasts will be generated on a DFU level, serving as a raw forecast to be adjusted where needed. Thus, market-intelligence and statistical forecasts will both be used. The final goal is to reach a state where top-down forecasting is applied, enabling more accurate raw forecasts. Also, the forecast horizon should be changed from a fixed 12-month horizon, to an 18- (and later 24-) month rolling horizon, with improved data-maintenance being emphasized. Lastly, it is recommended to roll-out statistical forecasting to other regions and to learn from other regions. As a precaution, a demand planner should be assigned explicitly to the MEATI region, to have an extra resource in place dedicated to manage the change from pure market intelligence to a mixed form of forecasting.

7.2 Generalization of Findings

This research has focused on Dow Coating Materials, and finally relate to the operating region of Europe. Now, detailed findings such as accuracies and the allocation of specific forecast methods are really only applicable to this setting. However, the methodology used in this research can be applied to any other region or industry as it entails a structural way of assessing the potential of statistical forecasting. Furthermore, some of the findings will hold in general. It was found that accuracy raises for higher aggregation levels, and that frequently ordered and high volume items are better forecastable. These findings can be used to support decisions on where to apply statistical forecasting in other regions, business units or companies. Besides that, this research ends with recommendations to redesign the forecasting process by implementing statistical forecasting. With respect to forecast evaluation, implementation of statistical forecasting, top-down forecasting, as well as the structural integration of judgmental forecast input, the recommendations are generally applicable and do not limit themselves merely to DCM. All aspects considered can serve as a guideline for companies finding themselves at the start of such a redesign, either in the chemical or any other industry.

7.3 Limitations

The research started with DCM-wide analyses of the current state and performance of forecasting processes. However, considering the potential of statistical forecasting the research had to be scoped to only address the European region. Timewise it was not feasible to extend the analysis to other regions.

During the project, data was gathered using SAP. For the greater part, this data is very reliable, however – as indicated in this work – there are outliers influencing the data. Most of these outliers have been addressed, but it cannot be guaranteed that all data is correct. Another limitation considering the data relates to the calculation of the value add of a market intelligence forecast versus the seasonal naïve forecast. As not every product is sold every year, especially in smaller regions, the available data to calculate the SN-forecast accuracy varied for each region. In some cases this was considerably less than for the most recent forecasts (market-intelligence), as for some Planning Base level and Chemistries there are only a few DFU's to populate these levels. This can have a significant effect on the results, as was the case for the Paraloids Solid and Paraloids Solution chemistries in most areas.

Furthermore, the inter-region comparison of forecasting performance relates the performance to a volatility measure, the coefficient of variation. This measure is independent of scale, and thus, it is useful to compare across time-series. However, in the case of seasonal demand, this measure is unable to differentiate between pure volatility and seasonality. But, since only 10 months of data could be used for this analysis, it was not possible to deseasonalize the data first. Therefore, in the end, the CoV results do not fully capture the real variability of a certain region.

Currently, forecasts are made using market-intelligence and are manually inserted. Therefore, packaging requirements can be accounted for, meaning that forecasts are rounded to packaging sizes. The statistical forecasts used in this research do not comply with this, and therefore, accuracies might deviate a little. However, this difference should be minimal, considering the size of total volumes being forecasted.

7.4 Further Research

This research has provided the potential of statistical forecasting for a specific operating region of DCM, and there certainly are ways to move forwards with this research as a basis. A follow-up project within DCM can be started to assess the impact of a top-down forecasting approach on packaging and logistic departments. Eventually, due to the benefits as described in this research, the goal is to end up with TD-forecast approach where this is possible. Also, the potential of statistical forecasting in could be determined in other regions making use of the methodology outlined in this research. Another research-avenue leads to the application of more sophisticated models, such as fuzzy-logic or multiple regression analysis. Incorporating the effect of other variables than just a time-series of demand can lead to valuable insights and a strengthened capability of capturing future fluctuations in demand. However, this requires a thorough understanding of these methods, and should therefore be implemented only if sufficient knowledge of this matter is available within the company.

Furthermore, the association of forecast error to costs has not been called-upon during this research. This is a difficult practice, as it involves many variables, estimations and assumptions. There are methods that simplify the calculations to give a ballpark estimate of the costs (Kahn, 2003), but they only show an indication of what the costs could be without providing certainty. To further support the movement of gaining a more accurate forecast, a study that reveals close estimates of the costs of forecast error will be of great support. The monetary value of forecast error will certainly support the decisions related to the forecast process as made by the management. Besides the relation with costs, a valuable insight could be given by identifying the processes related to forecast errors (such as rush-orders, and customer services) and to address the impact of a forecast error on those processes.

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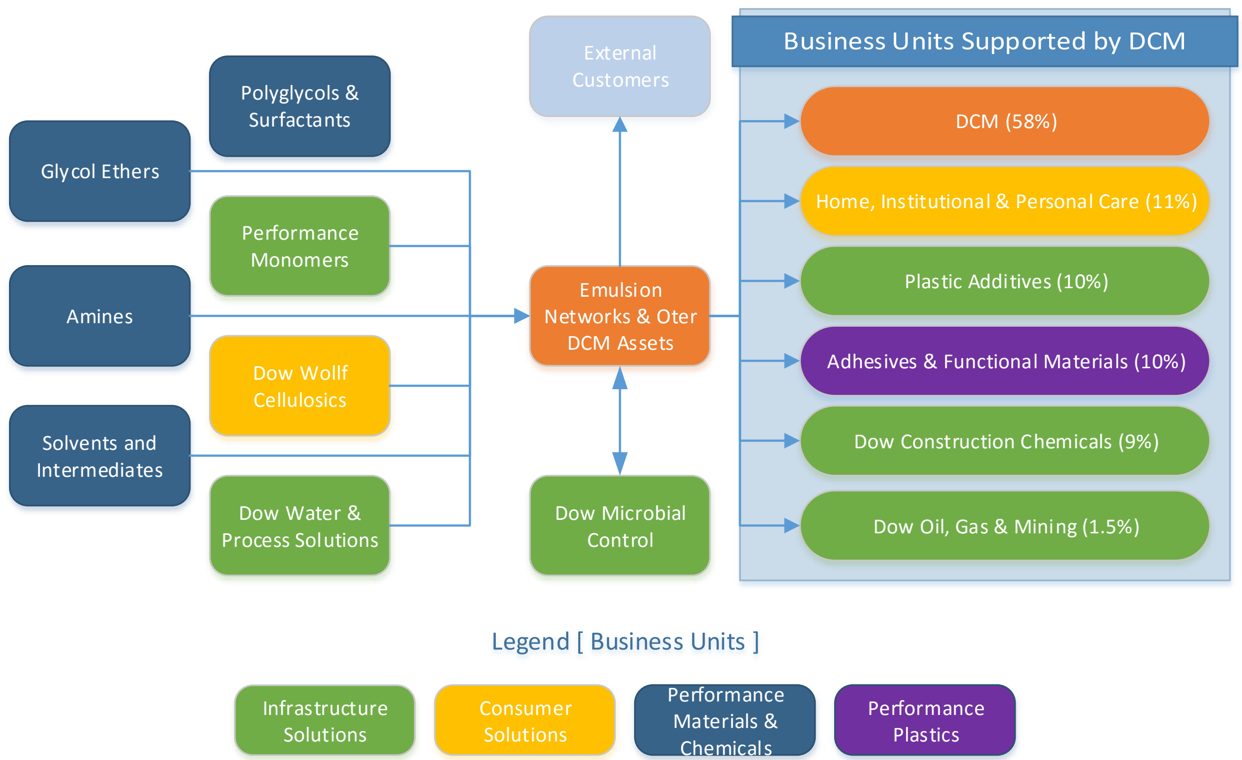
Appendices

1 Appendix I

The figure below represents an overview of raw material inputs, and subsequent flows of finished goods to other business units within Dow. Note that a part of the products also flows directly to customers external from Dow.

Figure 17: A visualization of good flows for DCM (process inputs and outputs)



2 Appendix II

This overview gives a detailed view on what functions exist within the demand planning process. Furthermore, it indicates how much FTE is accounted for by a specific function, and in addition the column Area (+Type) informs on the region and – if applicable – the segment of the business to which this function applies.

Table 19: Overview of Demand Planning Resources in each area

Area or Organization	Asia Pacific Caribbean (APAC)			Europe, Middle-East, Africa & India (EMEAI)			Latin America (LAA)			North America NAA			Total FTE
	Name	Time (%)	Area + Type	Name	Time (%)	Area	Name	Time (%)	Area	Name	Time (%)	Area	
DCM	Yumiko Siato (DSP)	50%	Japan & Korea	Sabine Wiegand (DP)	100%	EMEAI	Juan Carlos (DP)	7.5%	LAA	Bernadine Cataldo (DM)	100%	NAA	
	Neale Keast (DSP)	50%	Australia & New Zeeland	Murali N (DSP)	33%	IBPS	Garcia Marquez (DP)	7.5%	LAA	Deborah Miller (DP)	100%	NAA	
	Rachel Ni (DSP)	50%	China (Architectural)	Stephen Lima (DM)	100%	EMEAI							
	Ellen Zhen (DSP)	50%	China & SE Asia (Industrial)										
	Sherry Shen (DSP)	50%	SEA excl. Thailand (Architectural)										
	Verena Abrantes (DSP)	20%	Thailand (Architectural)										
	Lydia Su (DSP)	50%	APAC (Functional)										
	Janna Goh (BSCL)	15%	APAC (Support Reports)										
	Sophie Liu (AA)	20%	APAC (Regional S&OP)										
Total FTE		3.55			2.33			0.15			2.00		8.18
DPA	Sing Hng Ng (DP)	20%	APAC	Joelle Martig (DSP)	50%	EMEAI	Claudia Danezi /Luciana Rovay	30%	LAA	Steve Zigrye (DP)	40%	NAA	
Total FTE		0.20			0.50			0.30			0.40		1.4
PM	Ivana Zhou	12%	APAC	Jullien Lambert (D&SC Specialist)	10%	EMEAI	Mariana Martini (DP)	12%	LAA	Colleen Casy	12%	NAA	
Total FTE		0.12			0.10			0.12			0.12		0.46
Total FTE EA		3.87			2.93			0.57			2.52		9.89

Table 20 and Table 21 provide an overview of pain points, as referred to during the As Is analysis. Where Table 20 provides an overview of pain points and the section they belong to, Table 21 gives an overview of what prioritization is given to these pain points according to system users.

Table 20: Count of Pain Points as Identified in the Demand Planning Questionnaire

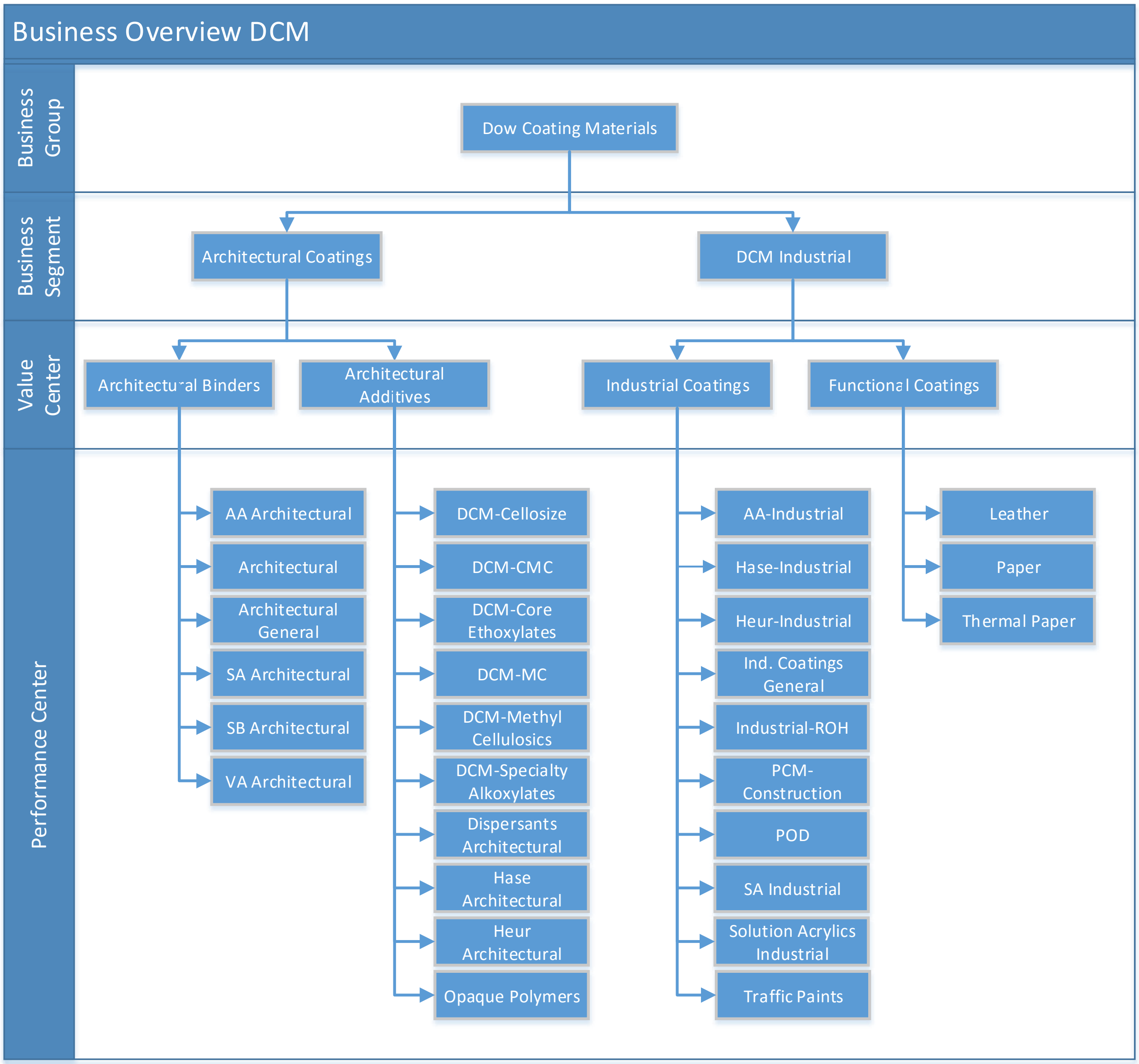
Area	Section	Section Summary	Total
APO	Statistical Forecasting	Complexity and training plus system issues	16
	Data Issues	Month End APO load, maintenance in APO and ECC issues	15
	Access	CVCs locked by other users in ZSDP94	4
	Process	Audits and Market intelligence loads	3
APO Total			**38**
DSR	Manual Reports	Manual reports created to support role	7
	Forecast Consumption Report	Request for more info (e.g. consignment, BP and PY volumes)	6
	Education	Training for Commercial on DP and Bex Analyzer (DPA)	4
	Data Issues	Waiting for batch jobs and data alignment with APO	3
	New Report	A DSR report showing 'Actual Invoiced' + APO forecast	3
	DSR Issues	Sales names in DSR	2
	Forecast Bias Report	Batch job on WD+3 delays audits	1
DSR Total			**26**
Organization	S&OP Process	Complexity, Lack of training and System issues	13
	Business Plan	Lack of coordination and communication	5
	Inter-Regional	Lack of communication or sharing learnings	3
	Education	Training for Commercial and DP designed around DP	2
	Resource Time	Split role leaves little time for effective DP	1
Organization Total			**24**
Grand Total			**88**

Table 21: Pain points organized by Section with a Prioritization per Region and Business

Area	Section Summary	Total PP	1 TO 16 PRIORTISATION				
			DCM APR	DCM EMEAI	DPA Global	PM Global	Average Score
APO	Month End APO load, maintenance in APO and ECC issues	**15**	2	2	1	5	3
APO	Complexity and lack of training plus system issues	**16**	6	1	2	9	5
ORG	Complexity, Lack of training and System issues	**13**	1	7	12	3	6
DSR	Request for more info e.g. consignment, BP and PY volumes	**6**	4	5	11	2	6
APO	CVCs locked by other users in ZSDP94	**4**	7	6	7	10	8
DSR	Waiting for batch jobs and data alignment with APO	**3**	8	10	6	6	8
APO	Audits and Market intelligence loads	**3**	3	8	8	14	8
DSR	A DSR report showing 'Actual Invoiced' + APO forecast	**3**	5	3	14	12	9
DSR	Manual reports created to support role	**7**	10	4	3	16	8
DSR	Sales names in DSR	**2**	15	9	5	8	9
DSR	Training for Commercial on DP and Bex Analyzer (DPA)	**4**	9	11	4	15	10
ORG	Lack of coordination and communication	**5**	13	15	9	4	10
ORG	Lack of communication or sharing learning's	**3**	14	12	10	7	11
ORG	Split role leaves little time for effective DP	**1**	16	16	13	1	12
DSR	Batch job on WD+3 delays audits	**1**	12	14	15	11	13
ORG	Training for Commercial and DP designed around DP	**2**	11	13	16	13	13

3 Appendix III

Figure 18: Hierarchical levels within DCM



4 Appendix IV

Figure 19: CVC Design & Attributes

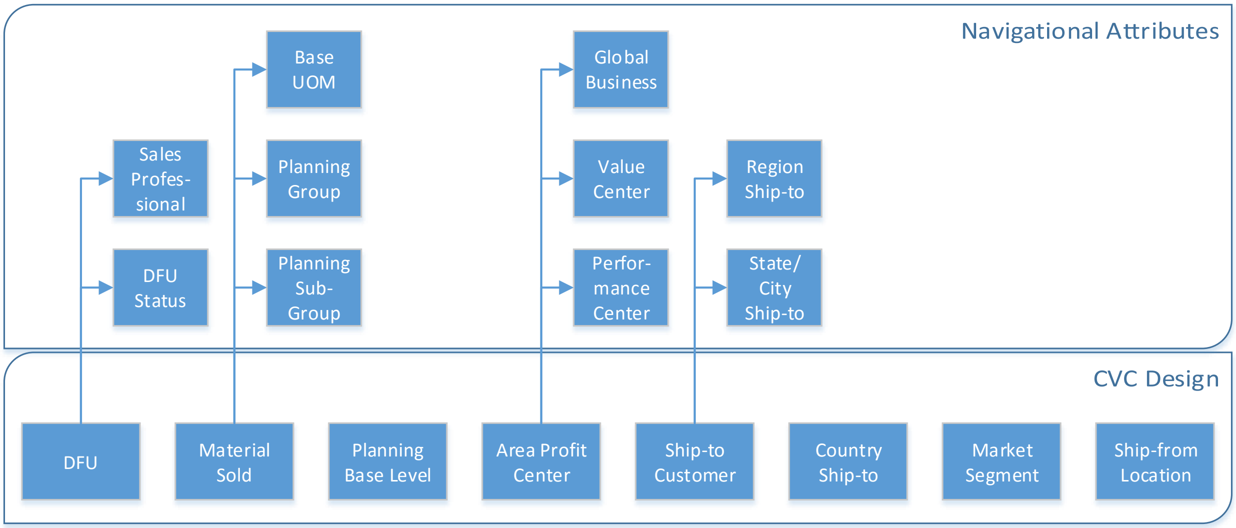


Figure 20: The main CVC characteristics (orange) and the derived characteristics

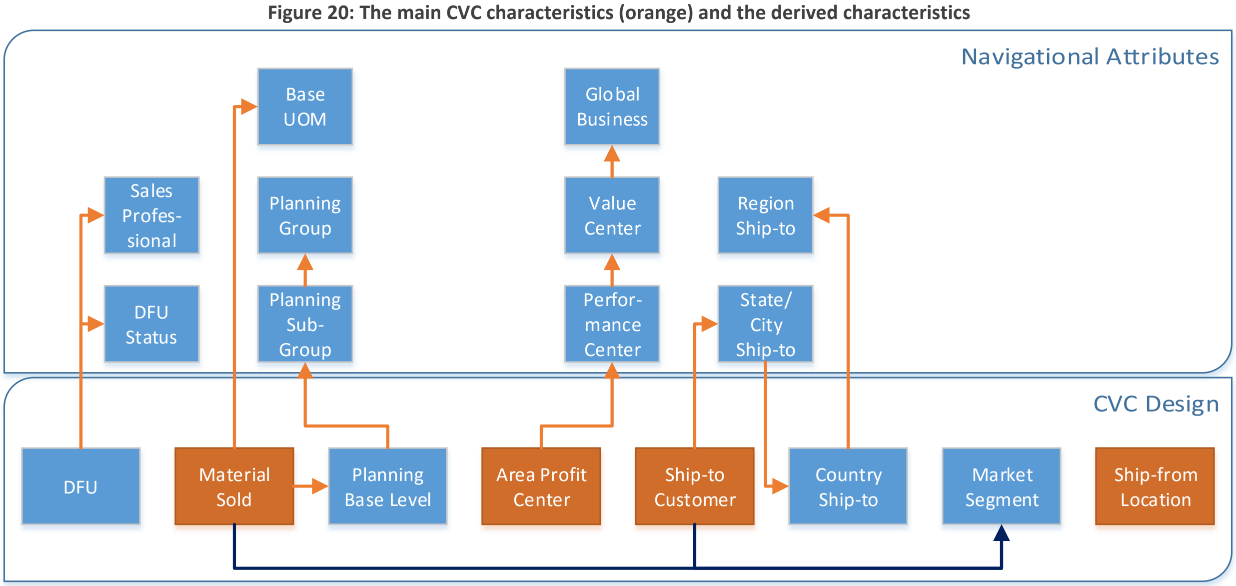
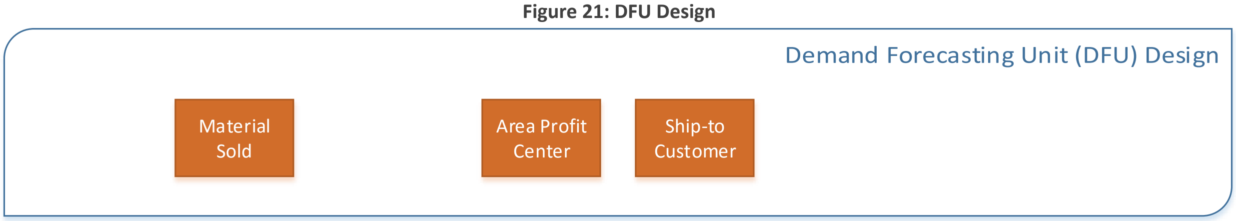


