

BRIDGING THE GAP BETWEEN FUTURE UNCERTAINTIES AND DEMAND FORECAST

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Executive Summary

In supply chain bottlenecks start from wrong demand forecasts that later affect the whole production process, it is therefore urgent that managers know the importance of understanding how to deal with demand fluctuations. In general, the main issues addressed are: the level of detail of the aggregation of demand, the categorization of demand in different classes and the association of the different demand categories to their specific statistical model. Nowadays, demand planners lack a general procedure to follow while making forecast for future previsions. The main goal of this research is two-folded: the creation of a universal forecasting process that can be both accessible for a managerial perspective and innovative compared to the theoretical works that have been performed until now. In this way managers would not see the forecasting process as a “black box” anymore because one of the main aim is to give accessible and adaptable explanations on how different mathematical models can be used according to the market at stake.

The analysis is divided into three main parts: the development of an up-to-date list of forecasting models for future demand is conducted in parallel to the construction of a new market’s demand classification. The results coming from these two first analyses are then linked together through the creation of a decision tree that managers would use to associate each market’s demand category to its specific set of statistical models. Therefore, the main contribution of this research is the development of precise strategies that managers can adopt to improve operational performance when demand is intermitted.

The main sources of information of this study are both the company taken under analysis and the past literature review. Concerning this latter, a lack of a universal view on intermitted demand is highlighted: the issue of classification is still in its infancy phase, the optimization of statistical forecasting methods is still an open topic for researchers and in addition to this when considering demand classification method, the past literature is hardly ever taking into account the different nature of items within an industrial context.

Accessibility, clarity and completeness are the three main requirements of the support looked for during this research. A prescriptive decision making tree is hence obtained as the final deliverable of this study, in order for the demand planners to take the best decisions during the forecasting journey. The exceptional advantage of this support is that compared to statistical tools where classification’s rules are represented by a group of numbers and formulas, decision trees give a symbolical reproduction of the decision making journey.

The final results highlight that the final model developed in this research performs better in the 59% of the cases under analysis. This research therefore embodies five main contributions to the past literature research: (1) the knowledge theory concerning the forecasting process is brought close to the everyday managerial practice (2) this work strongly contributes to the categorization of the market demand not only from a theoretical perspective but also from a practical one by implementing it in a real industrial case (3) thanks to the clustering of the demand, this research takes into account the different nature of items within the industrial context, (4) forecasting methods are not considered as a “black box” anymore by demand planners and (5) this research creates a holistic support that can help managers during their entire forecasting journey. Finally, conclusive recommendations are given both for future lines of research and for the company at stake.

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In addition, I further extend my gratitude to my parents, my life's guides, who have given me the value of perseverance in work and have taught me that the cultivation of our personal knowledge and intelligence is the key to success.

Finally, I gratefully thank Enzo Bermond for having been by my side during the whole of this journey and for having taught me that we were born not to be scared of our future but to build one.

Lastly, I would like to cite a quote that inspired me during this entire experience:

“Choose a work that you love and you won't have to work for a single day of your life” (Confucius)

Chapter 1

Research Problem

Supply chain management (SCM) is an emergent domain that is gaining more and more importance from both an academic and an industrial point of view. Nowadays SCM is represented by a broad and varied spectrum of different topics linked together that are continuously evolving and transforming, this is the main reason why it is a growing subject of study for researchers coming from different domains.

What distinguishes Supply Chain Management from other forms of managerial subjects is its intrinsic nature of aligning and linking all the services respectively with their different needs along the chain. The term “service” means all the operations / different departments that intervene along the chain: marketing, demand planning, sells, buyers, finance, etc. The uniqueness of supply chain management nevertheless represents at the same time its main challenge: the ability to globally incorporate all the operations along the chain and make them jointly work as well as collaborate together. However, today’s research still lacks a global view, or in other terms, in describing a comprehensive picture of all the elements that build the supply chain. Before starting to approach any kind of supply chain topic or area, it is essential to be aware of the fact that every single part of the chain is closely correlated to another one. Changes and modifications in one element of the chain will inevitably impact all the others: if the consequences of the generated actions are positive then an overall positive impact on the final performance is detected but if consequences are negative, all the chain will be affected with irreversible damages.

In supply chain bottlenecks start from wrong demand forecasts that later affect the whole production process, it is therefore urgent that managers know the importance of understanding how to deal with demand fluctuations. Nowadays, demand planners are increasingly using their personal knowledge and personal opinion while doing forecasts and according to Jha, A. et al. (2005) this is the main cause of the low accuracy of their future forecast. The challenge regarding how to deal with demand variability and its future uncertainties has been widely studied in literature (Kalchschmidt et al., 2006). In every case, the main issues addressed are: the definition of the level of detail of the demand aggregation level, the categorization of demand in different patterns and the association of the different demand categories to their specific statistical model.

1.1 Research relevance

In this research the demand forecasting process in a multinational setting is analyzed. Nowadays, demand planners lack a general procedure to follow while making forecast for future previsions. The main goal of this research is two-folded: the creation of a forecasting process that can be both accessible for a managerial perspective and innovative compared to the theoretical works that have been performed until now. For these reasons, this research will try to link together both the company’s and the literature needs concerning the problem at stake. In order to deal with this, the analysis will be divided into three main parts: the development of an up to date list of statistical models for future demand forecast will be done in parallel with the construction of a new market’s demand classification. The results coming from these two first analyses will then be linked together through the creation of a decision tree that managers will use to associate each market’s demand category its specific set of statistical models. This would allow demand planners to have no more doubts when choosing which statistical model is best convenient for different market’s demand classes.