Figure 21: DFU Design



5 Appendix V

Figure 22: DCM EMEAI Weekly Process Flowchart

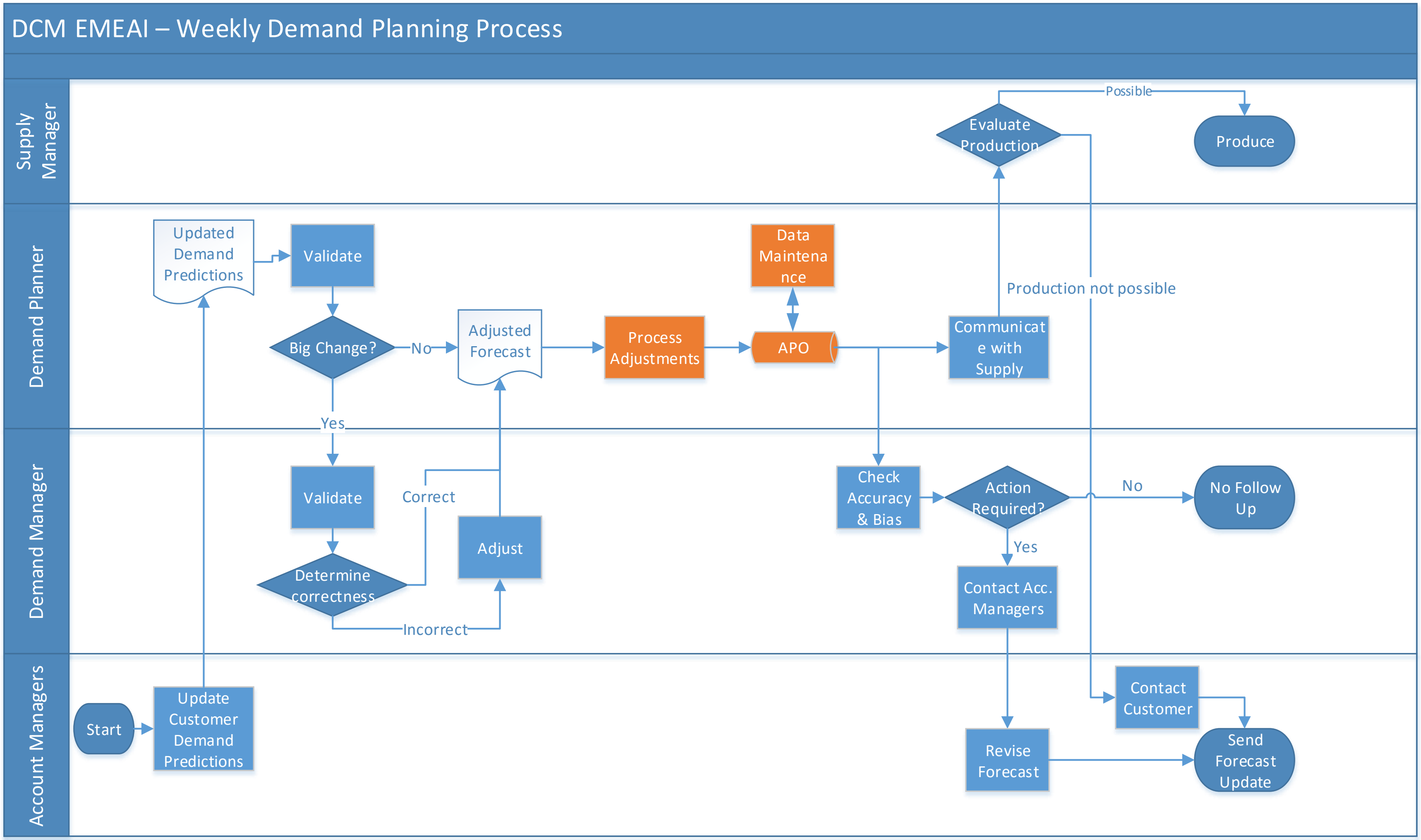


Figure 23: DCM EMEAI - Monthly Process Flowchart

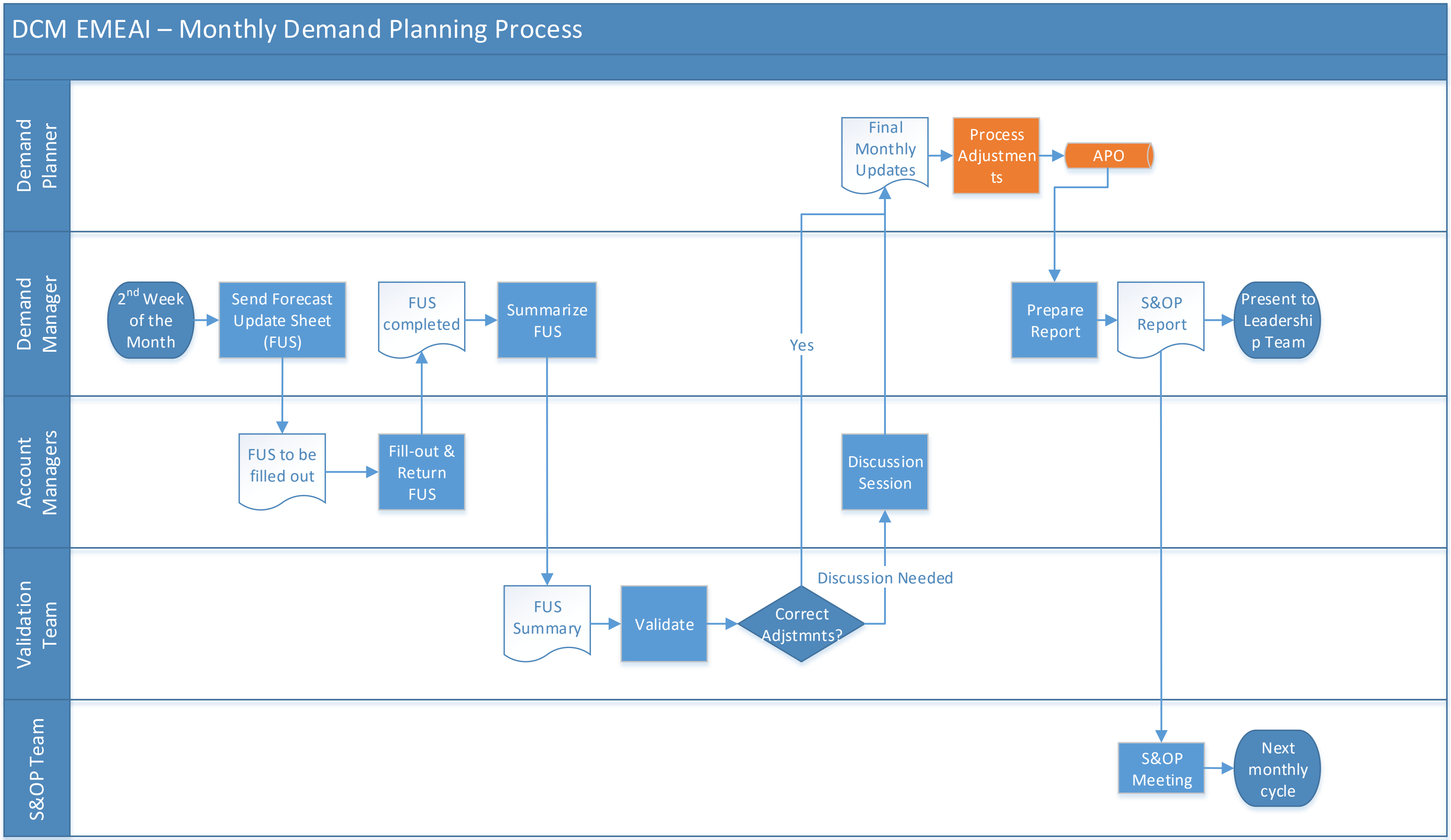


Figure 24: DCM APAC - Monthly Process Flowchart

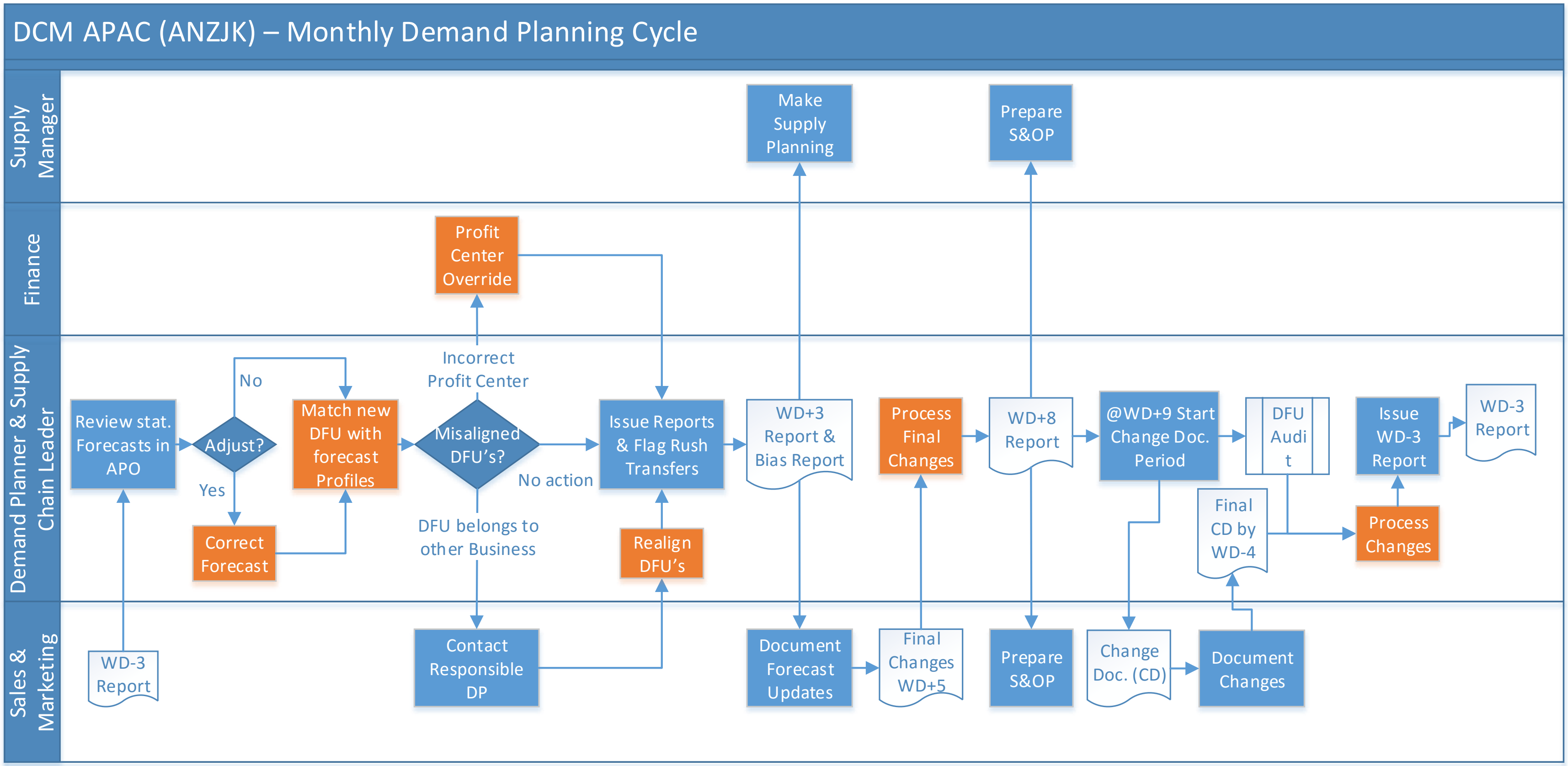
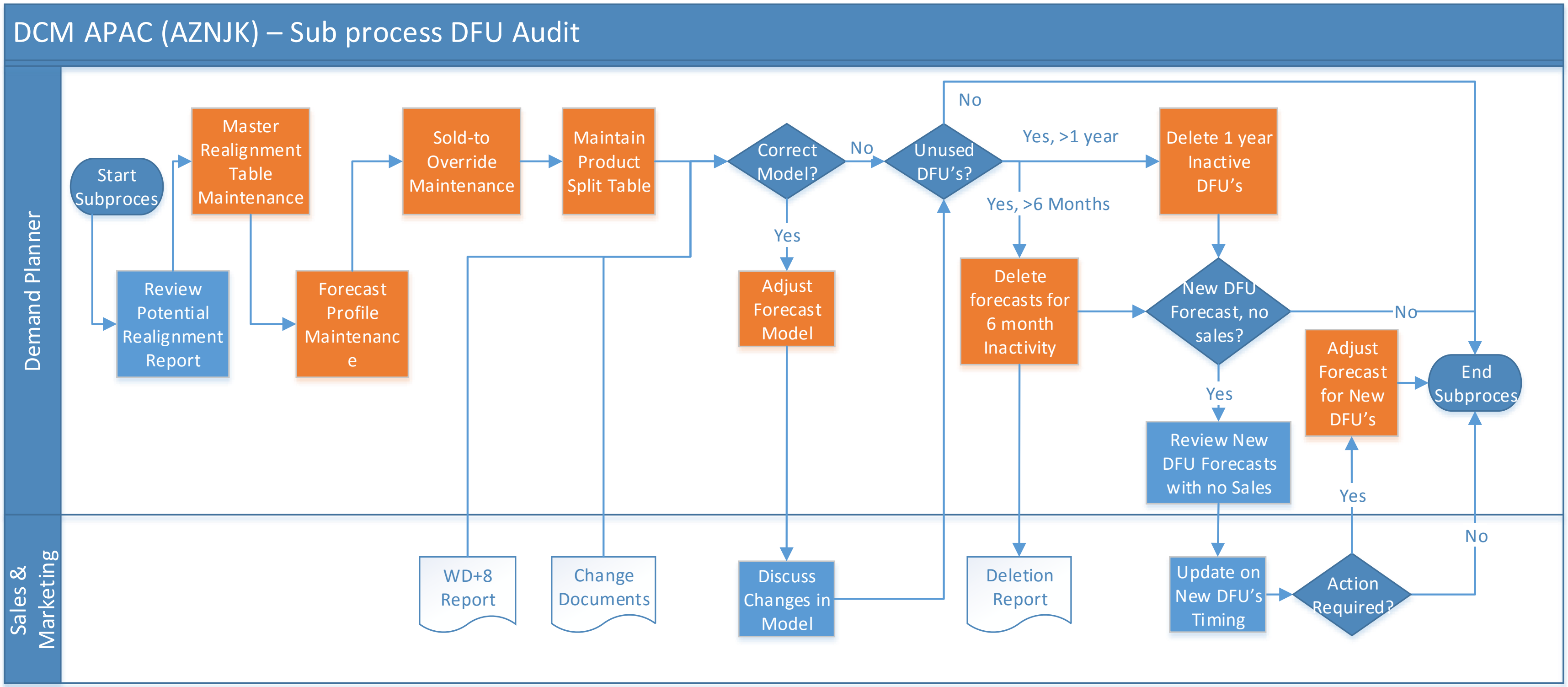


Figure 25: DCM APAC - Sub process DFU Audit Flowchart



6 Appendix VI

In the table below the following new parameters are introduced:

$$m = number\ or\ periods\ assessed$$
$$e_t = forecast\ error\ (X_t - F_t)$$
$$FN_t = A\ benchmark\ forecast\ (random\ walk, Naive\ forecast)$$

Table 22: Forecast Error Metrics tested by Makridakis and Hibon **(1995)**

Forecast Error Metric	Abbreviation	Formula / Method	
Mean Square Error (MSE)	MSE	$\frac{\sum(X_t - F_t)^2}{m} = \frac{\sum(e_t)^2}{m}$	Provides a quadratic loss function, and is a measure of uncertainty in forecasting. It is an absolute measure, and is influenced a great deal by outliers..
Mean Absolute Error	MEA	$\frac{\sum(X_t - F_t)}{m} = \frac{\sum e_t}{m}$	Absolute, but since it is not quadratic it is less influenced by outliers. Its linearity makes it more intuitive.
Mean Absolute Percentage Error	$MAPE_{reg}$	$\frac{\sum\left\|\frac{X_t - F_t}{X_t}\right\|}{m} \cdot 100\%$	A relative, easily and intuitively interpretable measure, making it size-independent. Can be used across forecasting horizons and series. However, it has a lack of statistical theory, and is troublesome when X_t is close to zero. The MAPE is also influenced a great deal by outliers: range is 0 to +∞
Symmetric Mean Absolute Percentage Error	$MAPE_{sym}$	$\left\|\frac{X_t - F_t}{(X_t + F_t)/2}\right\| /m \cdot 100\%$	Similar to $MAPE_{reg}$, except it does not depend on X_t being higher than F_t or vice versa and is influenced by outliers to a much lesser extent: range is 0-200%.
Median Absolute Percentage Error	MdAPE	Similar to $MAPE_{reg/sym}$, but instead of summing and averaging the median is found and used.	Not influenced by outliers, but the meaning is less intuitive while it merely indicates that half of the errors are smaller than the MdAPE value. Difficult to combine across horizons and/or series, and when new data is available.
Percentage Better	% Better	Requires the use of two forecast methods, and shows the percentage of time method A is better than B.	Intuitive, but does not take into account the size of error. Not influenced by extreme values. Useful for situations where size of errors is not important, such as auctions.
Average Ranking of Various Methods	RANKS	Ranks at least two methods in inverse order to the size of errors.	Ignores the size of errors, but is not influenced by extreme values. The method does not shows how much better a certain method is.
Theil's U-Statistic	U-Statistic	$\sqrt{\sum_{t=1}^{m} \frac{\left(\frac{X_t - F_t}{X_t}\right)^2}{\left(\frac{X_t - FN_t}{X_t}\right)^2}}$	Theil's U is greatly influenced by outliers, and can have infinite errors. The meaning of outcomes are hard to interpret.
McLaughlin's Batting Average	Batting Average	$\left[4 - \sqrt{\sum_{i=1}^{m} \frac{\left\|\frac{X_t - F_t}{X_t}\right\|}{\left\|\frac{X_t - FN_t}{X_t}\right\|}}\right] \cdot 100\%$	This metric is an improvement of Theils U, making it less influential to outliers. Also, McLaughin tried to add intuitiveness by relating it to the batting average in baseball.

Geometric Means of Square Error	GMMSE	$\left(\prod_t e_t^2\right)^{\frac{1}{m}}$	Compares the mean absolute error of two methods by computing geometric means. Less influenced by outliers than square means. Interpretability issues.
Geometric Men of Relative Absolute Errors	GMREA	$\left(\prod_t RAE_t\right)^{\frac{1}{m}}$ With $RAE_t = \frac{\left\lvert\frac{X_t - F_t}{X_t}\right\rvert}{\left\lvert\frac{X_t - FN_t}{X_t}\right\rvert}$	Compared to GMMSE, this metric is less influenced by outliers, easier to communicate than Theils-U, although it is "typically inappropriate for managerial decision-making" (Armstrong & Collopy, 1992).
Median Relative Absolute Error	MdRAE	$RAE_t = \frac{\left\lvert\frac{X_t - F_t}{X_t}\right\rvert}{\left\lvert\frac{X_t - FN_t}{X_t}\right\rvert}$	Similar to the MdAPE. Not influenced by outliers while allowing comparisons with a benchmark method. However, the meaning is not clear, even more so than that of MdAPE.
Differences of Naïve 2 (deseasonalized random walk) Less APE of a Certain Method	dMAPE	$\frac{\sum\left[\left\lvert\frac{X_t - FN_t}{X_t}\right\rvert - \left\lvert\frac{X_t - F_t}{X_t}\right\rvert\right]}{m}$	Explains how much better a forecast is than those of Naïve 2 or some other method. Relative and intuitive. It never occurs that one divides by zero, as is the case with GMRAE, MdRAE, Theil's-U, or Batting Average.
R-squared	R^2	$R^2 = \frac{\sum EE_t^2}{\sum TE_t^2}$	Refers to the forecasting error in relation to a benchmark, the mean. Relative and easy and intuitive to understand. Inappropriate when there is a strong trend in the data. Heavily used in regression analysis, but no place in forecasting.