The relevance of this research is given by the universal guide that will be delivered to demand planners: by following the final procedure derived at the end of this analysis, managers from any country, will be

able to make forecast by following the same path. This guide would enable all collaborators to work with the same process and this will help the central hub to collect information.

In this way managers will not see the forecasting process as a “black box” anymore because one of the main aim is to give accessible and adaptable explications on how different mathematical models can be used according to the market at stake. Since the final aim is to create a manual that can be adopted in the industrial context, what is essential is to build a model in a way that managers can use it as the main source of information for their decision making journey.

(Table 1: Future benefits of the research)

Future Benefits
Competitive advantage
Increase of the final profit
Better inventory management
Decreased deviation between actual demand and future forecast
Managers’ trust in statistical model
Understanding of how to associate demand patterns to statistical model
Efficient list of statistical models up to date
Accessible and universal support for forecast
Industrial implementation

1.2 Kalis Company

This section will be essential to identify and detail the research gap and the research proposal from the company’s point of view. Since the topic of this analysis has been derived from an industrial context, the company’s supply chain together with its forecasting problems will be identified. This approach will allow a better understanding of the problem at stake from a managerial perspective.

All the information concerning the company have been retrieved by the author of this paper through unstructured interviews to several managers within the company: a broad range of Kalis departments has been listened to in order to have an overall view on the company’s supply chain. For confidentiality reasons, both the name and the personal data of the company have been hidden in the report. The name of the company “Kalis” has been invented by the author of this research

More information about Kalis Company and its organization are given in Annex A.1 and A.2.

The company’s organization structure

Kalis Company is composed by four brands according to which four different product typologies can be identified:

- Kalis Age: skin care product
- Kalis Men: perfumes for men
- Kalis Women: perfumes for women
- Kalis beauty: make-up

In general, all four brands aim to have a premium position in the market, to be at the top of the pyramid and therefore to reach and élite, niche customer segment. This is a significant aspect of the company in order to understand the company price politics and marketing decisions.

The company's market is worldwide and subsidiaries are situated in three different main regions: Europe, the Asia Pacific area and America. Given its strong international dimension, Kalis has subsidiaries in 27 different countries around the world, each of them characterized or not by a local stock. In order to help the reader in the lecture, stock and inventory management will be discussed later in this section.

Concerning the production, Kalis has two principal fabrication sites, which differ according to the products manufactured (skin care, make-up or perfumes) and for a few line of products, the company takes advantage of the outsourced production.

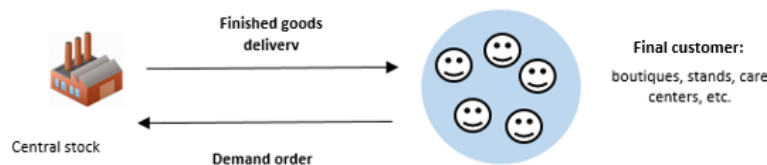
The company supply chain

Once the production process ends, all the finished goods are finally sent to the company central warehouse. Here, the entire set of orders coming from all the 27 subsidiaries around the world are collected and get prepared to be distributed around the world. Therefore, the central warehouse is the primary hub where the initial distribution process takes place.

Next step is the delivery process. The company's subsidiaries are divided into two main groups:

- The "direct deliveries", which is to say those subsidiaries that do not have their own stock
- Subsidiaries provided by their own stock

The first category, subsidiaries that do not possess their own stock, relies on the central stock: all the orders are made directly to it and goods are directly delivered from the company central stock to the single local retailer. In Figure 1, an example of direct delivery is detailed, for instance for the French customers:



(Figure 1: direct delivery)

For the second category, subsidiaries provided by their own stock, there's an intermediate step between the local single customer (boutiques, shops, care centers, etc.) and the central warehouse. Before reaching the individual client, finished goods are firstly collected in the local stock. The process is presented in Figure 2:

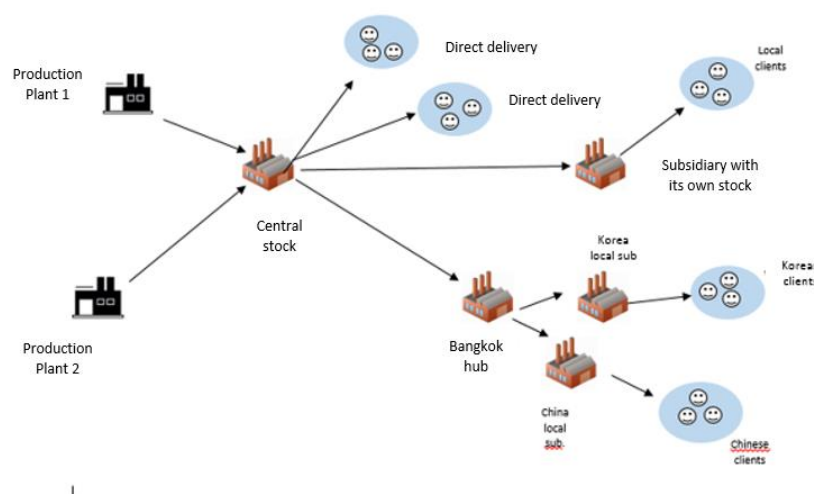


(Figure 2: subsidiaries with stock)

It is easy to notice that in this case the central warehouse is not dealing directly with the local clients in the country, but the subsidiary has its own local stock. Therefore, it is the local subsidiary task to collect all the single local client's order, to sum them and send the final total demand order to Kalis' central stock.

There is, however, the exception of the Asian region: since the Asian market is one of the largest for the group, there is the need for a second intermediary along the chain. The central stock directly sends to Bangkok all the goods demanded by the Asian market and then it is Bangkok's role to distribute all the products to Kalis' Asian subsidiaries with stock. After this initial step, the process carries on as for the second category of subsidiaries described above: it is each of the Asian local subsidiary job to collect their country total demand as well as to distribute the finished products to every single local client.

In order to have a clear idea of the company supply chain explained, an explicative figure is presented below:



(Figure 3: Kalis group supply chain)

Past demand management

In Kalis the forecast process is individually run by each local subsidiary on a monthly base. The process is then locally supervised by two different figures, the demand and the supply planner, that have respectively two different roles:

- **Supply planner** is responsible for the stock: in order to satisfy the future demand, he has to quantify the amount of goods to be asked to the central warehouse when the local stock is not enough and cannot answer to the total local demand orders. On a monthly basis the supply planner send a DOP “distribution order proposition” to the central stock
- **Demand planner** is in charge of the future demand forecast for his region, on a long term horizon. Once in a month, usually towards the end demand forecasts for the next 18 months are published on the digital platform and no more modifications on the data published are possible after this date. These demand forecasts will be then used by the supply planner to make orders to the central stock

Finally, every month the supply planner is in charge of communicating to the central stock the subsidiaries order needs which will then inform the fabrication sites to start the production.

To recapitulate, the replenishment process for every single subsidiary in Kalis is as follows:



(Figure 4: the replenishment process)

Once all the subsidiary finished goods are collected in the central stock and they are ready to be distributed, the ordered quantity can start to be shipped to the respective country.

Given this first description, it is now possible to analyze more in detail the future demand forecasting process adopted by the group.

In order to build the future forecasts, the demand planner utilizes the past Total Demand that is the sum of three different types of demand:

$$\text{Total Demand} = \text{Regular Demand} + \text{Promo Demand} + \text{Free Demand}$$

- The *Regular* is the value of the demand when the market is stable without considering promotions. When the product reaches the maturity phase during its lifecycle, the total demand can be considered equal to the regular factor, since no special events or external factors are likely to happen.
- The *Promo* demand refers to all exceptional events that are not taking place on a long-term base. For instance, the launch of a new product line, is a time when special offers are proposed to clients for advertising and marketing reasons special offers are made to the clients. Therefore, it is important for the demand planner to be able to anticipate possible future promo demand in order to add the corresponding factor to the total forecast.
- The *Free* demand consists of all those products given for free in order to attain the clients' attention. To promote new products, to boost sales of a particular line, testers and products' samples are often given for free.

Thanks to past data analysis, the demand planner will be able to make future forecast: at the beginning of the month he receives on his digital platform the actual demand of the previous month. Here is where the Demand Planner has to act: according to the month at stake, he can decide to change the automatic demand generated by the computer with the so called "Modified Demand", which is indeed manually computed; by default the Modified demand is considered equal to the regular demand; the changes that the demand planner can bring to the Modified Demand consist in adding to the regular demand the promo and the free demand, according to the month and market at stake. The demand planner will add the Promo and Free demand according to what he is expecting from the next months: for instance, if it is foreseen that during the next month there will be a new product line launch, the demand planner will have to add to the regular demand a promo demand, for advertisements reasons.

It is important to carefully understand this process since the statistical model for future forecasts is based on times series analysis which means that future estimations are derived from historical data. Therefore, according to the composition of the Modified Demand, the mathematical model will give different results on future previsions.

Future forecast process

At the end of each month, on the publication day, the demand planner has to send the future demand forecast, for the next 18 months on the supply chain platform. These long term forecast are updated every month by the demand planner of each country

The future forecast is composed by the Manual, the Promo and the Free forecast.

$$\text{Total Forecast} = \text{Manual forecast} + \text{Promo forecast} + \text{Free forecast}$$

As one can see, the three forecasts correspond respectively to the Regular, Promo and Free Demand. The manual forecast is manually computed by the demand planner but it also exists the “Calculated Forecast” which is automatically computed by the computer. It is up to the Demand Planner whether to choose to manually make provisions (through the Manual Forecast) or to rely on the computer calculus (Calculated Forecast).

However, this is where the model encounters a problem: the “Calculated Forecast” is based on a statistical model. Every time the Demand Planner opts to use this automatic procedure, they have to choose among 20 different Statistical models needed for the computation. Nowadays, this choice is randomly made by the demand planner because there is a lack of knowledge on the mathematics behind all the different statistical models, therefore the deviation between the actual demand and the previous forecast is too big and this can be seen and analyzed through the Key Performance Indicators: as it is stated in Weber, A., & Thomas, R. (2005), “*the measurement of performance is important because it identifies current performance gaps between current and desired performance and provides indication of progress towards closing the gaps*”. This is why it is essential for companies to quantify their reduction of inventory costs and its achievement of customer satisfaction targets.

The company’s forecasting issues

To have a first glance on the principal issues faced by the company, which are going to be explained in more in details in the next Chapter, a schematic list of the main problems that need to be solved and that will contribute to identify the main research questions is given below:

- Mistrust of demand planners in statistical models because of an overall lack of technical knowledge
- Long and out of date list of statistical models available in the company’s software for forecast: the majority of the models is underperforming and need to be either modified or taken out from the list
- Lack of a common procedure during the future demand forecasting process among demand planners from different subsidiaries. Each manager is acting individually without any guideline that can support him during the decision process
- Lack of the market’s demand classification: multinationals nowadays have subsidiaries all around the world, each of them characterized by different product lines, customer’s specificities, etc. The lack of a procedure on how to categorize the market’s demand is one of the main causes of the confusion around the future forecast process
- Need to associate different demand patterns to its statistical models for future forecast: nowadays, it is impossible for the company to have a stable relations between the specific market demand and its related statistical model because of the bottlenecks that have been highlighted in the previous points.