Table 23: Classification of the major accuracy (error) measures (Makridakis & Hibon, 1995)

		Evaluation is done		
		On a single method	On more than one method	In comparison to a benchmark
Character of Measure	Absolute	MSE MAE GMMSE	RANKS	
	Relative to a Base or other Method		% Better	U-Statistic Batting Average GMRAE MdREA
	Relative to the size of errors	MAPE MdAPE	DMAPE MAPE MdAPE	R^2 dMAPE

Table 24: Type and extent of use for major accuracy (error) measures
******* = heaviest use, * = Least Use**

To report or use the results of forecasting methods		To make comparisons (evaluations) between and among methods	
MSE	*****	RANKS	****
MAPE	*****	% Better	****
MAE	***	dMAPE	***
MdAPE	**	Theils-U	**
GMMSE	*	Batting Average	**
		GMRAE	*
		MdRAE	*
		MAPE	****
		MdAPE	*

Table 25: Classification of accuracy (error) measures according to their intuitiveness

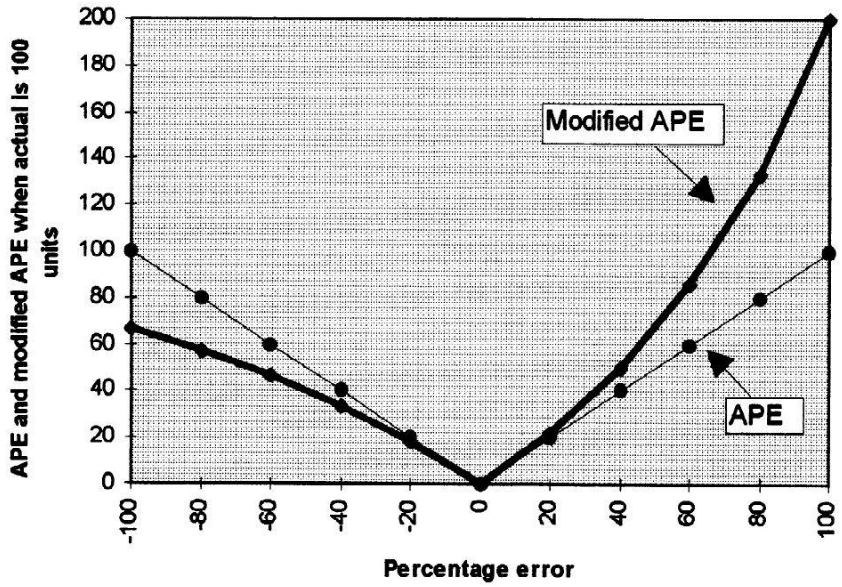
Common Sense Meaning	Some Intuitive Meaning	Little or no Intuitive Meaning
MAPE	RANKS	MSE
% Better	Batting Average	Theil's-U
dMAPE	MdAPE	GMREA
	MAE	MdREA
		GMMSE

Table 26: Classification of accuracy (error) measures according to statistical and user oriented criteria
******* = heaviest use, * = Least Use**

			Statistical Criteria					
			Reliability			Discrimination		
			High	Medium	Low	High	Medium	Low
User Oriented Criteria	Informativeness (and Usage)	Reporting or Using Results		$MAPE_{Sym}$ *****	MSS ***** $MAPE_{Reg}$***** MAE *** MdAPE ** GMMSE *	MSE ***** $MAPE_{reg}$***** MAE *** MdAPE **	$MAPE_{Sym}$ *****	GMMSE *
		Making Comparisons	RANKS **** Theuil's-U ** Batting Avg. **	% Better *** dMAPE ** GMRAE * MdRAE * $MAPE_{Sym}$***	$MAPE_{Reg}$ *** MdAPE *	dMAPE *** GMRAE * $MAPE_{Reg}$ *** MdAPE *	% Better **** Theil's-U ** $MAPE_{Sym}$ ***	RANKS **** % Better **** GMRAE *
	Intuitiveness (and understandability)	Common Sense Meaning		$MAPE_{Sym}$ ***** % Better **** dMAPE ***	$MAPE_{Reg}$ *****	$MAPE_{Reg}$ ***** dMAPE ***	$MAPE_{Sym}$ ***** % Better ****	
		Some Intuitive Meaning	RANKS **** Batting Avg. **		MAE *** MdAPE **	MAE *** MdAPE **		RANKS **** Batting Avg. ** MdRAE *
		Little or No Intuitive Meaning	Theils's-U **	GMRAE * MdRAE *	MSE ***** GMMSE *	MSE ***** GMMSE *	Theil's-U **	GMMSE *

The graph below shows the asymmetry of the sMAPE, compared to the MAPE. The sMAPE deviates quite a lot when percentage errors tend to become larger, especially in the case of positive errors.

Figure 26: Illustration of the (a)symmetry of the MAPE and sMAPE (Goodwin & Lawton, 1999)



7 Appendix VII

Regions and Sub-Regions for both the Asia Pacific and Caribbean region, as well as for the Europe Middle-East Africa and India region

Table 27: APAC sub-regions

APAC	
ANZJK	GCSEA
Australia	China
New Zeeland	Hong-Kong
Japan	Indonesia
Korea	Vietnam
	Malaysia
	Philippines
	Singapore
	Thailand
	Taiwan

Table 28: EMEAI sub-regions

EMEAI	
EUROPE	MEATI
Albania	Morocco
Austria	Angola
Belgium	United Arab Emirates
Belarus	Bangladesh
Switzerland	Bulgaria
Czech Republic	Bahrain
Germany	Ivory Coast
Denmark	Cameroon
Spain	Congo
Estonia	Algeria
Finland	Egypt
France	Ghana
United Kingdom	Greece
Hungary	India
Ireland	Iraq
Italy	Israel
Kazakhstan	Jordan
Lithuania	Kenya
Moldova	Kuwait
Malta	Lebanon
The Netherlands	Liberia
Norway	Libya
Poland	Sri Lanka
Portugal	Mali
Russian Federation	Nigeria
San Marino	Nepal
Serbia	Oman
Slovak Republic	Pakistan
Slovenia	Qatar
Sweden	Romania
Ukraine	Saudi Arabia
	Senegal
	Togo
	Tunisia
	Turkey
	Tanzania
	Uganda
	South Africa

8 Appendix VIII

The next two figures show the demand patterns for individual chemistries in the NAA region. Also, order frequencies can be seen in Figure 29, where the data labels indicate what percentage of volume is accounted for by a certain group (bottom), and the percentage share of DFU's having this frequency (top).

Figure 27: NAA Sales per Chemistry (high volumes)

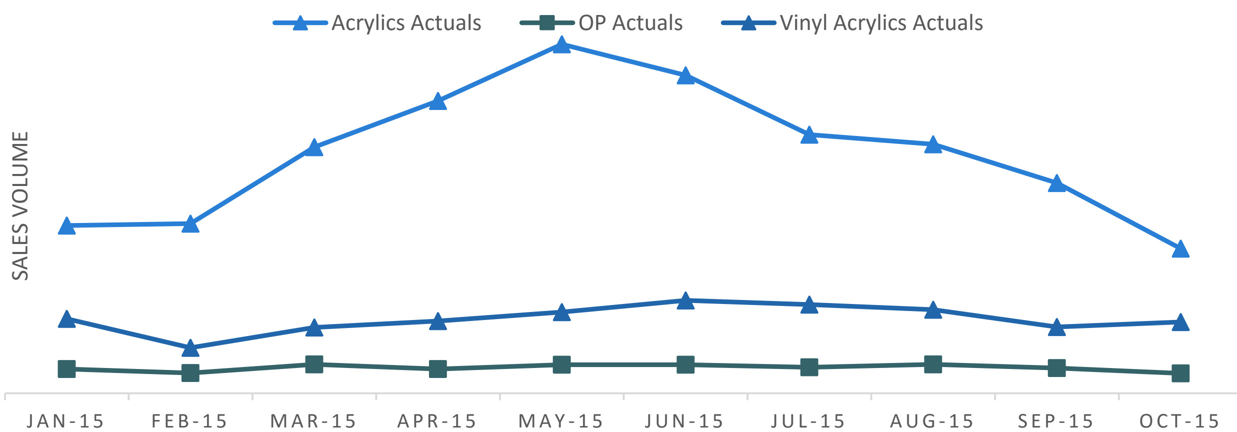


Figure 28: NAA Sales per Chemistry (low volumes)

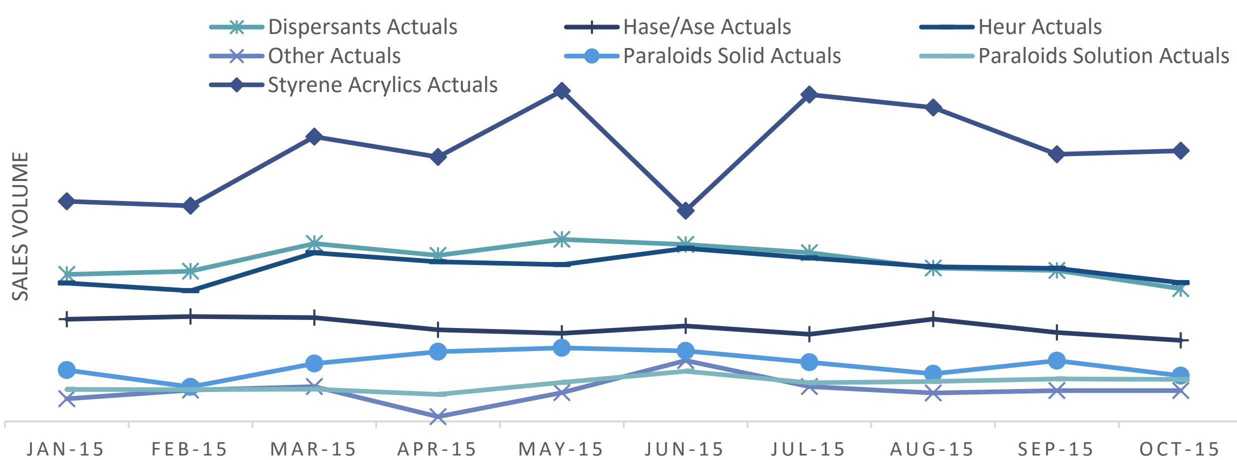
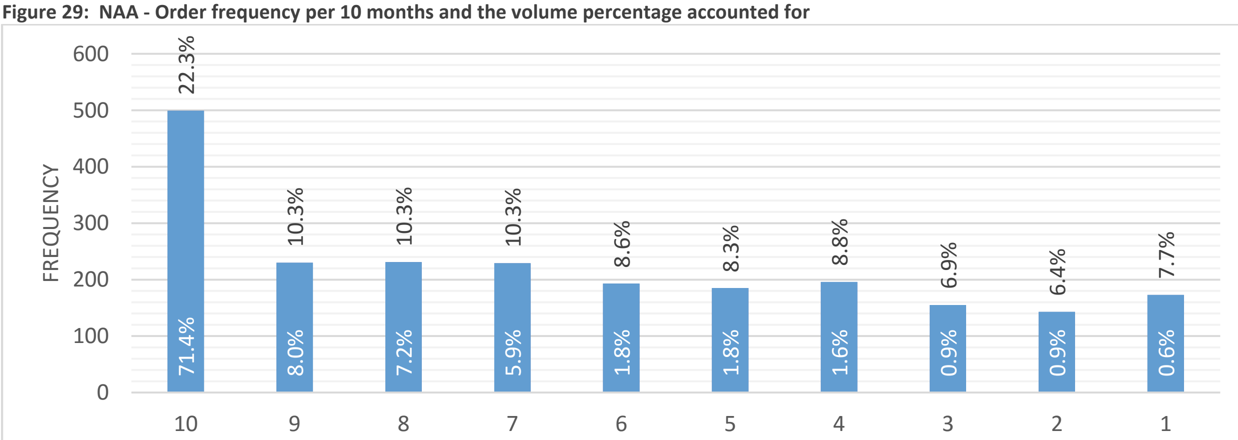


Figure 29: NAA - Order frequency per 10 months and the volume percentage accounted for



The following figures (Figure 30 to Figure 41) provide the demand patterns for chemistries with high and low volumes for Europe, MEATI, ANZJK, and GCSEA respectively. Scales do vary, so interpretation of graphs has to be done with caution.

Figure 30: European Sales per Chemistry (High Volumes)

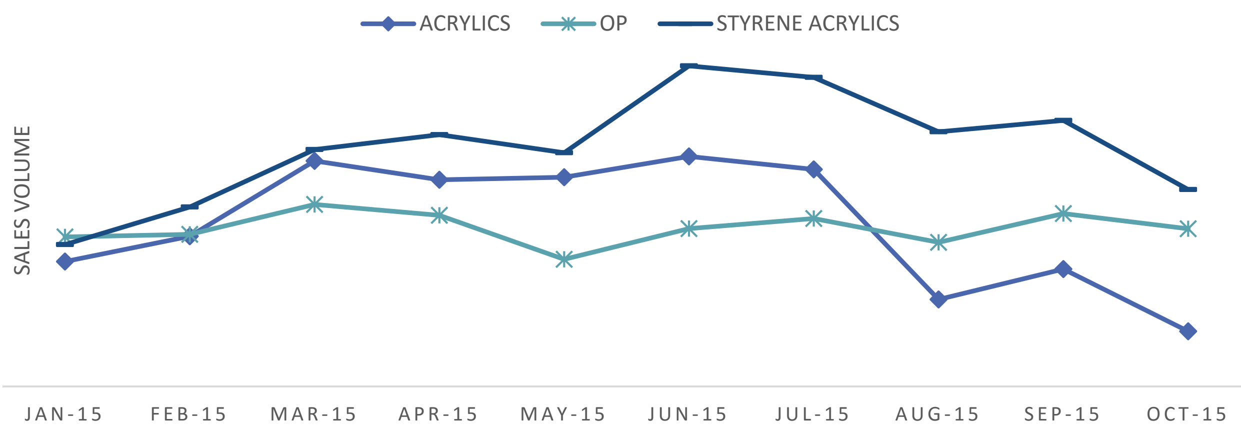


Figure 31: European Sales per Chemistry (low Volumes)

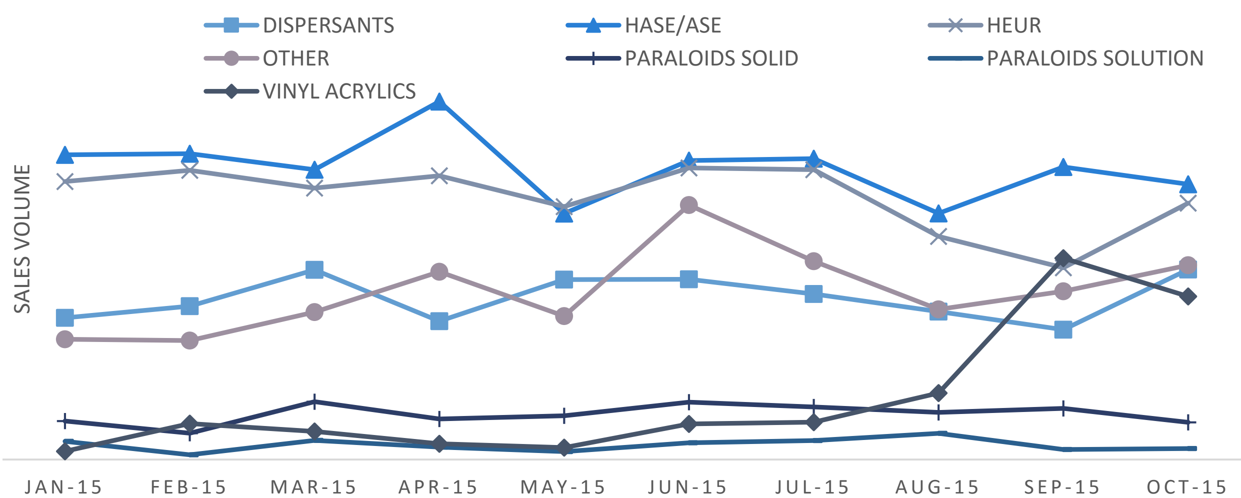


Figure 32: Europe - Order frequency per 10 months and volume percentage accounted for

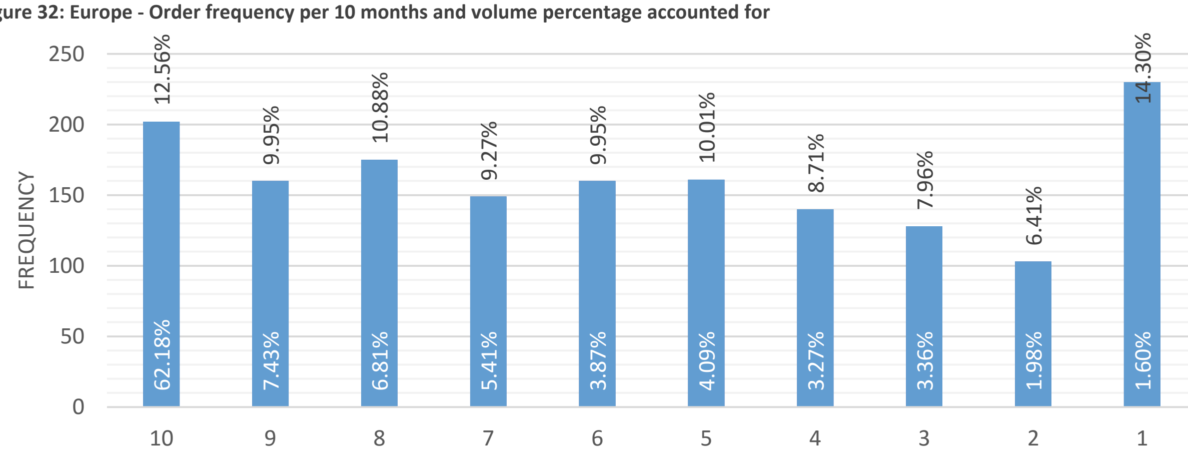


Figure 33: MEATI sales per Chemistry (High Volumes)

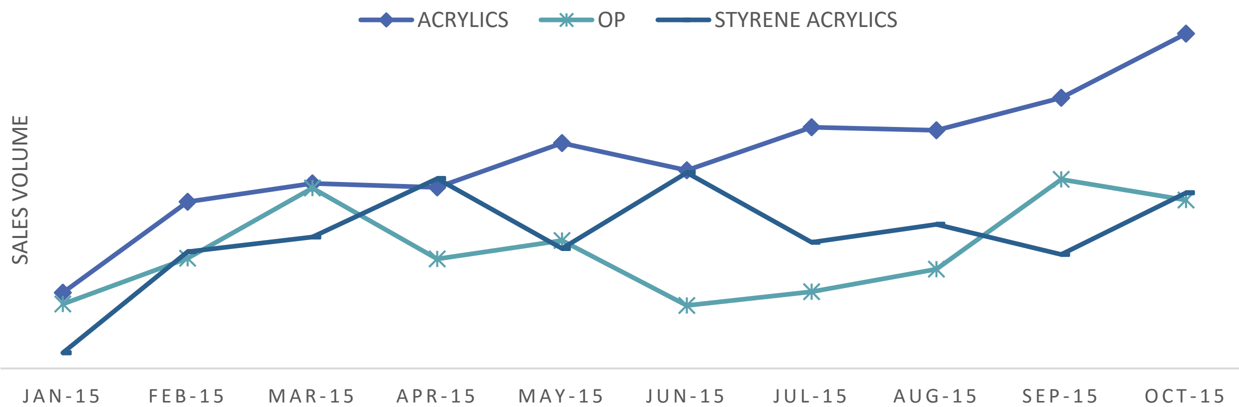


Figure 34: MEATI sales per Chemistry (Low Volumes)

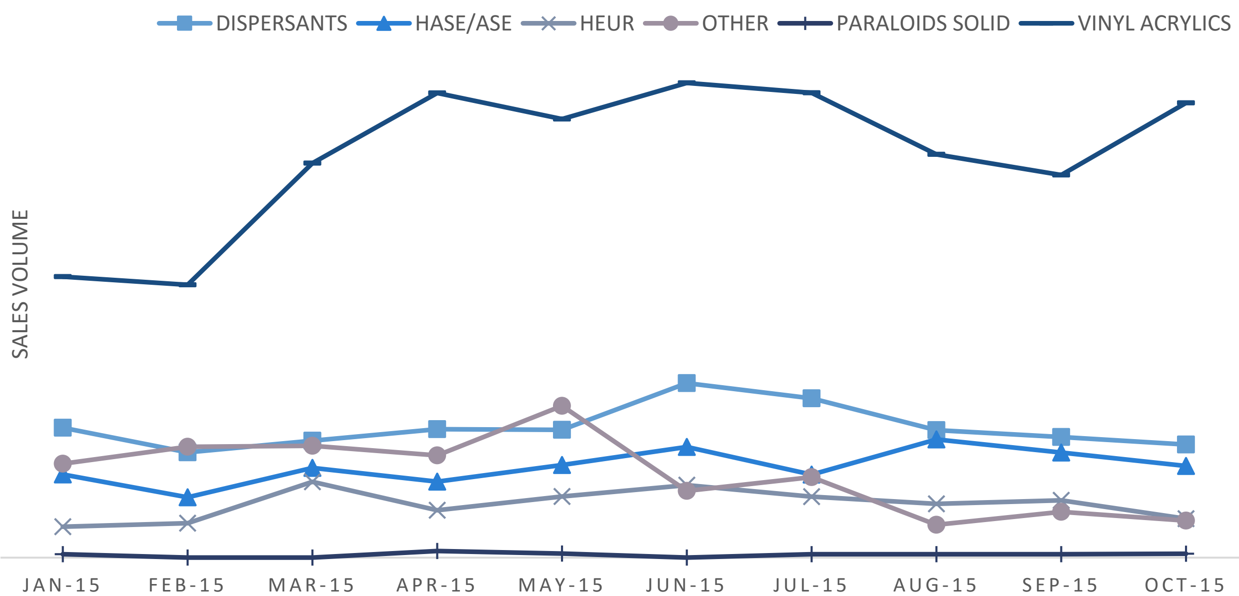


Figure 35: MEATI - Order frequency per 10 months and volume percentage accounted for

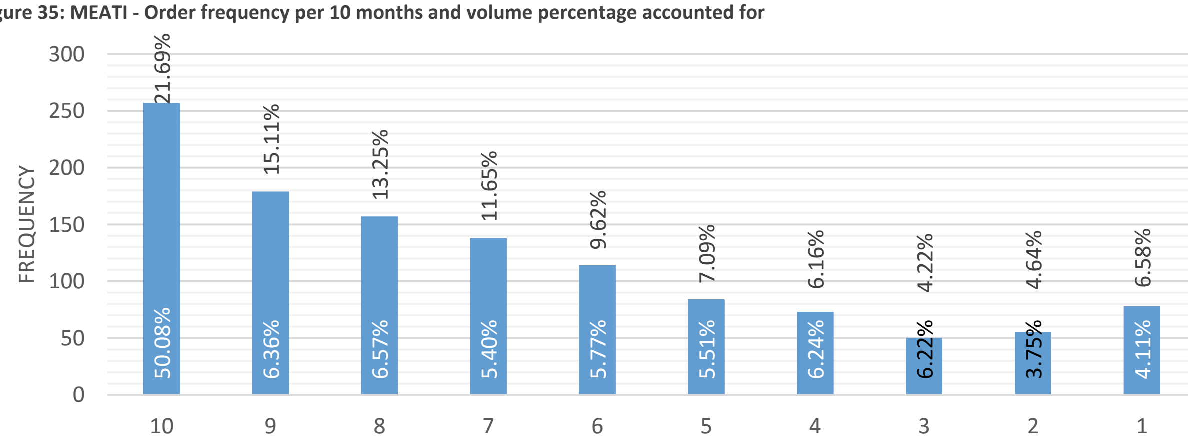


Figure 36: ANZJK Sales for Acrylics Chemistry (High Volume)

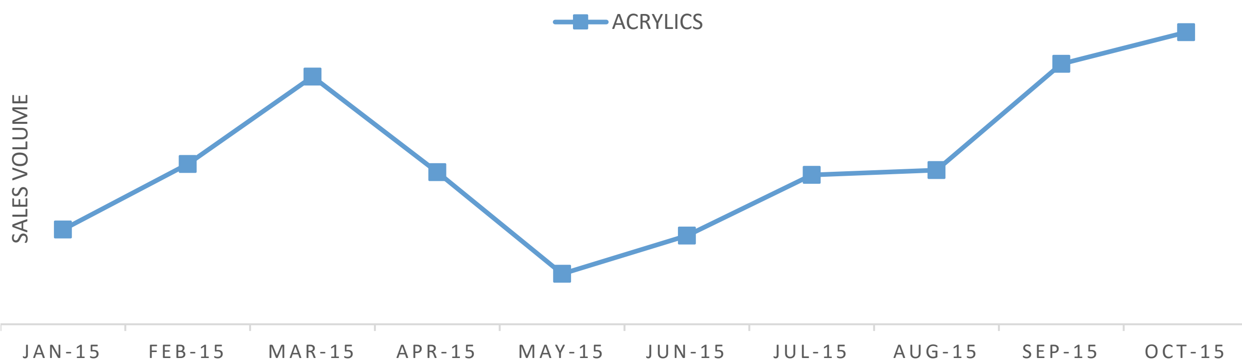


Figure 37: ANZJK Sales per Chemistry (Low Volumes)