Besides the company’s description and thanks to the personal experience of the researcher in the industrial context, these are the main problems that it is possible to identify at this first stage of the research.

1.3 Research objective: the intended deliverable

The scope of this research is to deliver a final model to support the managers’ decision making journey during the future demand forecast process in a multinational context. At the end of the analysis, demand planners will receive a final model that will help them to classify their market and consequently associate it to its related statistical model to compute future forecast.

The main contribution of this research:

- Define specific guidelines that can help managers to better understand and manage demand. More specifically, the final scope is to determine precise strategies that managers can adopt to improve operational performance when demand is intermitted.

In order to give a clear final deliverable, it is helpful to define both the minimum and the maximum contents of the final guidelines that industrial managers should follow in the future during their forecasting journey:



- Minimum only theoretical approach:
 - Market demand pattern classification
 - Limited literature documentation regarding only statistical models used by Kalis
 - Partial list of statistical forecasting models
 - No associative model between different demand patterns and statistical model
- Satisfying:
 - Demand pattern classification
 - In depth literature documentation on both Kalis and new statistical forecasting models
 - Complete list of statistical forecasting models related to respective market demand patterns
 - Theoretical evaluation of results
- Maximum concrete application of results:
 - Demand pattern classification
 - In depth literature documentation on both Kalis and new statistical forecasting models
 - Complete list of statistical forecasting models associated to respective market demand patterns
 - Industrial implementation to evaluate results

1.4 Research questions

In this first step, the main objective is to gather the client's questions, that is to say the problems that the company needs to solve and their obstacles. Interviews, questionnaires and literature reviews are the main means used to collect the maximum data possible.

In order to achieve the final design deliverable derived in the previous sections, stemming from the company's needs that have been addressed in section 1.2 and from the paper's objectives in section 1.3, the main design question can be addressed:

“What is the future demand forecasting model that can support the decision making journey in a multinational company such as Kalis Group?”

To help answering the main question, the analysis will be supported by several intermediate questions that contribute to the final aim of the study: the sum of the three different analysis will give all the means to solve the main inquiry. The sub questions are developed and explained in the following sections.

SQ1: Demand pattern classification

The forecasting method chosen by the demand planners, strongly depends on the market's nature. Nowadays, research has still not succeeded in determining a reliable classification method to help demand planners understanding the nature of their market. Kalis group has tried to realize a first classification procedure but the study is still in its early stages. During the analysis, the current model will be updated and the main factors that characterize markets demand will be found. To help solving this issue the following question is addressed:

SQ1: “How can the markets portfolio of a multinational be classified?”

The current issue is now how to implement the market classification. Multinationals are characterized by subsidiaries around the world, different product types, different brands. Which element needs to be prioritized during the classification process? Should the classification be done according to the product line, to the region or to the market profit? Which are the rules to follow in a multinational context? Most of all, how can the current variability and frequency factors be computed?

The main goal of this analysis is to find the best practice that can be applied by managers in a multinational setting to classify their market demands patterns. In the past researches only a few industrial applications regarding demand classification have been performed, it is hence one of the goal of this paper to further extend previous literature from an operational point of view: the concrete application in Kalis will contribute to improve literature from an operational perspective

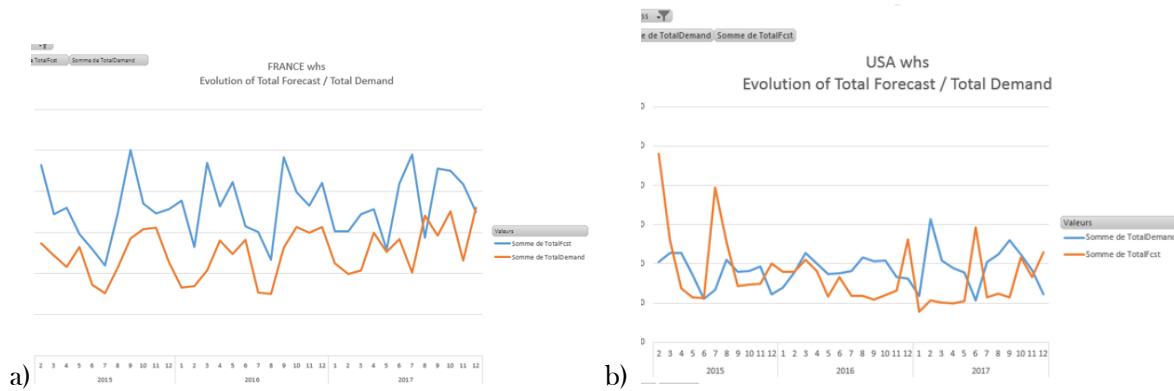
SQ2: Statistical models

Nowadays statistical models for future demand forecasts are considered by managers as a “black box” (N. Saccani, & A. Bacchetti, 2012), that is to say that they represent something unknown and therefore hard to rely on. In Kalis this is the main cause of the supply chain bottleneck: a redundant list of mathematical models that needs to be filtered and renewed. Because of several factors, more and more managers make previsions according to their manual calculus and personal judgments and when they choose to use the statistical method, they always apply the easiest ones because of their lack of technical knowledge. This is the effect of a discrepancy between theory and practice.

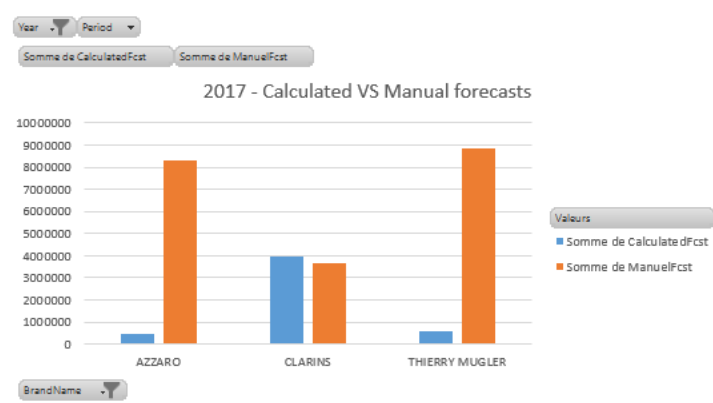
The main reasons of this occurrence are:

- A general lack of technical knowledge about the mathematics behind the models.
- Long and out to date list of statistical models
- Uncertainties about the adoption of new statistical methods that still have to be technically validated
- The perceived loss of control by demand planners when relying on computers calculus (N. Saccani, & A. Bacchetti, 2012)
- Communication issue between the central administration and the subsidiaries: the forecasting process is individually done by each demand planner with not enough communication with Kalis central hub

The consequences of these factors are easily remarkable in the following graph realized by the database in Kalis containing all the past records of demands forecasts. More specifically, the first two graphs represent the gap of demands retrieved in 2017 for the two of the biggest markets for Kalis. The third graph represents an overall lack of trust in the statistical models that results in manually computing the future demand instead of relying on the software.



(Figure 5: deviation between total forecast and total demand in a) France and b) USA)



(Figure 6: sum of manually and calculate computed demand forecasts)

All the mistakes committed during the forecasting process by the demand planners represent an important loss for the group, this is why today the company to analyze and find a solution to estimate the best decisional model

In order to overcome this issue, which is common to all multinationals with a broad spectrum of subsidiaries, item types and brands, the problem will be solved by answering the following question:

SQ2: “How can statistics model future demand trend?”

The first sub question will help to have an overall understanding of existing statistical models that can represent different trends. First, thanks to literature, an overall review of statistical models for future demand forecasts will be presented. Then, through concrete simulations of Kalis data, the list of models used today by Kalis will be filtered and optimized.

SQ3: Statistical models for future demand forecast

Thanks to the results given by the SQ1 and SQ2 the different markets demand categories as well as a reliable list of statistical models will be known for future forecasts, thus the final association between these two last elements will be finalized. This step of the analysis is probably the most delicate because at the end of it the final manual of managerial guidelines will be realized: the demand planner will know exactly how to recognize the nature of the market at stake and consequently which statistical model is linked to it.

According to what it has just been said, a third sub question will be addressed:

SQ3: “Which statistical forecasting models must be used to forecast the demand of different markets?”

The final solution of this analysis will help demand planners to easily associate the type of market they are working on to its related statistical model without uncertainties. What it is therefore urgent to do is to provide them with a clear procedure to follow while making future forecasts and reminding them that they still are at the center of the decision making process even if affiliated by a machine. They will finally notice that the calculated demand forecast will both reduce the overall lead time of the all procedure and improve the final forecast performance.

Finally, Table 2 gives a global overview on the research questions just described together with their specific role:

(Table 2: sub questions and relative research method)

Sub-Question	Source	Embedded unit of analysis	Goal
1. How can the markets portfolio of a multinational be classified?"	Documentation Kalis records of last three years demand pattern	27 subsidiaries of Kalis group	The best practice that can be applied by managers in a multinational setting to classify their market demands patterns from an operational point of view
2. How can statistics model future demand trend?"	Documentation Kalis list of current statistical models used	Kalis group	The list of the main statistical models for future demand forecast will be derived: this first will help multinationals to both delate from their list of models those who are useless and innovate those that are out of date
3. Which statistical forecasting models must be used to forecast the demand of different markets?"	Documentation Archive of Kalis KPIs Kalis records of last three years of actual demand patterns	27 subsidiaries of Kalis group	Statistical models' accessibility Procedure to follow to associate the type of market to its related statistical model without uncertainties

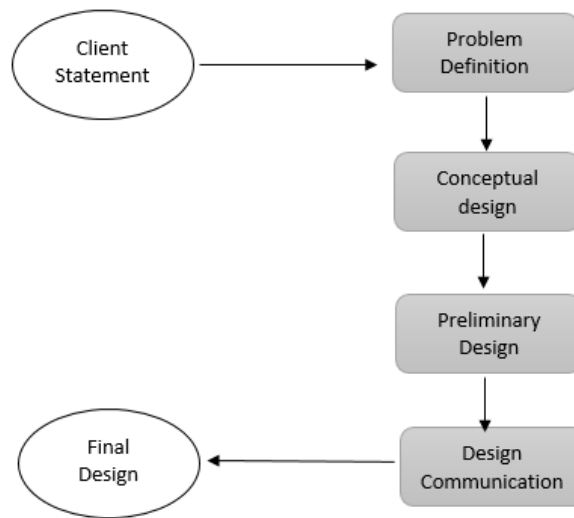
Now that all the research questions have been identified, it is possible to describe how they will be approached: this topic will be described during next section where the research design and methodology will be discussed in detail.

1.5 Research design and methodology

In this section the design process to reach the final deliverable is depicted in order to translate the company's needs into concrete research's functions (Dym, C. L., & Little, P.)

For the case at stake the ultimate function of the final deliverable, a supportive model for future forecast, will be to find an accessible and universal model to associate different future demand patterns to their specific statistical model. Once again, the scope of the process design is to deconstruct the main problem into sub problems in order to translate the company's statements into more concrete solutions; thanks to this decomposition, research questions will be addressed later in the paper.