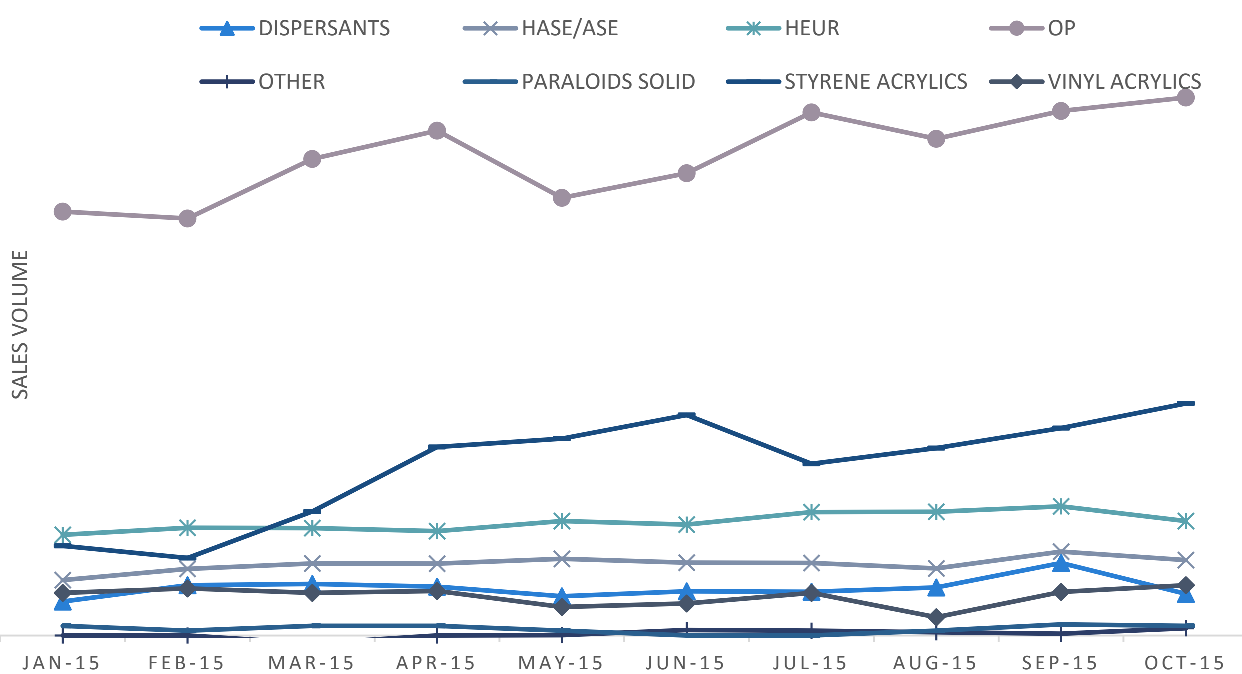


Figure 38: ANZJK - Order frequency per 10 months and volume percentage accounted for

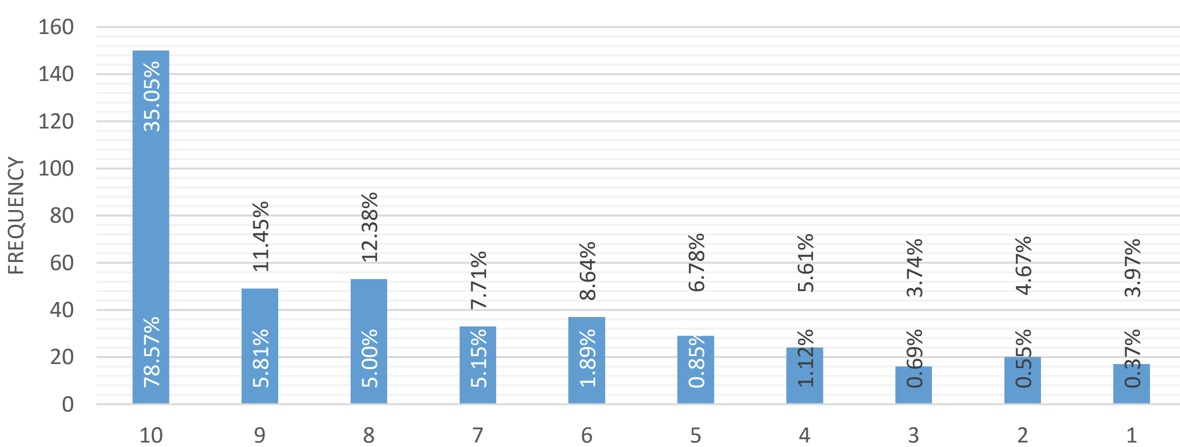


Figure 39: GCSEA Sales per Chemistry (High Volumes)

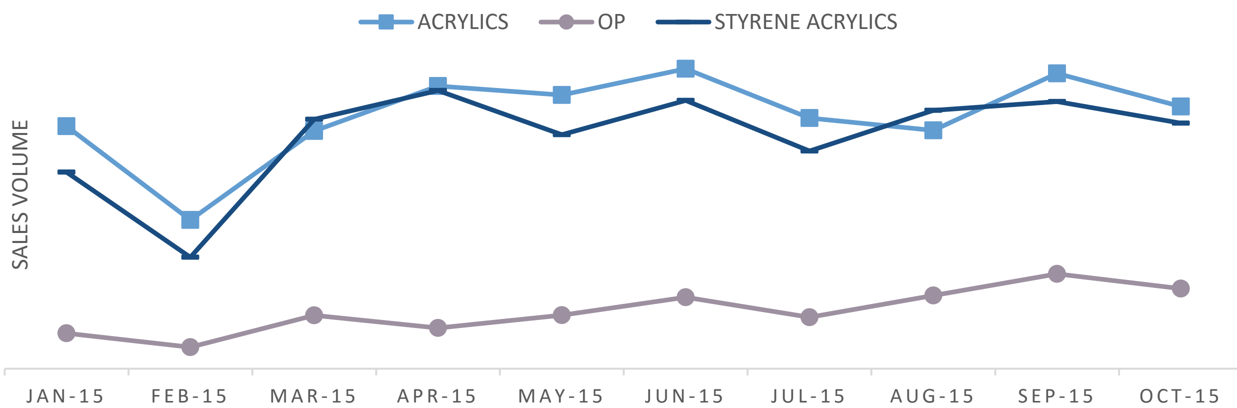


Figure 40: GCSEA Sales per Chemistry (Low Volumes)

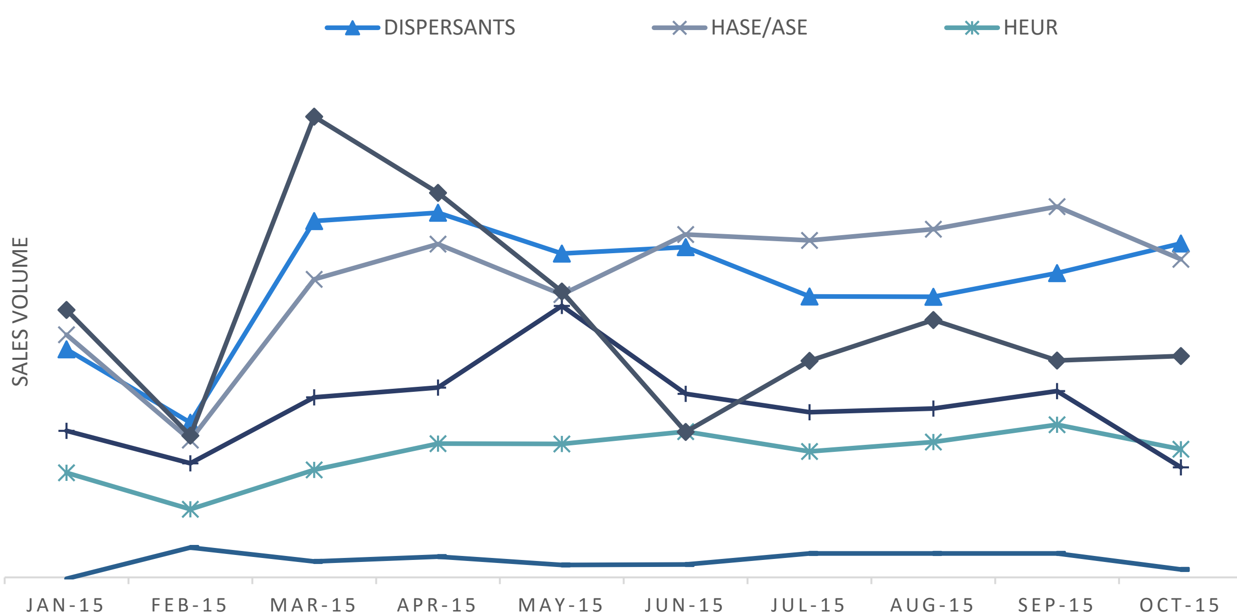


Figure 41: GCSEA - Order frequency per 10 months and volume percentage accounted for

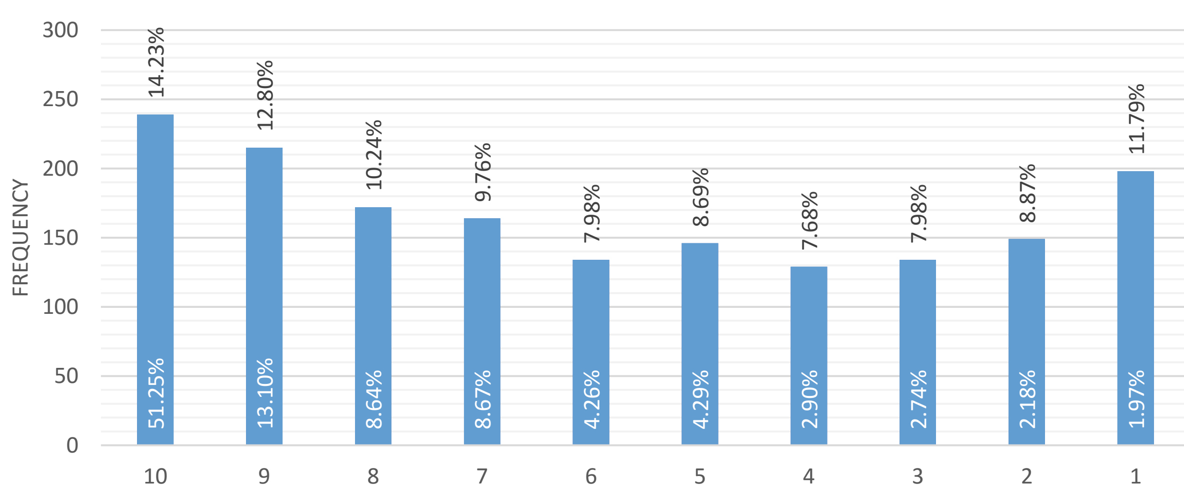


Figure 42: LAA Sales per Chemistry

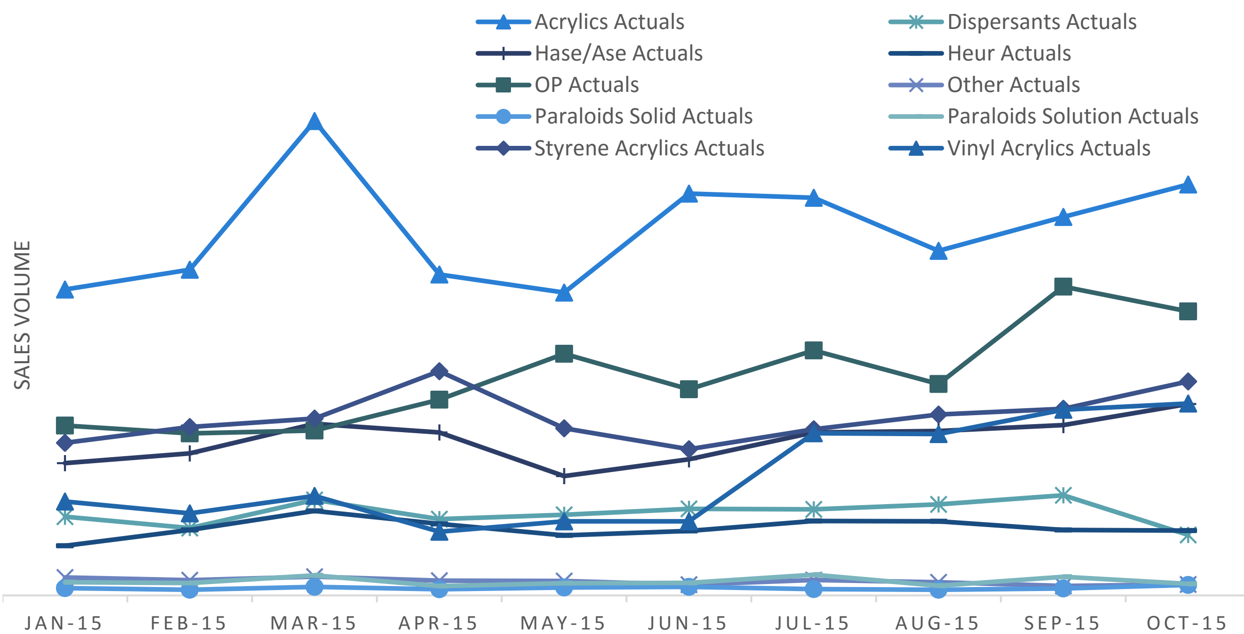
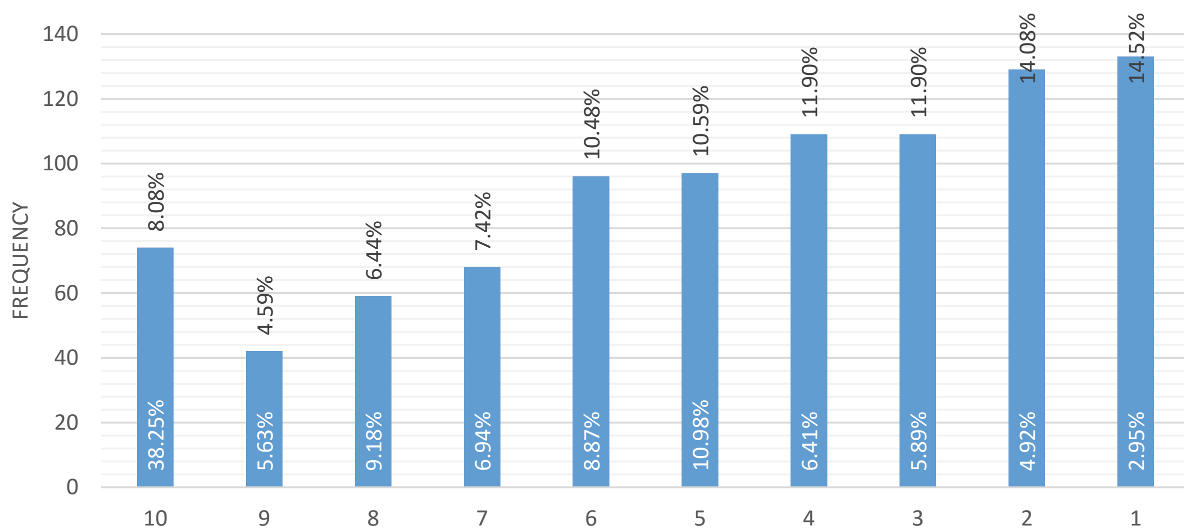


Figure 43: LAA - Order frequency per 10 months and volume percentage accounted for



9 Appendix IX

The following sections shows additional tables, representing data used in the forecast performance analysis (section 4). Red headers stand for NAA, blue related to EMEAI, while purple and yellow represent APAC and LAA respectively.

Table 29: NAA – Base Bulk Level Metric Results for Lag 0-3 on MI & SN Forecasts

PB LEVEL	MAPE			sMAPE		
	MI	SN	Δ	MI	SN	Δ
NAA-Lag 0	47.80%	48.26%	**-0.46%**	47.09%	50.49%	**-3.40%**
NAA-Lag 1	46.59%	46.53%	**0.06%**	47.10%	50.44%	**-3.34%**
NAA-Lag 2	47.12%	46.92%	**0.20%**	47.94%	51.08%	**-3.14%**
NAA-Lag 3	53.82%	46.51%	**7.30%**	50.69%	51.43%	**-0.74%**

Table 30: NAA - Chemistry Level Metric Results for Lag 0-3 on MI & SN Forecasts

Chemistry Level	MAPE			sMAPE			wMAPE	
lag 1	MI	SN	Δ	MI	SN	Δ	2015	SN
ACRYLICS	**34.02%**	**36.49%**	**-2.48%**	35.15%	42.16%	-7.01%	**17.28%**	**18.60%**
DISPERSANTS	29.95%	31.35%	-1.40%	36.02%	41.49%	-5.47%	0.89%	0.94%
HASE/ASE	28.53%	29.18%	-0.65%	31.92%	34.67%	-2.75%	0.51%	0.52%
HEUR	27.93%	32.26%	-4.34%	31.38%	45.82%	-14.44%	0.80%	0.93%
OP	25.67%	30.02%	-4.35%	27.33%	36.58%	-9.25%	**3.15%**	**3.68%**
OTHER	31.94%	9.78%	22.16%	42.03%	63.30%	-21.27%	0.20%	0.05%
PARALOIDS SOLID	**47.40%**	**47.16%**	**0.24%**	**71.11%**	**78.01%**	**-6.90%**	0.49%	0.50%
PARALOIDS SOLUTION	33.47%	31.90%	1.56%	**46.81%**	**54.13%**	**-7.32%**	0.22%	0.21%
STYRENE ACRYLICS	**38.05%**	**33.29%**	**4.76%**	**45.27%**	**43.56%**	**1.71%**	1.99%	1.74%
VINYL ACRYLICS	18.40%	21.77%	-3.36%	19.30%	23.28%	-3.98%	**4.02%**	**4.63%**

Table 31: NAA - sMAPE results per Order Frequency

DFU Level	sMAPE								
DO	**MI**				**SN**				**Frequency**
#	Lag 0	Lag 1	Lag 2	Lag 3	Lag 0	Lag 1	Lag 2	Lag 3	#
1	53.98%	53.91%	53.43%	54.77%	80.58%	75.87%	60.16%	76.11%	173
2	70.80%	72.82%	74.87%	77.06%	60.11%	61.82%	63.27%	62.44%	143
3	59.68%	58.67%	60.47%	63.94%	60.32%	61.24%	62.35%	65.30%	154
4	62.20%	62.59%	61.90%	63.81%	64.12%	64.45%	66.88%	67.16%	196
5	59.18%	60.47%	61.56%	61.57%	65.06%	65.03%	65.08%	65.62%	185
6	60.68%	60.96%	61.15%	63.37%	62.85%	62.35%	63.25%	63.08%	194
7	53.78%	53.89%	54.65%	56.28%	58.17%	57.66%	59.05%	60.61%	228
8	53.47%	53.51%	54.08%	55.55%	55.85%	55.57%	55.38%	55.73%	231
9	45.63%	46.02%	46.68%	48.86%	51.53%	52.30%	52.89%	52.73%	230
10	37.55%	38.00%	38.67%	42.71%	43.22%	43.72%	44.05%	44.38%	500

Table 32: NAA - sMAPE results for Top/Bottom DFU's with 10 out of 10 months having demand

DFU Level	sMAPE		
	Top 25	Bottom 25	Δ
NAA-Lag 0	24.74%	42.10%	-17.35%
NAA-Lag 1	25.98%	41.46%	-15.48%
NAA-Lag 2	29.66%	41.93%	-12.27%
NAA-Lag 3	37.90%	45.79%	-7.89%

Table 33: NAA - Percentage share in Absolute Error per Lag-forecast, related to the number of Lag-forecasts inserted

DFU Level	Percentage Share of Total Absolute Error				
	Lag 0	**Lag 1**	**Lag 2**	**Lag 3**	**Volume**
0 FCST Values	3.13%	3.01%	2.86%	2.25%	1.26%
1 FCST Value	0.66%	0.77%	0.73%	0.59%	0.32%
2 FCST Values	0.42%	0.42%	0.50%	0.45%	0.19%
3 FCST Values	0.79%	0.85%	0.75%	0.66%	0.36%
4 FCST Values	95.00%	94.95%	95.17%	96.05%	97.88%

Table 33 above shows 5 categories. Zero forecast-values means that there is not a single lag-forecast that has been filled out. ‘1 FCST Value’ refers to all the DFU’s for which – during 10 months – only one certain lag-forecast has been inserted. In contrary, 4 forecast-values means that all lag-forecasts are at least filled out in one of the months. The volume column shows the volume represented by a group.