In the selected design, four different stages can be identified with each of them being characterized by outputs and inputs. The output of each phase serves as an input of the following one. Figure 7 below illustrates a prescriptive model of the chosen design where each step's tasks are depicted along with their respective meaning



(Figure 7: prescriptive model of the research design chosen)

Client Statement

In this first step of the design, the main aim is to gather the client's, Kalis company, questions, problems to solve and obstacles. These have been addressed in Section 1.2 and 1.4:

- No relation between observed demand and demand forecast
- Loss of sales because of wrong forecasts
- Mistrust of statistical models / Lack of technical skills
- Need to classify different markets patterns
- No operational approach in the theory

Problem Definition

This phase is a first attempt in translating the company's wishes in more concrete engineering propositions with the main tasks focusing on clarifying the client's requirements, on identifying the possible constraints of the research and on establishing the functions of the design and to give a clearer vision of the analysis' objectives.

Requirements

- Prescriptive: universal and accessible model that explains how to take the best decision
- Procedural: low computational cost and time, model easy to understand
- Performance: lower the deviation between actual demand and forecast

Constraints

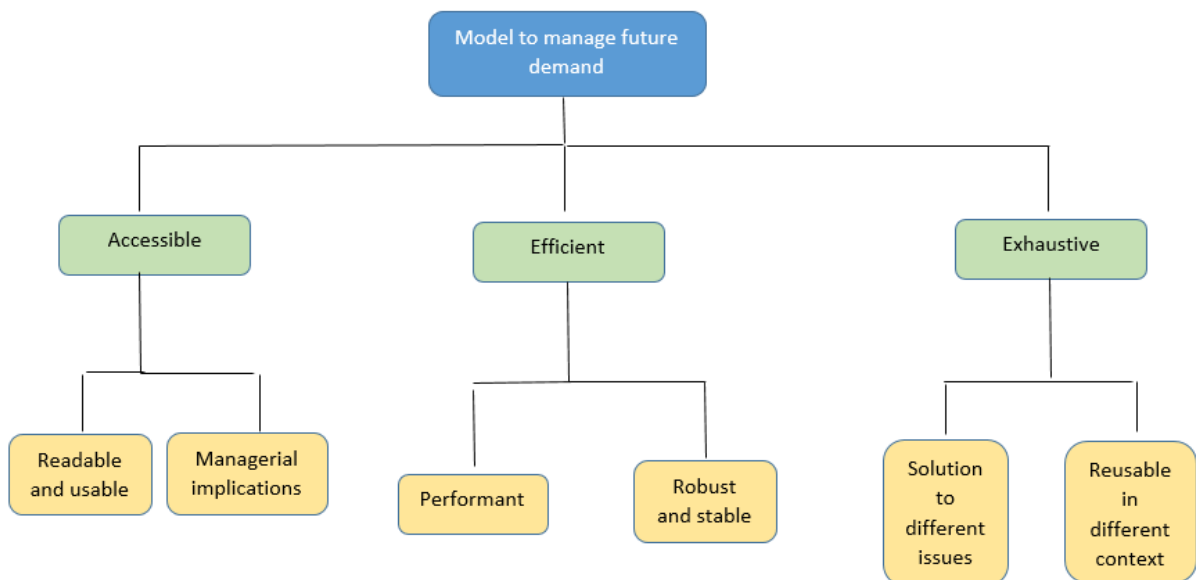
- Luxury markets
- No judgmental adjustments in the forecast
- Basic products (products in the maturity phase of their life cycle, see Annex A.3)
- No promotions and lunch

Functions

- Support to decision making for future forecasts
- Suggest how to categorize the market
- How to associate demands patterns to specific statistical models
- How to explain forecasting statistical model

Objectives

The objectives tree can help decomposing the main goal of the research into sub steps that can make the final objectives easier to handle and help to understand how the research analysis is structured:



(Figure 8: objective tree)

Conceptual Design

In this phase, according to the company's wishes and to what the analysis can do to satisfy them, different alternatives and schemes of possible designs are derived; several concepts are developed and confronted against each other in order to reach the best final solution. In order to achieve this the quality function deployment (QFD) matrix is useful because it allows to evaluate the correlations between customers' wishes and possible solutions: indeed this advanced tool allows to derive the design specifications with the ultimate goal of increasing the quality of the final results. The QFD matrix plots use requirements against engineering attributes and try to establish correlation relationships between them. This allows both the positive and the negative interactions between problems and solutions to be highlighted and hence the optimal alternative can be selected

		Possible solutions									
		Association of demand pattern to statistical model	Evaluation indicators	Routine to follow	Final deliverable: supportive written manual	Final deliverable: oral exposition of to the	List of statistical models explained	Classification of demand patterns according to mathematical indicators	Classification of demand patterns according to customers tastes	Classification of demand according to products specificities	Classification of demand according to each specific item
Client's wishes	Usability										
	Supportability										
	Stability in time										
	Reusability in different industries										
	Adaptability in different markets										
	Accessibility										
	Performant										
	Logic										
	Reduction of time waste										
	Reduction of cost										

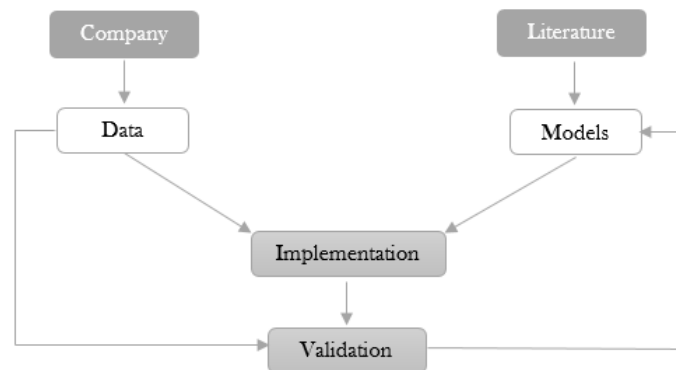
(Figure 9: Quality Functions Deployment matrix)

Several solutions were addressed in order to tackle different clients' needs. From Figure 9 it is easy to notice the most satisfying and the most limited ones. Stemming from this analysis, the preliminary design specifications can be more clearly derived.

Preliminary Design

By building on the outputs of the previous steps, it is possible to identify the main attributes of a preliminary design. At such an early stage, the main tasks focus on the modelling of the conceptual design and the attempt to test and evaluate it.

The main structure of the conceptual design that will help the analysis to build and structure the final deliverable is as follows:



(Figure 10: preliminary research design)

As it is easy to notice from the Figure 10, both the company and the literature are the two main inputs of the Implementation phase, that can be seen as the trial and error phase of the research. Respectively, the company is providing the research with real time data and the literature is providing with the means to analyse these data: forecasting models. The output of this testing phase, the concrete analysis results, will be the input for the next phase, the evaluation phase, where the validity of results found will be tested. A feedback cycle can be noticed in the design process straight after this phase. If results are not convincing enough or are not giving the desired performance, the process goes back to the first step and a new trial and error phase starts thanks to the lessons learnt by the previous analysis.

According to this, one of the main task at this stage is to clarify how to evaluate the final results: this is one of the most delicate and important phase of the analysis. Thanks to the evaluation phase better results can be obtained through the feed of new information given by the output of a process back into the same process. This feedback is repeated until the final results are successfully performing.

Evaluation procedure

In the case at stake, simulations of future forecast and computer analysis will be the main subject of the evaluation procedure and its main means will be the comparison between the old and new values of the company's performance indicators that will give a quantified idea on whether the solutions found are reliable or not:

- Mathematical indicators to measure the performance of different statistical models
- Comparison between new results and previous underperforming results of the company

Design communication

In this last stage the main goal is to find a way to document and present the final design solutions and specifications so that the client, in this case Kalis group, is able to access and implement the concepts proposed. During this phase, the client's feedbacks and advices are the main source of information to improve the quality of the final deliverable. The two main tasks of this final step are given below, respectively the design fabrication specifications and its related justifications:

- **Fabrication specifications**
Supportive manual to future demand decision making process divided in three parts: markets demand classification, statistical model, association between demand pattern and statistical model