Table 34: EMEAI - DFU Level Metric Results for Lag 0-3 on MI & SN Forecasts

DFU LEVEL	MAPE			sMAPE			PE			
EUROPE	MI	SN	Δ	MI	SN	Δ	MI	% Neg	SN	% Neg
EUR-Lag 0	52.26%	63.85%	-11.59%	45.37%	52.74%	-7.37%	-12.76	41.36	-15.97	38.11
EUR-Lag 1	55.75%	65.37%	-9.62%	47.86%	53.72%	-5.86%	-14.07	41.59	-16.42	37.90
EUR-Lag 2	56.78%	67.02%	-10.25%	48.81%	54.77%	-5.96%	-14.07	41.50	-17.33	38.18
EUR-Lag 3	68.40%	67.33%	1.07%	52.14%	55.90%	-3.76%	-27.24	44.82	-16.34	37.99
MEATI	MI	SN	Δ	MI	SN	Δ	MI	% Neg	SN	% Neg
MEATI-Lag 0	79.09%	72.62%	6.47%	51.40%	60.66%	-9.26%	-37.51	41.62	-19.92	39.73
MEATI-Lag 1	81.30%	78.70%	2.59%	54.73%	62.08%	-7.36%	-36.67	42.32	-24.56	38.33
MEATI-Lag 2	80.66%	78.19%	2.47%	57.76%	64.12%	-6.35%	-32.46	41.36	-20.47	36.67
MEATI-Lag 3	87.96%	77.47%	10.49%	61.43%	68.20%	-6.77%	-38.07	42.26	-13.31	33.50

Table 35: EMEAI - Average of top 5 MAPE values per lag-forecast

Chemistry Level	MAPE			
Europe	Lag-0	Lag-1	Lag-2	Lag-3
2015	777.21%	829.24%	827.48%	1053.74%
SN	1060.46%	1130.65%	1139.72%	1144.42%
Δ	-283.26%	-301.41%	-312.24%	-90.68%
MEATI	Lag-0	Lag-1	Lag-2	Lag-3
2015	1349.77%	1238.62%	1076.85%	1101.92%
SN	430.56%	513.92%	491.62%	465.11%
Δ	919.21%	724.70%	585.23%	636.81%

Table 36: EMEAI - Base Bulk Level Metric Results for Lag 0-3 on MI & SN Forecasts

Base Bulk LEVEL	MAPE			sMAPE		
EUROPE	MI	SN	Δ	MI	SN	Δ
EUR-Lag 0	42.00%	51.37%	-9.37%	43.83%	52.75%	-8.92%
EUR-Lag 1	43.74%	51.07%	-7.34%	46.31%	53.55%	-7.24%
EUR-Lag 2	44.67%	52.17%	-7.51%	47.10%	55.15%	-8.05%
EUR-Lag 3	58.46%	52.65%	5.80%	51.16%	56.17%	-5.01%
MEATI	MI	SN	Δ	MI	SN	Δ
MEATI-Lag 0	43.70%	33.28%	10.43%	48.02%	57.02%	-9.00%
MEATI-Lag 1	43.17%	33.14%	10.03%	51.79%	58.15%	-6.36%
MEATI-Lag 2	42.85%	32.32%	10.53%	55.03%	60.41%	-5.38%
MEATI-Lag 3	45.90%	34.20%	11.70%	58.52%	66.76%	-8.24%

Table 37: EUROPE - Chemistry Level Metric Results for Lag 0-3 on MI & SN Forecasts

Chemistry Level	MAPE			sMAPE			wMAPE	
EUROPE Lag-1	MI	SN	Δ	MI	2014	Δ	MI	SN
ACRYLICS	31.64%	30.63%	*1.01%*	38.91%	43.10%	*-4.19%*	**8.49%**	**8.20%**
DISPERSANTS	31.30%	26.09%	*5.21%*	41.60%	41.02%	*0.58%*	0.64%	0.53%
HASE/ASE	32.87%	38.45%	*-5.58%*	39.11%	49.51%	*-10.40%*	1.19%	1.42%
HEUR	36.49%	36.54%	*-0.05%*	41.34%	48.59%	*-7.25%*	1.19%	1.21%
OP	18.53%	23.83%	*-5.30%*	20.04%	27.14%	*-7.10%*	**5.02%**	**6.48%**
OTHER	21.30%	9.32%	*11.98%*	**55.66%**	**58.93%**	***-3.27%***	0.45%	0.19%
PARALOIDS SOLID	**50.51%**	**44.42%**	***6.09%***	**75.14%**	**68.97%**	***6.17%***	0.30%	0.26%
PARALOIDS SOLUTION	**42.48%**	**46.96%**	***-4.48%***	46.55%	58.71%	*-12.16%*	0.08%	0.08%
STYRENE ACRYLICS	27.86%	18.87%	*8.98%*	33.55%	44.53%	*-10.98%*	**9.27%**	**6.47%**
VINYL ACRYLICS	**52.56%**	**28.85%**	***23.70%***	**61.86%**	**60.95%**	***0.91%***	0.30%	0.13%

Table 38: MEATI - Chemistry Level Metric Results for Lag 0-3 on MI & SN Forecasts

Chemistry Level	MAPE			sMAPE			wMAPE	
MEATI Lag-1	MI	SN	Δ	MI	2014	Δ	MI	SN
ACRYLICS	**31.71%**	**7.92%**	***23.79%***	44.28%	54.87%	*-10.59%*	**10.35%**	**2.62%**
DISPERSANTS	23.31%	10.61%	*12.70%*	47.09%	53.35%	*-6.26%*	0.55%	0.26%
HASE/ASE	**37.07%**	**22.43%**	***14.64%***	**60.35%**	**57.14%**	***3.21%***	0.60%	0.37%
HEUR	**38.82%**	**29.51%**	***9.32%***	**58.05%**	**64.14%**	***-6.09%***	0.35%	0.28%
OP	29.64%	6.75%	*22.89%*	37.99%	45.19%	*-7.20%*	**7.59%**	**1.71%**
OTHER	17.03%	0.93%	*16.10%*	**55.62%**	**13.76%**	***41.86%***	0.17%	0.02%
PARALOIDS SOLID	**62.50%**	**44.45%**	***18.05%***	**94.07%**	**72.01%**	***22.06%***	0.04%	0.05%
STYRENE ACRYLICS	26.66%	13.77%	*12.89%*	37.87%	50.83%	*-12.96%*	**7.23%**	**3.73%**
VINYL ACRYLICS	19.44%	16.51%	*2.92%*	25.22%	41.01%	*-15.79%*	**1.47%**	**1.31%**

Table 39: EUROPE - sMAPE results per Order Frequency

DFU Level	sMAPE								
EUROPE	**MI**				**SN**				**Frequency**
DO	Lag 0	Lag 1	Lag 2	Lag 3	Lag 0	Lag 1	Lag 2	Lag 3	#
1	49.84%	69.34%	71.18%	67.10%	70.18%	72.10%	79.15%	84.78%	202
2	54.91%	59.90%	65.69%	70.44%	73.32%	75.60%	79.00%	80.71%	160
3	55.27%	64.20%	66.21%	67.31%	70.58%	70.25%	71.36%	73.29%	175
4	52.99%	56.32%	58.83%	61.58%	68.19%	69.31%	71.85%	74.91%	149
5	47.29%	50.80%	51.71%	55.04%	56.42%	58.30%	59.83%	60.56%	160
6	47.30%	50.82%	50.99%	53.64%	54.87%	57.83%	58.05%	58.88%	161
7	49.22%	52.25%	52.72%	54.56%	56.55%	57.48%	58.42%	59.25%	140
8	48.83%	50.62%	51.66%	54.86%	52.99%	53.48%	54.66%	55.78%	128
9	49.07%	50.93%	51.25%	54.60%	54.80%	55.63%	55.30%	56.25%	104
10	37.61%	38.73%	39.47%	43.85%	44.76%	45.37%	46.41%	47.50%	229

Table 40: MEATI - sMAPE results per Order Frequency

DFU Level	sMAPE								
MEATI	**MI**				**SN**				**Frequency**
DO	Lag 0	Lag 1	Lag 2	Lag 3	Lag 0	Lag 1	Lag 2	Lag 3	#
1	44.91%	65.54%	87.57%	89.71%	63.68%	63.68%			257
2	50.47%	64.83%	70.85%	79.53%	102.63%	103.64%	111.42%	126.78%	179
3	55.46%	62.50%	68.58%	77.67%	59.88%	69.32%	69.87%	72.93%	157
4	53.36%	58.15%	63.86%	69.61%	80.92%	88.06%	91.62%	90.75%	138
5	59.27%	64.17%	67.39%	70.82%	65.68%	64.53%	65.94%	70.78%	114
6	53.53%	55.77%	59.18%	62.25%	63.20%	68.20%	71.54%	77.35%	84
7	59.81%	64.65%	67.80%	71.44%	67.20%	68.50%	68.91%	74.33%	73
8	56.78%	60.65%	61.02%	63.05%	54.60%	56.13%	60.87%	61.44%	50
9	50.03%	51.04%	52.85%	55.82%	59.13%	56.15%	59.83%	61.18%	55
10	40.68%	41.70%	43.04%	44.25%	35.86%	33.41%	32.95%	34.84%	78

Table 41: EMEAI - Percentage share in Absolute Error per Lag-forecast, related to the number of Lag-forecasts inserted

DFU Level	Percentage Share of Total Absolute Error											
# FCST VALUES	**EUROPE**	**Lag 0**	**Lag 1**	**Lag 2**	**Lag 3**	**Volume**	**MEATI**	**Lag 0**	**Lag 1**	**Lag 2**	**Lag 3**	**Volume**
0 FCST Values		6.82%	6.26%	6.07%	5.17%	3.21%		12.45%	11.19%	10.62%	9.58%	7.99%
1 FCST Value		2.86%	3.42%	3.31%	2.84%	1.75%		3.86%	3.48%	3.30%	3.08%	2.49%
2 FCST Values		1.25%	1.32%	1.46%	1.40%	0.73%		3.63%	3.02%	2.85%	2.56%	2.12%
3 FCST Values		2.62%	3.26%	3.61%	3.58%	1.39%		5.23%	5.51%	5.29%	4.74%	3.48%
4 FCST Values		86.46%	85.74%	85.55%	87.01%	92.92%		74.84%	76.80%	77.93%	80.03%	83.92%

Table 42: APAC - DFU Level Metric Results for Lag 0-3 on MI & SN Forecasts

DFU LEVEL	MAPE			sMAPE			PE			
ANZJK	MI	SN	Δ	MI	SN	Δ	MI	% Neg	SN	% Neg
ANZJK-Lag 0	46.25%	54.97%	-8.72%	38.17%	45.46%	-7.29%	-14.76	42.90	-16.39	42.17
ANZJK-Lag 1	47.41%	57.58%	-10.17%	39.32%	46.04%	-6.72%	-14.34	42.86	-18.93	42.41
ANZJK-Lag 2	48.67%	57.22%	-8.56%	40.47%	46.82%	-6.35%	-14.40	42.67	-17.24	42.87
ANZJK-Lag 3	57.04%	57.85%	-0.81%	43.55%	48.06%	-4.52%	-24.72	46.89	-15.99	42.04
GCSEA	MI	SN	Δ	MI	SN	Δ	MI	% Neg	SN	% Neg
GCSEA-Lag 0	78.03%	100.69%	-22.65%	49.63%	59.72%	-10.09%	-42.80	45.36	-58.95	46.86
GCSEA-Lag 1	86.24%	105.34%	-19.10%	53.29%	60.85%	-7.56%	-51.33	44.14	-63.54	47.39
GCSEA-Lag 2	93.59%	111.96%	-18.37%	55.31%	61.82%	-6.51%	-58.56	43.45	-70.14	48.15
GCSEA-Lag 3	121.67%	115.13%	6.54%	60.37%	63.73%	-3.36%	-89.21	43.03	-71.99	48.14

Table 43: APAC - Average of top 5 MAPE values per lag-forecast

Chemistry Level	MAPE			
ANZJK	Lag-0	Lag-1	Lag-2	Lag-3
2015	439.08%	455.69%	456.43%	508.62%
SN	487.47%	534.58%	509.38%	522.64%
Δ	-48.39%	-78.88%	-52.94%	-14.02%
GCSEA	Lag-0	Lag-1	Lag-2	Lag-3
2015	1897.83%	1764.07%	2048.20%	2692.36%
SN	1813.96%	1949.02%	2073.22%	1971.96%
Δ	83.86%	-184.96%	-25.02%	720.40%

Table 44: APAC - Base Bulk Level Metric Results for Lag 0-3 on MI & SN Forecasts

Base Bulk LEVEL	MAPE			sMAPE		
ANZJK	MI	SN	Δ	MI	SN	Δ
ANZJK-Lag 0	39.96%	43.34%	-3.38%	38.23%	46.50%	-8.26%
ANZJK-Lag 1	40.67%	49.01%	-8.34%	39.82%	47.31%	-7.50%
ANZJK-Lag 2	40.73%	49.28%	-8.55%	40.79%	48.88%	-8.09%
ANZJK-Lag 3	45.97%	48.92%	-2.95%	43.93%	49.91%	-5.98%
GCSEA	MI	SN	Δ	MI	SN	Δ
GCSEA-Lag 0	57.85%	76.76%	-18.91%	50.60%	63.09%	-12.49%
GCSEA-Lag 1	63.96%	73.24%	-9.28%	54.10%	63.58%	-9.48%
GCSEA-Lag 2	69.85%	68.61%	1.24%	56.69%	64.91%	-8.22%
GCSEA-Lag 3	85.12%	65.84%	19.28%	61.22%	67.05%	-5.83%

Table 45: ANZJK - Chemistry Level Metric Results for Lag 0-3 on MI & SN Forecasts

Chemistry Level	MAPE			sMAPE			wMAPE	
ANZJK Lag-1	MI	SN	Δ	MI	SN	Δ	MI	SN
ACRYLICS	**31.07%**	**29.57%**	**1.50%**	33.02%	37.66%	-4.64%	**20.05%**	**19.10%**
DISPERSANTS	28.09%	31.73%	-3.64%	**35.85%**	**44.04%**	**-8.20%**	0.46%	0.52%
HASE/ASE	28.12%	25.17%	2.96%	30.95%	38.53%	-7.58%	0.69%	0.62%
HEUR	28.47%	29.98%	-1.51%	30.64%	35.67%	-5.04%	1.19%	1.26%
OP	18.65%	28.67%	-10.02%	19.49%	31.21%	-11.72%	**3.50%**	**5.36%**
OTHER								
PARALOIDS SOLID	**48.77%**	**45.18%**	**3.59%**	**79.37%**	**46.08%**	**33.29%**	0.17%	0.13%
STYRENE ACRYLICS	**37.21%**	**41.16%**	**-3.94%**	**44.43%**	**84.40%**	**-39.97%**	**2.41%**	**2.21%**
VINYL ACRYLICS	29.88%	50.31%	-20.42%	31.52%	50.03%	-18.51%	0.36%	0.62%

Table 46: GCSEA- Chemistry Level Metric Results for Lag 0-3 on MI & SN Forecasts

Chemistry Level	MAPE			sMAPE			wMAPE	
GCSEA Lag-1	MI	SN	Δ	MI	SN	Δ	MI	SN
ACRYLICS	35.32%	32.99%	2.33%	40.36%	49.35%	-8.99%	**12.95%**	**12.09%**
DISPERSANTS	41.88%	47.26%	-5.38%	**55.23%**	**71.71%**	**-16.49%**	1.47%	1.65%
HASE/ASE	34.69%	32.04%	2.65%	43.18%	52.29%	-9.11%	1.24%	1.15%
HEUR	37.77%	41.47%	-3.70%	44.97%	60.01%	-15.04%	0.53%	0.58%
OP	32.36%	24.59%	7.76%	37.32%	40.43%	-3.12%	**4.81%**	**3.65%**
OTHER	**43.25%**	**37.92%**	**5.33%**	45.61%	51.05%	-5.43%	0.90%	0.80%
PARALOIDS SOLID	**52.83%**	**71.52%**	**-18.69%**	**51.19%**	**54.25%**	**-3.06%**	0.11%	0.13%
STYRENE ACRYLICS	40.18%	33.54%	6.64%	49.17%	55.65%	-6.48%	**13.76%**	**11.50%**
VINYL ACRYLICS	**53.00%**	**55.05%**	**-2.05%**	**54.73%**	**59.50%**	**-4.77%**	1.65%	1.58%

Table 47: ANZJK - sMAPE results per Order Frequency

DFU Level	sMAPE								
ANZJK	**MI**				**SN**				**Frequency**
DO	Lag 0	Lag 1	Lag 2	Lag 3	Lag 0	Lag 1	Lag 2	Lag 3	#
1	13.46%			67.50%					17
2	61.98%	64.28%	90.29%	74.28%	109.52%	108.80%	114.24%	108.88%	20
3	59.17%	56.60%	56.58%	57.80%	61.72%	55.05%	64.44%	68.19%	16
4	32.26%	30.91%	25.61%	29.24%	48.48%	50.29%	50.18%	51.56%	24
5	41.11%	41.68%	41.95%	40.36%	43.36%	44.27%	46.00%	50.91%	29
6	52.63%	53.06%	55.20%	60.33%	53.27%	60.55%	65.29%	62.19%	37
7	39.30%	39.37%	41.13%	44.71%	44.17%	43.98%	43.56%	43.43%	33
8	40.98%	43.82%	43.53%	46.02%	42.88%	43.82%	45.52%	46.10%	53
9	37.57%	38.74%	40.95%	44.35%	49.57%	50.36%	51.20%	51.77%	49
10	35.78%	36.45%	37.23%	40.59%	43.85%	43.81%	44.08%	44.79%	150

Table 48: GCSEA - sMAPE results per Order Frequency

DFU Level	sMAPE								
GCSEA	**MI**				**SN**				**Frequency**
DO	Lag 0	Lag 1	Lag 2	Lag 3	Lag 0	Lag 1	Lag 2	Lag 3	#
1	43.37%	71.09%	91.89%	86.15%			71.83%	68.90%	197
2	53.13%	53.78%	65.49%	68.33%	71.05%	73.12%	75.95%	66.34%	149
3	47.21%	59.89%	60.03%	68.23%	68.37%	64.87%	68.18%	74.21%	135
4	49.62%	56.43%	59.01%	62.89%	74.31%	76.48%	78.68%	81.07%	129
5	54.85%	60.05%	62.20%	65.64%	62.91%	66.41%	64.70%	66.78%	146
6	53.38%	55.60%	56.85%	62.87%	63.65%	70.86%	73.83%	74.49%	134
7	52.37%	56.44%	57.76%	62.12%	64.83%	66.54%	69.26%	71.28%	163
8	56.78%	60.65%	61.02%	63.05%	54.60%	56.13%	60.87%	61.44%	173
9	50.03%	51.04%	52.85%	55.82%	59.13%	56.15%	59.83%	61.18%	215
10	40.68%	41.70%	43.04%	44.25%	35.86%	33.41%	32.95%	34.84%	239

Table 49: APAC - Percentage share in Absolute Error per Lag-forecast, related to the number of Lag-forecasts inserted

DFU Level	Percentage Share of Total Absolute Error											
		Lag 0	**Lag 1**	**Lag 2**	**Lag 3**	**Volume**		**Lag 0**	**Lag 1**	**Lag 2**	**Lag 3**	**Volume**
0 FCST Values	**ANZJK**	2.09%	2.01%	1.95%	1.63%	0.74%	**GCSEA**	10.09%	8.56%	8.07%	6.93%	5.77%
1 FCST Value		0.50%	0.63%	0.58%	0.50%	0.22%		2.36%	2.33%	2.16%	1.80%	1.50%
2 FCST Values		0.09%	0.08%	0.08%	0.11%	0.03%		1.12%	0.98%	0.97%	0.86%	0.69%
3 FCST Values		0.91%	1.01%	1.00%	0.92%	0.41%		2.09%	2.33%	2.15%	1.97%	1.29%
4 FCST Values		96.41%	96.26%	96.38%	96.85%	98.59%		84.33%	85.81%	86.66%	88.43%	90.75%

Table 50: LAA - Chemistry Level Metric Results for Lag 0-3 on MI & SN Forecasts

Chemistry Level	**MAPE**			**sMAPE**			**wMAPE**	
lag 1	MI	SN	Δ	MI	SN	Δ	MI	SN
ACRYLICS	29.96%	13.80%	16.16%	**51.74%**	**53.40%**	**-1.65%**	**9.14%**	**4.09%**
DISPERSANTS	34.64%	25.75%	8.89%	45.76%	53.90%	-8.14%	2.26%	1.66%
HASE/ASE	27.90%	16.24%	11.66%	39.45%	54.01%	-14.56%	**3.53%**	**2.01%**
HEUR	33.57%	17.78%	**15.79%**	39.96%	38.96%	1.00%	1.79%	0.93%
OP	28.18%	21.78%	6.40%	33.80%	69.53%	-35.73%	**5.13%**	**4.12%**
OTHER	47.12%	44.14%	**2.98%**	**47.15%**	**50.23%**	**-3.07%**	0.52%	0.49%
PARALOIDS SOLID	19.19%	12.38%	6.80%	64.39%	62.78%	1.61%	0.08%	0.05%
PARALOIDS SOLUTION	**35.10%**	**19.39%**	**15.71%**	**52.43%**	**42.08%**	**10.35%**	0.38%	0.21%
STYRENE ACRYLICS	**39.33%**	**21.94%**	**17.40%**	**46.55%**	**56.79%**	**-10.24%**	**5.77%**	**3.06%**
VINYL ACRYLICS	33.07%	20.65%	12.41%	45.64%	62.64%	-17.00%	3.16%	2.09%

Table 51: LAA - sMAPE results per Order Frequency

DFU Level	**sMAPE**								
LAA	**MI**				**SN**				**Frequency**
DO	Lag 0	Lag 1	Lag 2	Lag 3	Lag 0	Lag 1	Lag 2	Lag 3	#
1					83.14%	87.65%	94.66%	87.54%	133
2					56.25%	54.03%	57.60%	68.34%	129
3	69.81%	70.14%	71.03%	70.93%	64.16%	66.40%	68.68%	70.75%	109
4	68.63%	68.32%	63.75%	62.84%	67.09%	65.63%	66.46%	65.44%	109
5	57.54%	58.42%	55.92%	57.24%	52.76%	54.40%	57.70%	58.07%	97
6	55.87%	58.99%	59.82%	62.14%	51.08%	54.67%	56.85%	58.70%	96
7	55.31%	54.97%	54.72%	53.29%	50.30%	52.23%	52.89%	56.06%	68
8	52.01%	51.36%	51.60%	53.45%	47.81%	51.58%	53.40%	54.08%	59
9	49.17%	51.12%	52.28%	53.35%	44.97%	47.47%	49.78%	52.53%	42
10	51.07%	53.73%	54.70%	52.52%	42.72%	44.13%	44.83%	47.99%	74

Table 52: LAA - Percentage share in Absolute Error per Lag-forecast, related to the number of Lag-forecasts inserted

DFU Level	**Percentage Share of Total Absolute Error**				
LAA	**Lag 0**	**Lag 1**	**Lag 2**	**Lag 3**	**Volume**
0 FCST Values	15.73%	15.21%	15.23%	14.09%	12.50%
1 FCST Values	3.54%	3.02%	3.02%	2.80%	2.48%
2 FCST Values	2.42%	2.19%	2.39%	2.66%	1.53%
3 FCST Values	2.83%	2.68%	2.16%	2.08%	1.43%
4 FCST Values	75.47%	76.90%	77.19%	78.37%	82.06%

10 Appendix X

Table 53: Chemistry Level comparison of CoV values based on Actual Sales

	EUROPE	MEATI	ANZJK	GCSEA	NAA	LAA
ACRYLICS	0.183	0.153	0.095	0.132	0.241	0.152
DISPERSANTS	0.138	0.162	0.218	0.216	0.100	0.149
HASE/ASE	0.110	0.188	0.105	0.227	0.088	0.142
HEUR	0.125	0.288	0.081	0.198	0.090	0.139
OP	0.047	0.131	0.091	0.169	0.051	0.230
OTHER	0.247	0.458		0.264	0.446	0.216
PARALOIDS SOLID	0.220	0.774	0.644	0.550	0.218	0.211
PARALOIDS SOLUTION	0.446				0.182	0.299
STYRENE ACRYLICS	0.130	0.138	0.319	0.160	0.165	0.139
VINYL ACRYLICS	1.110	0.183	0.251	0.383	0.118	0.424

Table 54: Chemistry Level Comparison of MAPE results per Area for lag 1 forecasts

	EUROPE	MEATI	ANZJK	GCSEA	NAA	LAA
ACRYLICS	31.64%	31.71%	31.07%	35.32%	34.02%	29.96%
DISPERSANTS	31.30%	23.31%	28.09%	41.88%	29.95%	34.64%
HASE/ASE	32.87%	37.07%	28.12%	34.67%	28.53%	27.90%
HEUR	36.49%	38.82%	28.47%	37.77%	27.93%	33.57%
OP	18.53%	29.64%	18.65%	32.36%	25.67%	28.18%
OTHER	21.30%	17.03%	-	43.25%	31.94%	47.12%
PARALOIDS SOLID	50.51%	62.50%	48.77%	52.83%	47.40%	19.19%
PARALOIDS SOLUTION	42.48%	-	-	0.00%	33.47%	35.10%
STYRENE ACRYLICS	27.86%	26.66%	37.21%	40.18%	38.05%	39.33%
VINYL ACRYLICS	52.56%	19.44%	29.88%	53.00%	18.40%	33.07%

11 Appendix XI

Table 55: Available Forecasting Methods available in in APO

Available Methods	Description
Constant Models	Uses models such as (weighted) moving average, and first-order exponential smoothing.
Croston Method	A forecasting strategy for products with intermittent demand, calculating the average interval between demands. Subsequently this is used in a form of the constant model to forecast demand.
Automatic Model Selection (1)	Method that subjects historical data to a regression analysis, to check if there is a significant trend pattern and selects a model based on the findings
Automatic Model Selection (2)	Method that checks historical data for seasonality. Applies only if one already knows there is a trend in the data.
Trend Model	Using first- or second-order exponential smoothing to incorporate a possible trend in the data.
Linear Regression	Uses simple linear regression, where the system calculates a line of best fit (for equation $y = a + bx$).
Seasonal Trend Model	Incorporates trend and seasonality effects, similar to the holt-winters method.
Seasonal + Linear Regression	Calculates seasonal indices to remove the seasonal influence from the data, subsequently linear regression is applied where after seasonality is added again by using the seasonal indices.
Median Method	Uses the median of the selected history as the forecast.
Seasonal Models	Applies a seasonal model, without incorporating any trend effects.
Manual Forecasting	Allows the user to set the basic value, and model level, trend, and seasonality parameters (α, β, γ) him or herself.
History	Functions as a seasonal naïve forecast, using historical values as a forecast
External Forecast	Applies an externally generated forecast.
No Forecast	No forecast is set when using this method.

Figure 44: CEE/WER - Demand Pattern for years 2013-2015

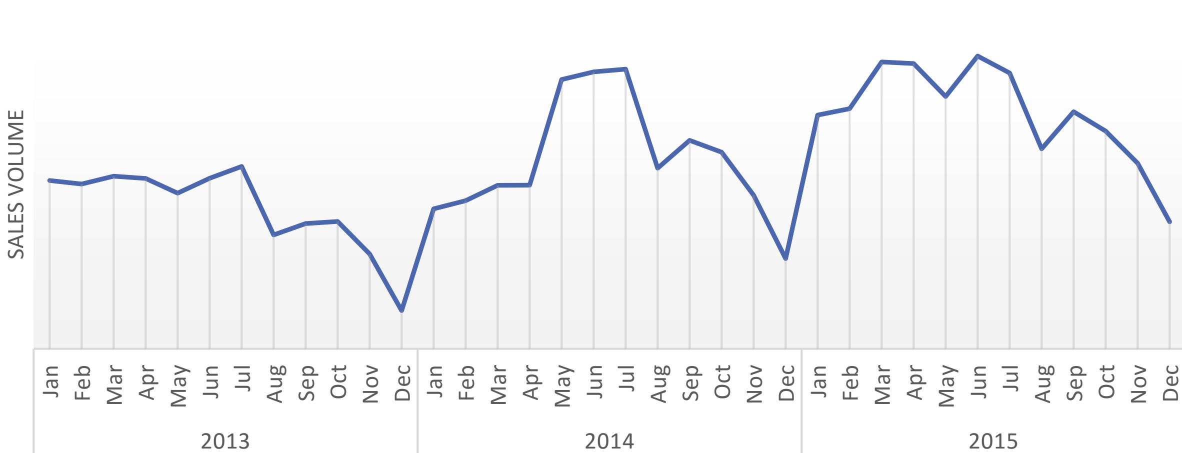


Figure 45: Greater Russia - Demand Pattern for years 2013-2015

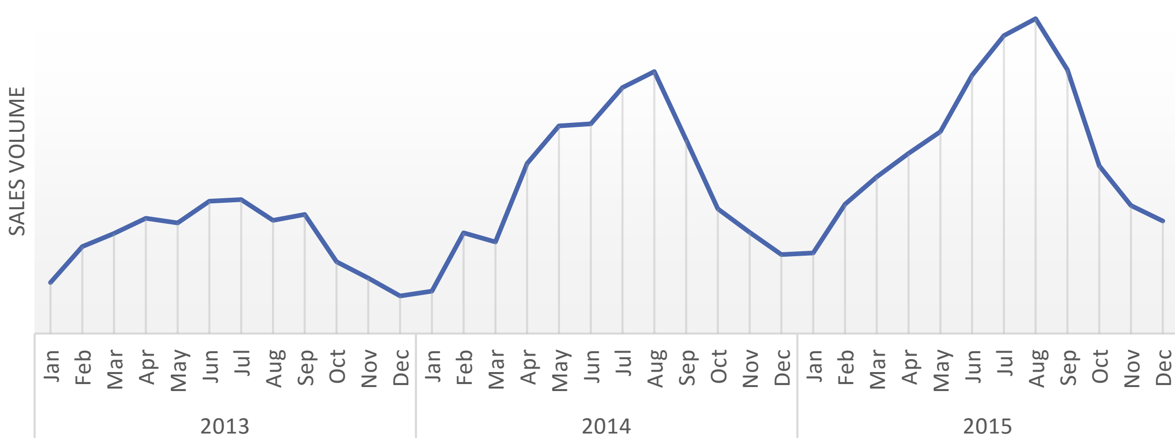


Figure 46: Europe - Chemistry Demand Profiles (High Volumes)

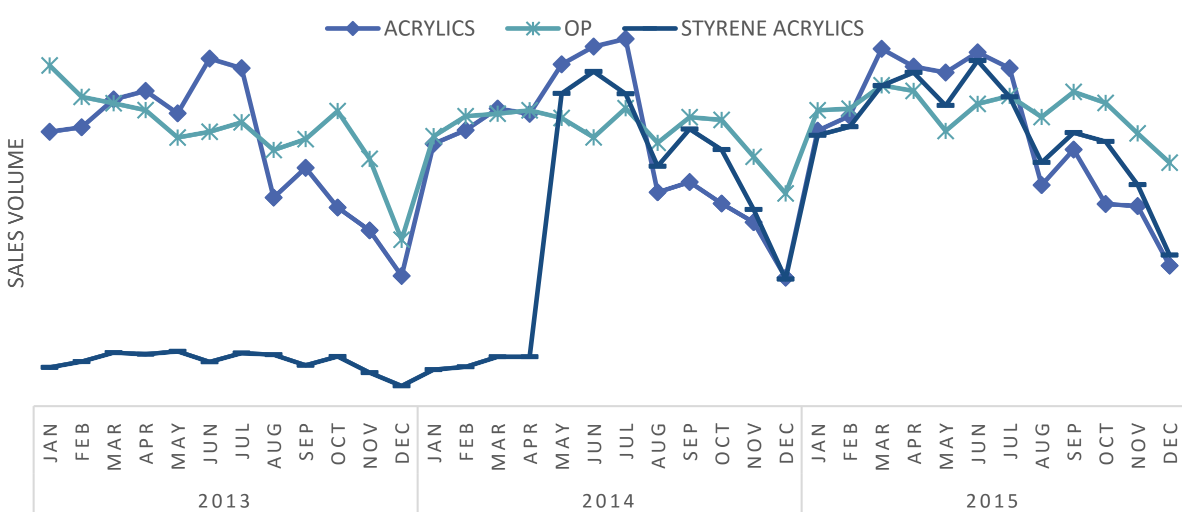


Figure 47: Europe - Chemistry Demand Profiles (Low Volumes)

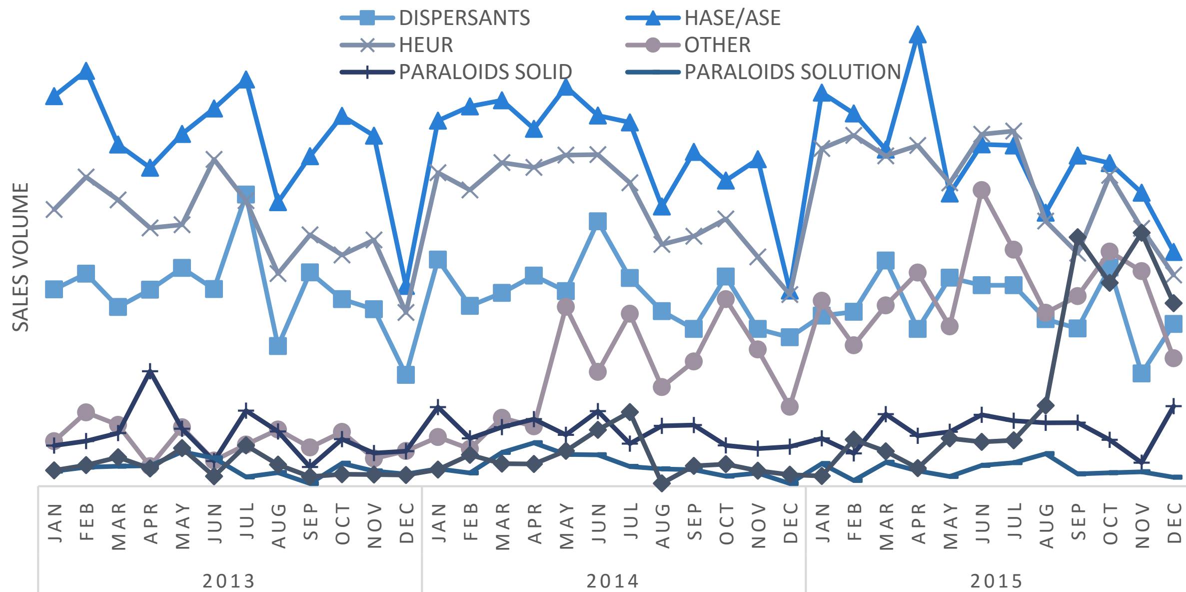


Figure 48: Greater Russia - Chemistry Demand Profiles (High Volume)

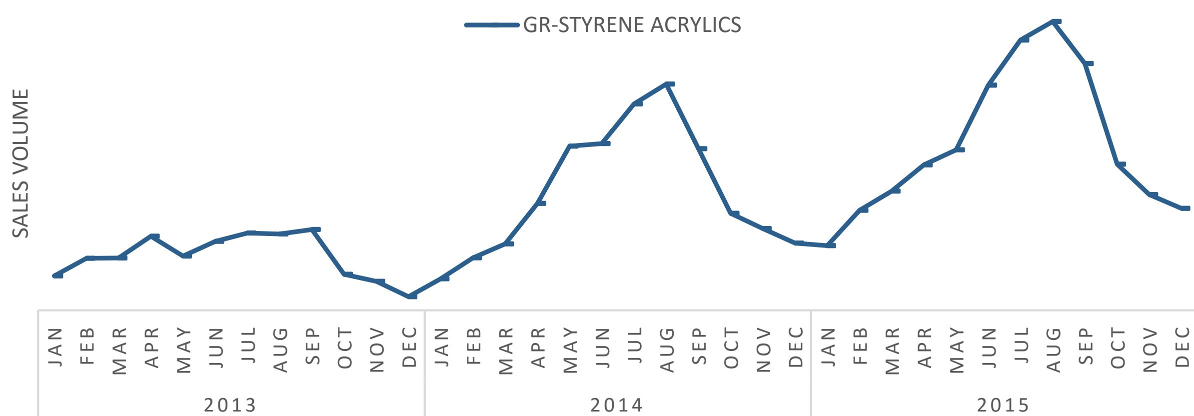


Figure 49: Greater Russia - Chemistry Demand Profiles (Low Volumes)

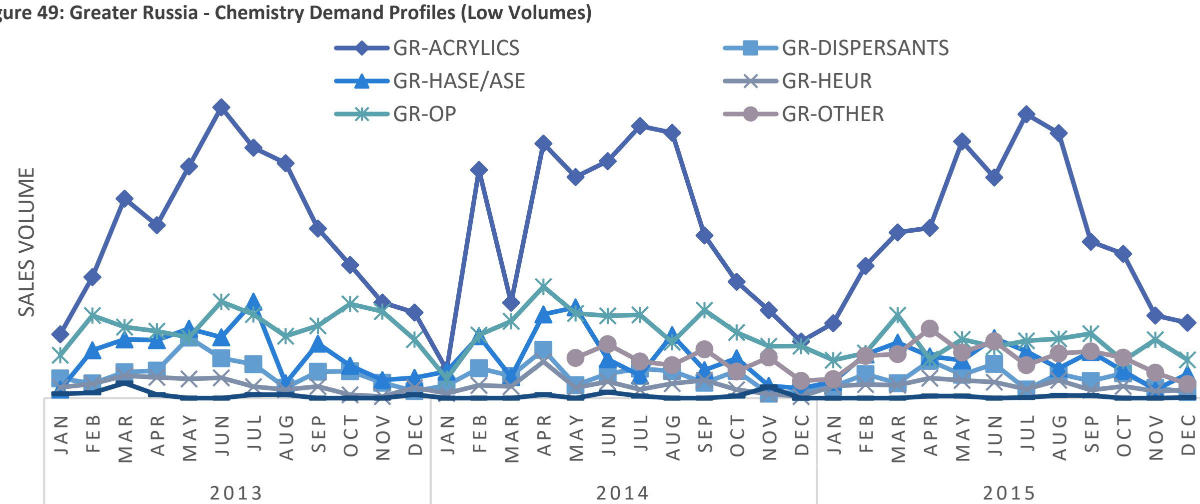


Figure 50: Europe - Profit Center Demand Patterns (Top 5 Volumes)

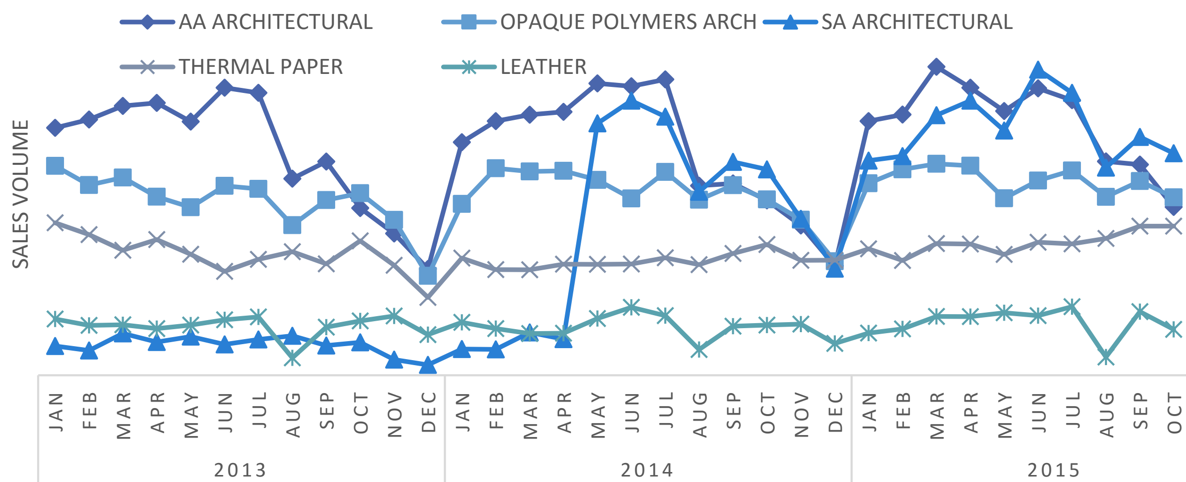


Figure 51: Europe - Profit Center Demand Patterns (Lower Volumes)

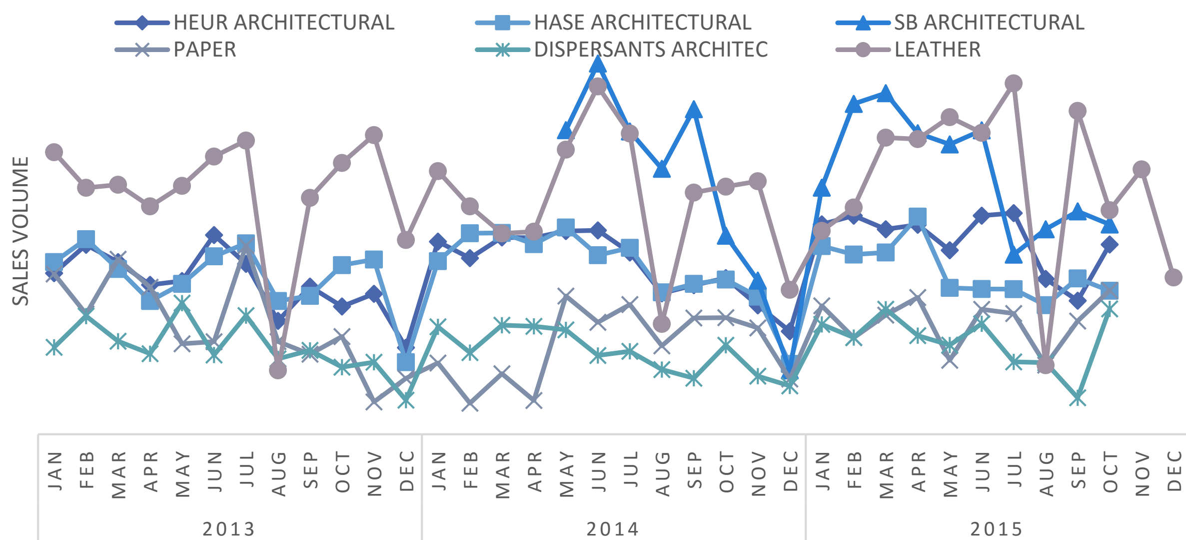


Figure 52: Greater Russia - Profit Center Demand Patters (Top 5 Volumes)

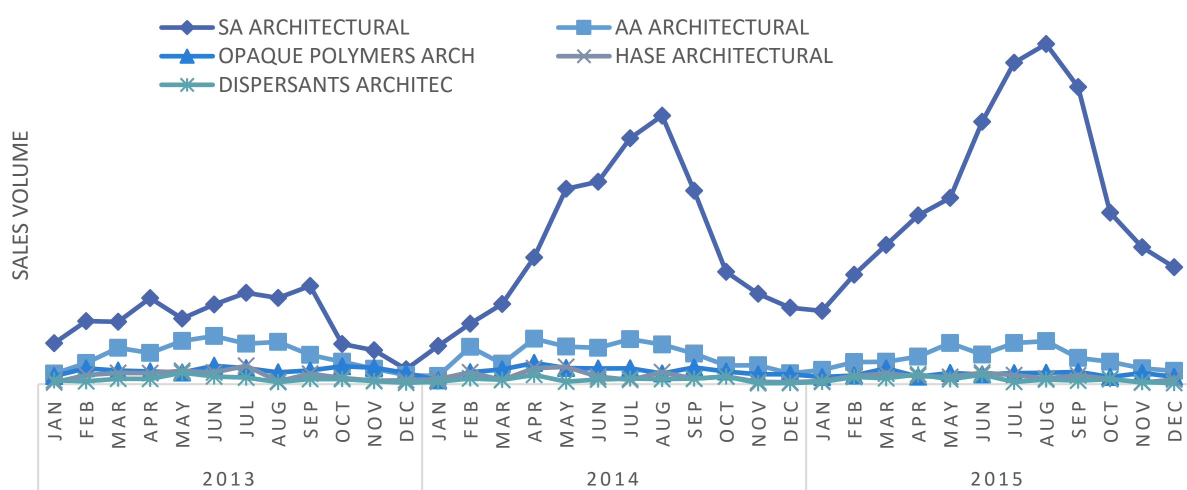


Figure 53: Greater Russia - Profit Center Demand Patters (Lower Volumes)

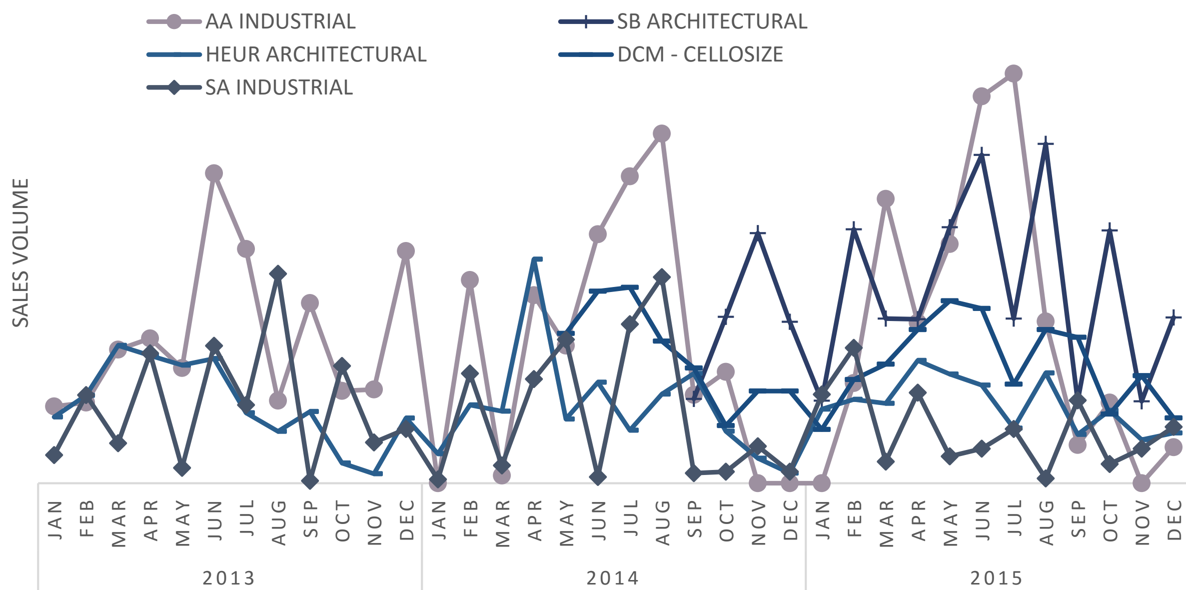


Figure 54: Europe - Base Bulk Product Replacement

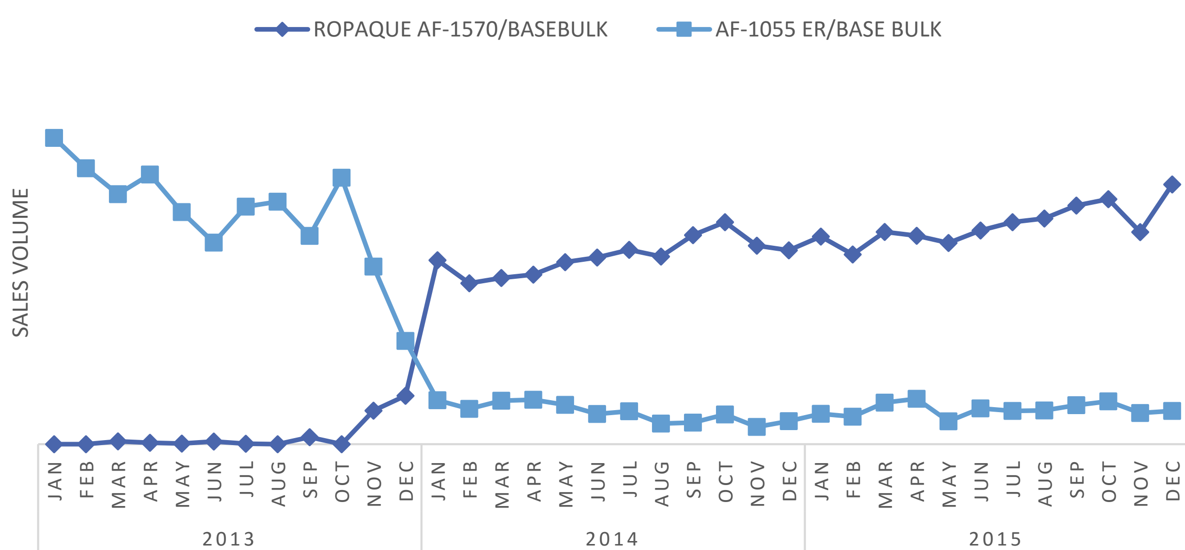


Table 56: CEE/WER - DFU level demand analysis

Demand in years	# DFU's	% 2013 Vol	% 2014 Vol	% 2015 Vol
2015	596	-	-	6.07
2014	371	-	1.48	-
2013	485	18.46	-	-
2014 + 2015	475	-	23.26	31.50
2013 + 2015	69	0.52	-	0.33
2013 + 2014	264	7.20	3.03	-
2013 + 2014 + 2015	1215	73.83	72.23	62.10
Subtotal		100%	100%	100%
All months	68	34.22	27.94	24.38

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Table 57: CEE/WER - Chemistry Lag-1 Forecast Value Add & Method Selection

Chemistry	Lag-1 Acc.	Stat Acc.	FVA APE	Method	% 2015 Vol.
ACRYLICS	95.48%	93.49%	**-1.99%**	**HW**	27.86%
DISPERSANTS	77%	86%	**8.53%**	**SE**	2.19%
HASE/ASE	89%	89%	**0.00%**	**HW**	4.04%
HEUR	92%	94%	**2.52%**	**HW**	3.70%
OP	92%	97%	**4.93%**	**HW**	29.80%
PARALOIDS SOLID	71%	75%	**3.47%**	**MA**	0.68%
PARALOIDS SOLUTION	53%	62%	**9.15%**	**MA**	0.21%
STYRENE ACRYLICS	96%	77%	**-18.60%**	**-**	27.90%
VINYL ACRYLICS	58%	24%	**-33.52%**	**-**	1.23%

Table 58: CEE/WER - Chemistry Lag-3 Forecast Value Add & Method Selection

Chemistry	Lag-3 Acc.	Stat Acc.	FVA APE	Method	% 2015 Vol.
ACRYLICS	86%	93%	**7.91%**	**HW**	27.86%
DISPERSANTS	69%	86%	**16.62%**	**SE**	2.19%
HASE/ASE	81%	89%	**8.49%**	**HW**	4.04%
HEUR	82%	94%	**12.19%**	**HW**	3.70%
OP	84%	97%	**12.55%**	**HW**	29.80%
PARALOIDS SOLID	59%	75%	**15.48%**	**MA**	0.68%
PARALOIDS SOLUTION	31%	62%	**31.09%**	**MA**	0.21%
STYRENE ACRYLICS	83%	77%	**-**	**-**	27.90%
VINYL ACRYLICS	17%	24%	**6.74%**	**HW**	1.23%

Table 59: CEE/WER - Profit Center Lag-1 Forecast Value Add & Method Selection

Profit Center	Lag-1 Acc.	Stat. Acc.	FVA APE	Method	% 2015 Vol.
AA ARCHITECTURAL	96%	94%	**-3%**	**HW**	21.63%
AA INDUSTRIAL	56%	76%	**19.4%**	**MA**	0.73%
ARCHITECTURAL	0%	0%	**-**	**-**	0.05%
ARCHITECTURAL GENERA	0%	61%	**60.5%**	**SE**	0.11%
DCM - CELLOSIZE	10%	74%	**64.7%**	**MA**	0.20%
DCM - CMC	29%	62%	**32.9%**	**SE**	0.11%
DCM - MC	43%	86%	**42.6%**	**SE**	0.58%
DCM - METHYL CELLULO	7%	37%	**29.4%**	**SE**	0.11%
DCM - SPECIALTY ALKO	0%	19%	**19.1%**	**HW**	0.05%
DISPERSANTS ARCHITEC	80%	88%	**8.0%**	**SN**	1.98%
HASE ARCHITECTURAL	89%	89%	**-0.3%**	**MA**	3.08%
HASE INDUSTRIAL	0%	28%	**27.8%**	**MA**	0.01%
HEUR ARCHITECTURAL	91%	92%	**1.0%**	**HW**	3.60%
HEUR INDUSTRIAL	17%	0%	**-17.2%**	**-**	0.00%
INDUSTRIAL COATINGS	0%	0%	**-**	**-**	0.00%
INDUSTRIAL ROH	0%	0%	**0.0%**	**SN**	0.02%
LEATHER	83%	85%	**1.8%**	**HW**	4.71%
OPAQUE POLYMERS ARCH	90%	97%	**7.1%**	**HW**	17.12%
PAPER	83%	80%	**-2.7%**	**MA**	2.47%
PCM - CONSTRUCTION	0%	1%	**1.0%**	**HW**	0.02%
POD	0%	0%	**-**	**-**	0.01%
SA ARCHITECTURAL	95%	79%	**-15.2%**	**-**	21.34%
SA INDUSTRIAL	80%	92%	**12.1%**	**HW**	1.57%
SB ARCHITECTURAL	85%	82%	**-2.9%**	**MA**	4.56%
SOLUTION ACRYLICS IN	74%	76%	**1.4%**	**MA**	0.81%
THERMAL PAPER	91%	93%	**2.0%**	**HW**	12.38%
TRAFFIC PAINTS	78%	79%	**0.9%**	**HW**	1.54%
VA ARCHITECTURAL	59%	26%	**-32.3%**	**-**	1.22%

Table 60: CEE/WER - Profit Center Lag-3 Forecast Value Add & Method Selection

Profit Center	Lag-3 Acc.	Stat. Acc.	FVA APE	Method	% 2015 Vol.
AA ARCHITECTURAL	87%	94%	**6.7%**	**HW**	21.63%
AA INDUSTRIAL	37%	76%	**39.2%**	**MA**	0.73%
ARCHITECTURAL	0%	0%	**-**	**-**	0.05%
ARCHITECTURAL GENERA	0%	61%	**60.5%**	**SE**	0.11%
DCM - CELLOSIZE	8%	74%	**66.2%**	**MA**	0.20%
DCM - CMC	19%	62%	**42.9%**	**SE**	0.11%
DCM - MC	27%	86%	**58.7%**	**SE**	0.58%
DCM - METHYL CELLULO	4%	37%	**32.8%**	**SE**	0.11%
DCM - SPECIALTY ALKO	0%	19%	**19.1%**	**PC**	0.05%
DISPERSANTS ARCHITEC	71%	88%	**17.3%**	**SN**	1.98%
HASE ARCHITECTURAL	77%	89%	**11.6%**	**MA**	3.08%
HASE INDUSTRIAL	0%	28%	**27.8%**	**MA**	0.01%
HEUR ARCHITECTURAL	81%	92%	**10.9%**	**HW**	3.60%
HEUR INDUSTRIAL	17%	0%	**-17.2%**	**-**	0.00%
INDUSTRIAL COATINGS	0%	0%	**-**	**-**	0.00%
INDUSTRIAL ROH	0%	0%	**-**	**-**	0.02%
LEATHER	76%	85%	**9.2%**	**HW**	4.71%
OPAQUE POLYMERS ARCH	83%	97%	**14.4%**	**HW**	17.12%
PAPER	59%	80%	**21.2%**	**MA**	2.47%
PCM - CONSTRUCTION	0%	1%	**1.0%**	**HW**	0.02%
POD	0%	0%	**-**	**-**	0.01%
SA ARCHITECTURAL	84%	79%	**-4.8%**	**-**	21.34%
SA INDUSTRIAL	64%	92%	**28.4%**	**HW**	1.57%
SB ARCHITECTURAL	62%	82%	**20.1%**	**MA**	4.56%
SOLUTION ACRYLICS IN	60%	76%	**15.6%**	**MA**	0.81%
THERMAL PAPER	84%	93%	**9.5%**	**PC**	12.38%
TRAFFIC PAINTS	62%	79%	**17.5%**	**HW**	1.54%
VA ARCHITECTURAL	12%	26%	**14.1%**	**SE**	1.22%

Table 61: CEE/WER - Base-Bulk Lag-1 Forecast Value add & Method Selection

Base Bulk Product	Lag-1 Acc.	Stat. Acc.	FVA APE	Method	% 2015 Vol.
731A/BASE BULK	71.55%	76.70%	**5.16%**	**SE**	1.18%
A 2001/BASE BULK	73.44%	74.08%	**0.65%**	**SN**	1.17%
AC-337 ER/BASE BULK	93.46%	90.45%	**-3.01%**	**-**	5.88%
AF-1055 ER/BASE BULK	80.52%	76.86%	**-3.67%**	**-**	1.60%
AVANSE 412M/BASEBULK	77.53%	74.94%	**-2.58%**	**HW**	0.80%
DCMAC LATEX DL 420G/BASE BULK	91.30%	92.10%	**0.80%**	**HW**	12.25%
DCMAC LATEX DL 450/BASE BULK	74.22%	79.92%	**5.70%**	**HW**	0.85%
DCMAC SA DA 437/BASE BULK	79.32%	89.33%	**10.01%**	**SN**	1.38%
ELASTENE 404/BASE BULK	74.89%	75.31%	**0.42%**	**HW**	0.86%
EXP-900 ER/BASEBULK	70.54%	79.99%	**9.46%**	**MA**	0.84%
JOD-438/BASEBULK	66.79%	65.95%	**-0.84%**	**SN**	1.03%
LATEX XZ 92094.01 EA BK	83.31%	76.25%	**-7.05%**	**-**	3.57%
LATEX XZ 92094.02 EA BK	81.93%	89.71%	**7.77%**	**HW**	0.97%
LATEX XZ 94338.00 EA BK	40.27%	52.02%	**11.75%**	**MA**	0.88%
ML-520/BASEBULK	76.5`1%	75.57%	**-0.94%**	**HW**	1.00%
Not assigned	55.99%	61.52%	**5.54%**	**MA**	1.08%
PRIMAL SF-016 ER/BASE BULK	88.44%	84.90%	**-3.54%**	**-**	1.15%
RM-2020E/BASE BULK	87.03%	89.86%	**2.83%**	**HW**	1.31%
ROPAQUE AF-1570/BASEBULK	93.11%	92.18%	**-0.93%**	**AD**	10.13%
SB-150/BASE BULK	75.70%	69.44%	**-6.26%**	**-**	1.24%
SF-06/BASE BULK	68.41%	76.69%	**8.29%**	**HW**	0.96%
TT-935 ER/BASE BULK	83.97%	80.95%	**-3.03%**	**-**	0.91%
ULTRA E/BASE BULK	89.62%	96.95%	**7.34%**	**HW**	14.88%
ULTRA OR-2/BASE BULK	83.65%	90.05%	**6.39%**	**HW**	1.09%

Table 62: CEE/WER - Base-Bulk Lag-3 Forecast Value add & Method Selection

Base Bulk Product	Lag-3 Acc.	Stat. Acc.	FVA APE	Method	% 2015 Vol.
731A/BASE BULK	63.82%	76.70%	**12.88%**	**SE**	1.18%
A 2001/BASE BULK	61.51%	74.08%	**12.58%**	**SN**	1.17%
AC-337 ER/BASE BULK	87.60%	90.45%	**2.84%**	**HW**	5.88%
AF-1055 ER/BASE BULK	78.49%	76.86%	**-1.63%**	**MA**	1.60%
AVANSE 412M/BASEBULK	67.02%	74.94%	**7.92%**	**HW**	0.80%
DCMAC LATEX DL 420G/BASE BULK	80.33%	92.10%	**11.77%**	**HW**	12.25%
DCMAC LATEX DL 450/BASE BULK	58.49%	79.92%	**21.43%**	**HW**	0.85%
DCMAC SA DA 437/BASE BULK	70.53%	89.33%	**18.80%**	**SN**	1.38%
ELASTENE 404/BASE BULK	61.07%	75.31%	**14.24%**	**HW**	0.86%
EXP-900 ER/BASEBULK	61.77%	79.99%	**18.22%**	**MA**	0.84%
JOD-438/BASEBULK	64.00%	65.95%	**1.94%**	**SN**	1.03%
LATEX XZ 92094.01 EA BK	63.20%	76.25%	**13.05%**	**SN**	3.57%
LATEX XZ 92094.02 EA BK	65.58%	89.71%	**24.13%**	**HW**	0.97%
LATEX XZ 94338.00 EA BK	41.83%	52.02%	**10.19%**	**MA**	0.88%
ML-520/BASEBULK	66.09%	75.57%	**9.48%**	**HW**	1.00%
Not assigned	46.74%	61.52%	**14.78%**	**MA**	1.08%
PRIMAL SF-016 ER/BASE BULK	80.56%	84.90%	**4.34%**	**HW**	1.15%
RM-2020E/BASE BULK	75.96%	89.86%	**13.89%**	**HW**	1.31%
ROPAQUE AF-1570/BASEBULK	84.82%	92.18%	**7.36%**	**HW**	10.13%
SB-150/BASE BULK	76.95%	69.44%	**-7.51%**	**-**	1.24%
SF-06/BASE BULK	61.02%	76.69%	**15.67%**	**HW**	0.96%
TT-935 ER/BASE BULK	77.11%	80.95%	**3.83%**	**MA**	0.91%
ULTRA E/BASE BULK	82.09%	96.95%	**14.86%**	**HW**	14.88%
ULTRA OR-2/BASE BULK	79.04%	90.05%	**11.01%**	**HW**	1.09%

Table 63: CEE/WER – DFU Lag-1 Forecast Value add & Method Selection

DFU	Current Acc.	Stat. Acc.	FVA APE	Method	% 2015 Vol.
00119031-E00020954-01534008	40.27%	52.02%	**11.75%**	**MA**	0.88%
00271803-E00020954-00865528	64.13%	53.28%	**-10.84%**	**-**	0.93%
00298084-E00021142-01534008	83.17%	70.47%	**-12.71%**	**-**	3.57%
00366380-E00020954-01534008	81.01%	74.48%	**-6.53%**	**-**	0.95%
10048115-E00020950-00786644	74.05%	80.77%	**6.72%**	**SN**	0.87%
10048115-E00020950-01592652	80.81%	89.06%	**8.25%**	**HW**	1.69%
10048115-E00020950-01594432	72.22%	76.24%	**4.02%**	**MA**	1.14%
10107314-E00020952-01776482	72.70%	67.54%	**-5.16%**	**-**	0.76%
10241300-E00020952-00490119	75.44%	68.08%	**-7.37%**	**-**	1.02%
10241300-E00020952-00866745	57.87%	64.02%	**6.15%**	**SN**	1.01%
10244882-E00016793-00084456	74.45%	64.60%	**-9.85%**	**-**	1.34%
10255268-E00020950-01776482	83.65%	83.32%	**-0.33%**	**SN**	1.09%
10269695-E00020952-01465003	75.67%	74.10%	**-1.57%**	**HW**	0.97%
10338810-E00020952-01375786	78.76%	77.92%	**-0.84%**	**HW**	0.72%
11032235-E00016793-00769526	94.09%	91.44%	**-2.64%**	**HW**	9.64%
11040246-E00020950-01830861	82.66%	90.19%	**7.53%**	**HW**	1.63%
11045997-E00017218-03094307	78.65%	75.18%	**-3.47%**	**-**	0.72%
11125403-E00020953-03068455	64.64%	0.00%	**-64.64%**	**-**	0.70%
99000000-E00020954-00323451	84.52%	74.46%	**-10.06%**	**-**	1.75%
99000000-E00020954-00861226	66.59%	50.26%	**-16.33%**	**-**	0.93%
99000000-E00020954-01131481	78.22%	63.60%	**-14.62%**	**-**	1.48%
99000000-E00020954-01136493	67.36%	66.18%	**-1.18%**	**SE**	0.85%
99000000-E00020954-01154654	73.59%	52.71%	**-20.87%**	**-**	1.12%
99000000-E00020954-01327609	83.24%	68.05%	**-15.20%**	**-**	0.81%

Table 64: CEE/WER – DFU Lag-3 Forecast Value add & Method Selection

DFU	Current Acc.	Stat. Acc.	FVA APE	Method	% 2015 Vol.
00119031-E00020954-01534008	40.27%	52.02%	**11.75%**	**MA**	0.88%
00271803-E00020954-00865528	64.13%	53.28%	**-10.84%**	**-**	0.93%
00298084-E00021142-01534008	83.17%	70.47%	**-12.71%**	**-**	3.57%
00366380-E00020954-01534008	81.01%	74.48%	**-6.53%**	**-**	0.95%
10048115-E00020950-00786644	74.05%	80.77%	**6.72%**	**SN**	0.87%
10048115-E00020950-01592652	80.81%	89.06%	**8.25%**	**HW**	1.69%
10048115-E00020950-01594432	72.22%	76.24%	**4.02%**	**MA**	1.14%
10107314-E00020952-01776482	72.70%	67.54%	**-5.16%**	**-**	0.76%
10241300-E00020952-00490119	75.44%	68.08%	**-7.37%**	**-**	1.02%
10241300-E00020952-00866745	57.87%	64.02%	**6.15%**	**SN**	1.01%
10244882-E00016793-00084456	74.45%	64.60%	**-9.85%**	**-**	1.34%
10255268-E00020950-01776482	83.65%	83.32%	**-0.33%**	**SN**	1.09%
10269695-E00020952-01465003	75.67%	74.10%	**-1.57%**	**HW**	0.97%
10338810-E00020952-01375786	78.76%	77.92%	**-0.84%**	**HW**	0.72%
11032235-E00016793-00769526	94.09%	91.44%	**-2.64%**	**HW**	9.64%
11040246-E00020950-01830861	82.66%	90.19%	**7.53%**	**HW**	1.63%
11045997-E00017218-03094307	78.65%	75.18%	**-3.47%**	**-**	0.72%
11125403-E00020953-03068455	64.64%	0.00%	**-64.64%**	**-**	0.70%
99000000-E00020954-00323451	84.52%	74.46%	**-10.06%**	**-**	1.75%
99000000-E00020954-00861226	66.59%	50.26%	**-16.33%**	**-**	0.93%
99000000-E00020954-01131481	78.22%	63.60%	**-14.62%**	**-**	1.48%
99000000-E00020954-01136493	67.36%	66.18%	**-1.18%**	**SE**	0.85%
99000000-E00020954-01154654	73.59%	52.71%	**-20.87%**	**-**	1.12%
99000000-E00020954-01327609	83.24%	68.05%	**-15.20%**	**-**	0.81%

Figure 55: CEE/WER – HASE/ASE Holt-Winters Values and Actual Sales profiles (89% accurate)

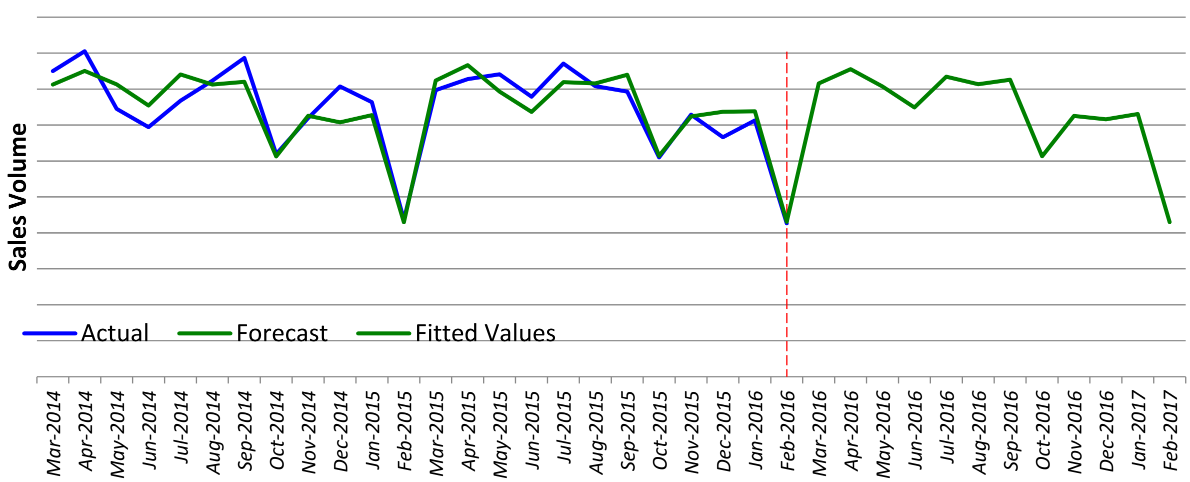
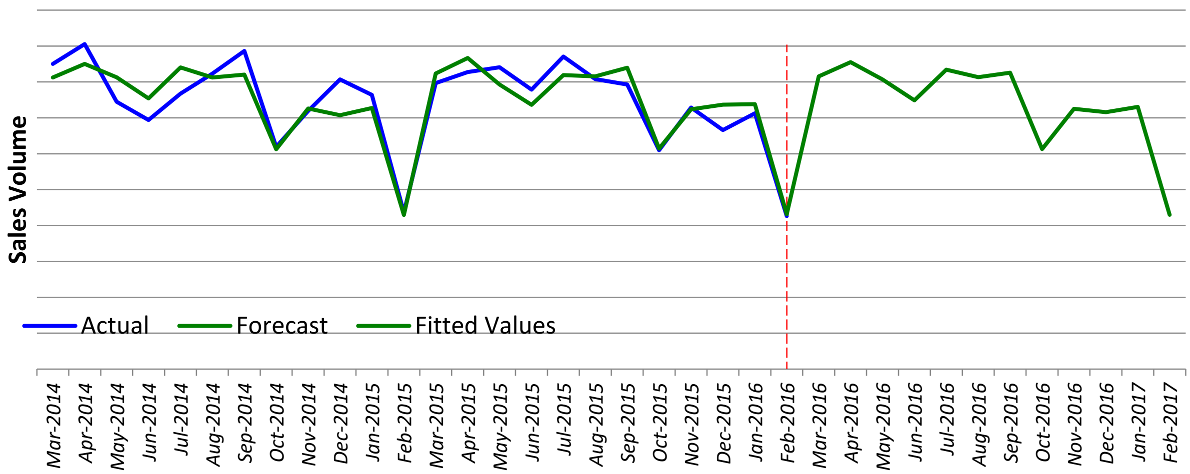


Figure 56: CEE/WER – HEUR Holt-Winters Values and Actual Sales profiles (94% accurate)



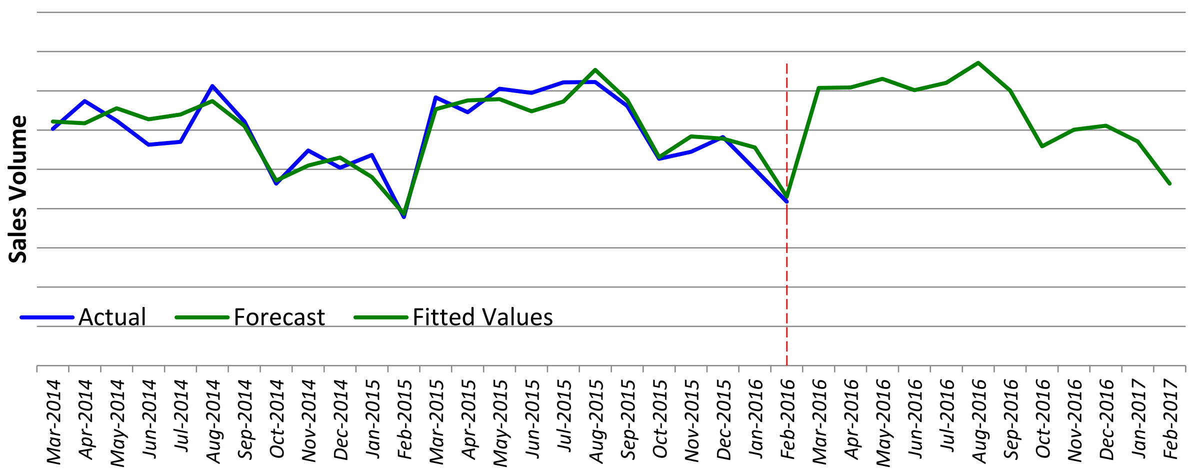


Figure 57: CEE/WER – OP Holt-Winters Forecast and Actual Sales profiles (97% accurate)

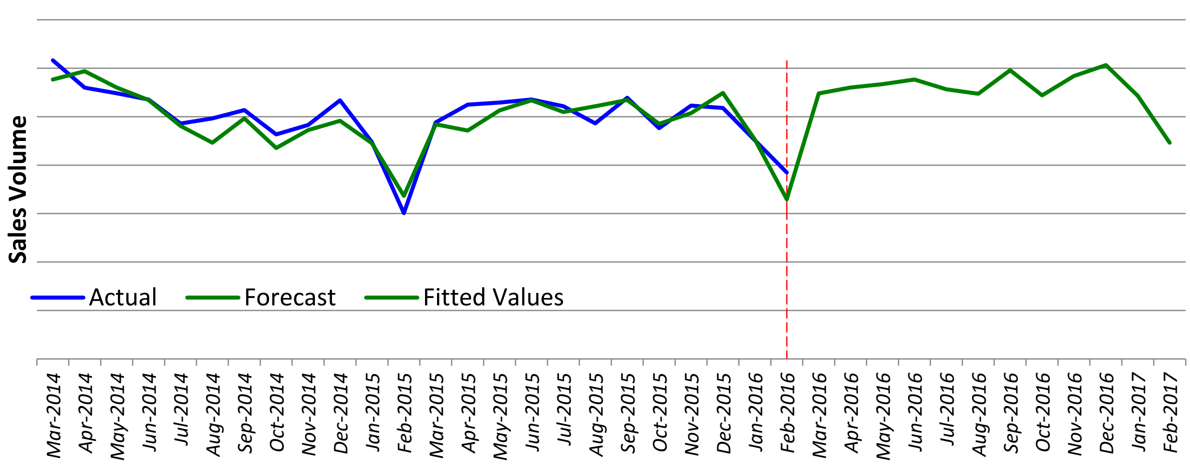


Figure 58: CEE/WER – Dispersants Simple Exponential Smoothing Forecast and Actual Sales profiles (86% accurate)

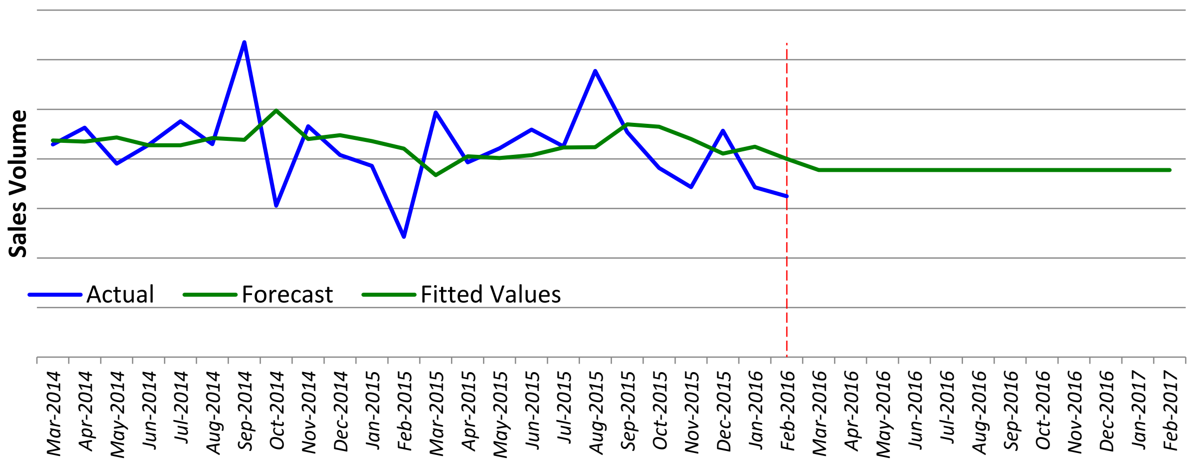


Figure 59: CEE/WER – Paraloids Solid Moving Average (12 Months) Forecast and Actual Sales profiles (75% accurate)

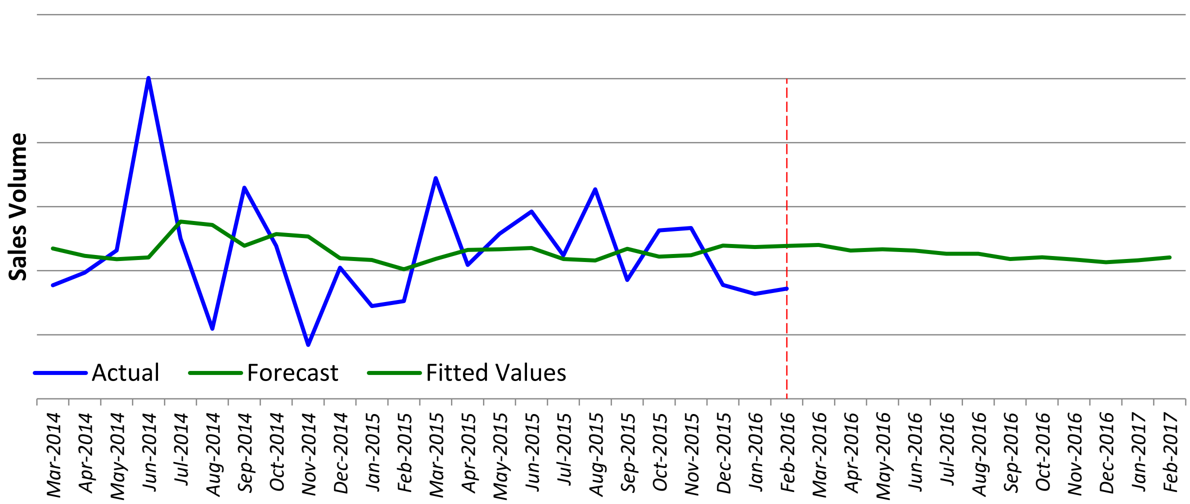


Figure 60: CEE/WER – Paraloids Solution Moving Average (12 Months) Forecast and Actual Sales profiles (62% accurate)

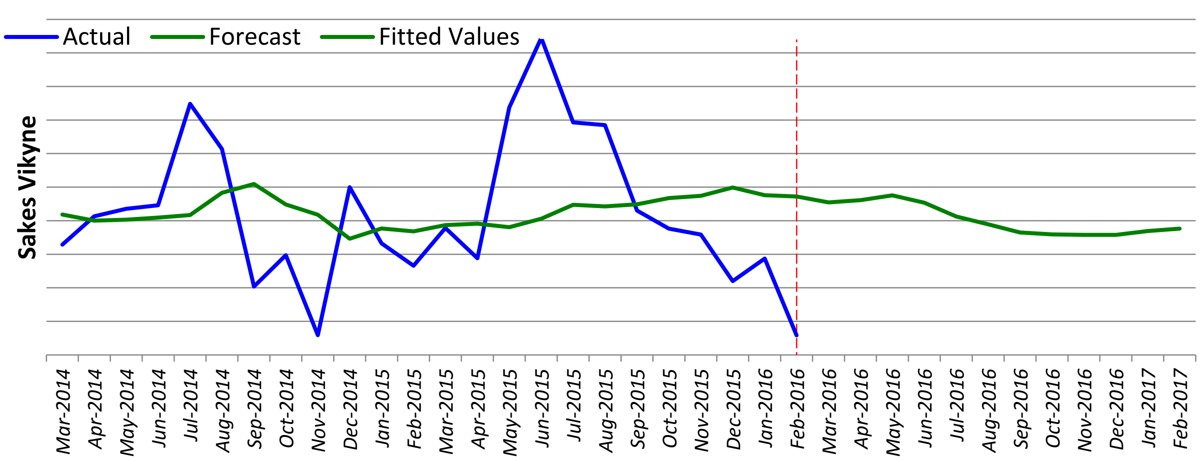


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Figure 61: Segmentation Matrix

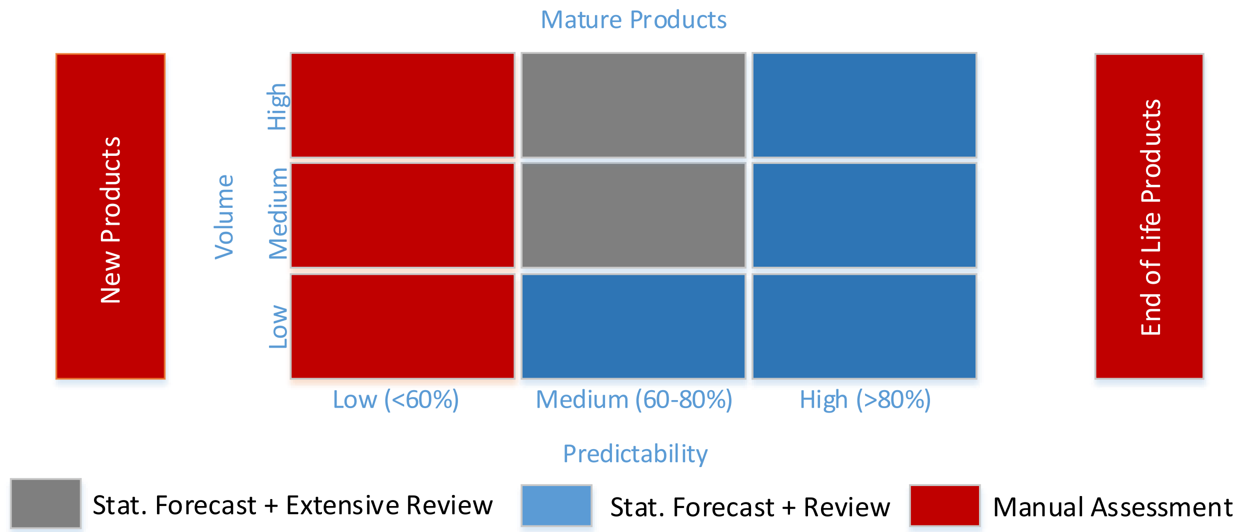

Figure 62: CEE/WER - DFU Segmentation Matrix

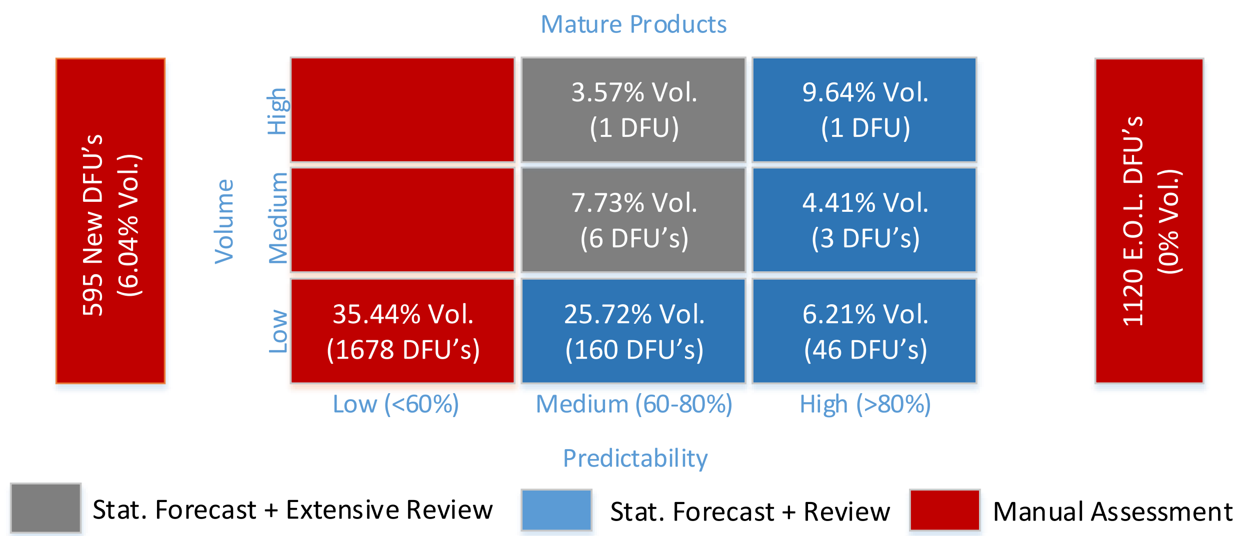

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Figure 63: CEE/WER Segmentation of Bottom Left Segment

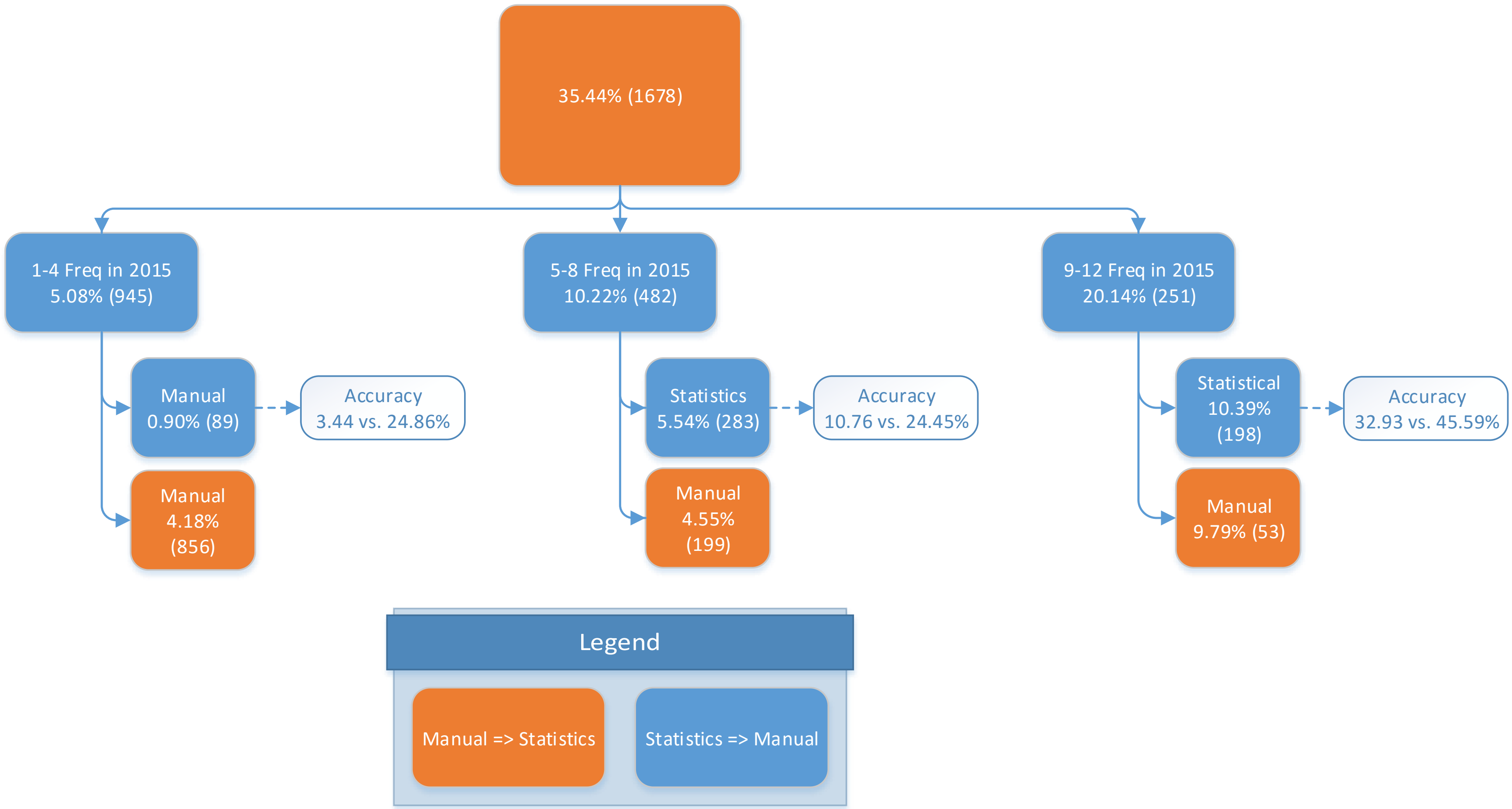

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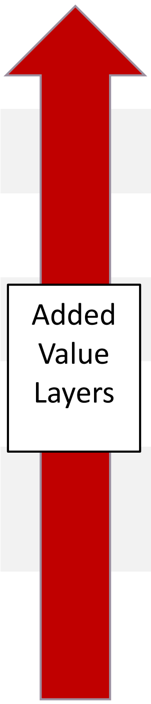
Table 65: Added Value Layers of a Forecast



Forecast (demand) level	What to use it for	Current Process	Statistical Forecasting
Production Planning Demand	Update Constrained Baseline Demand to support S&Oe	S&Oe: Supply Alignment	S&Oe: Supply Alignment
Constrained Demand (Consensus Forecast)	Short-term supply constraints, Long-term constraints/initiatives	S&Oe: Exception Management S&OP: IR, MBR	S&Oe: Exception Management S&OP: IR, MBR
Unconstrained Demand	Short-term feasibility requests Long-term strategic requests	S&Oe: Supply Alignment S&OP: Supply Review, IR	S&Oe: Supply Alignment S&OP: Supply Review, IR
Baseline Demand	***Non-Controversial*** adjustments from sales & marketing	Agreed during S&OP demand review	Agreed during S&OP demand review
Planner Adjusted Forecast	Building to the Demand Review: Manual Application of Level, Trend, Seasonality	***Heavy interaction*** DP and Commercial. (monthly forecast-update file) (+/- 3600)	***Minimal interaction*** by using management by exception
Raw Statistical Forecast	Basis for all forecasts, especially items with: • High predictability & High volume • High predictability & Low volume	**No statistical forecasting used**	Forecast is built by **statistical models at DFU** level (+/- 3600)