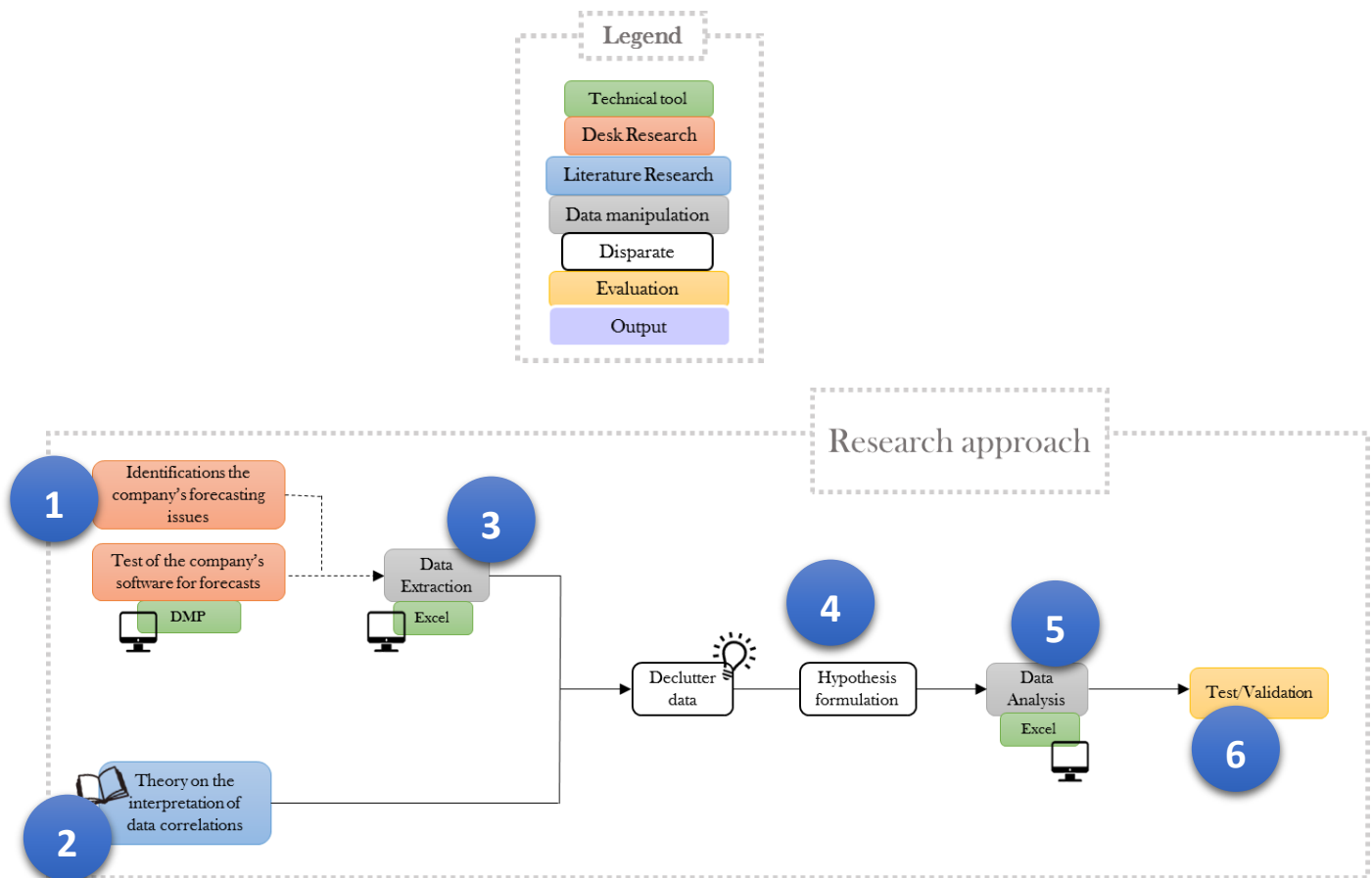
- **Justification**

Easy to access, adaptable to different context, exhaustive, stable in time

1.6 Research framework

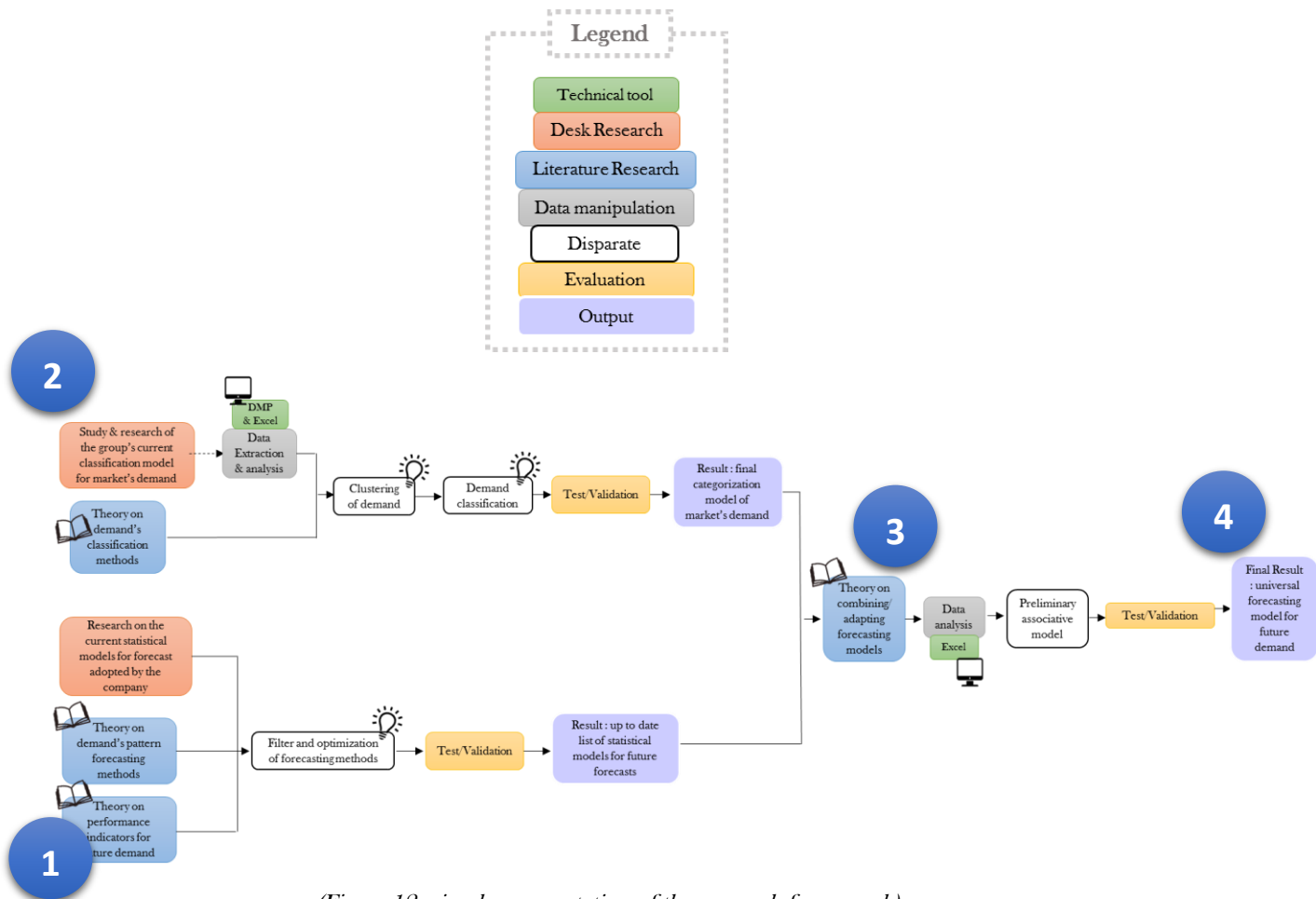
This section will focus on the framework of the research and how results from the different sub questions are linked to each other in order to provide a step by step answer to the main research question.

In the following research Armstrong's approach (Armstrong, 2001) has been taken as a base of depart for the research methodology; Armstrong divides this latter into six main steps: frame the problem, obtain information, select methods, evaluate methods and use forecasts. Regarding this research, the six main design stages identified by Armstrong have been adapted into five main phases: the presentation of the problem context (1), literature review (2), data extraction (3), hypothesis formulation (4), data analysis (5) and final evaluation (6). By following this structure, all results of each chapter can be linked to each other. Figure 11 can help summarize the so described research approach:



(Figure 11: presentation of the research approach)

The final model design and the general process adopted to collect and analyze data is represented in Figure 12 in order to have a first general view on the research structure:



(Figure 12: visual representation of the research framework)

The framework can be read as follows:

1 = during the first research question, the overall demand is initially classified into sub groups according to different product's attributes in order to help managers dealing with smaller amount of data. Then a new categorization for market demand will be carried out thanks to which each cluster will be associate to a specific demand's class (stable, erratic, lumpy, etc.).

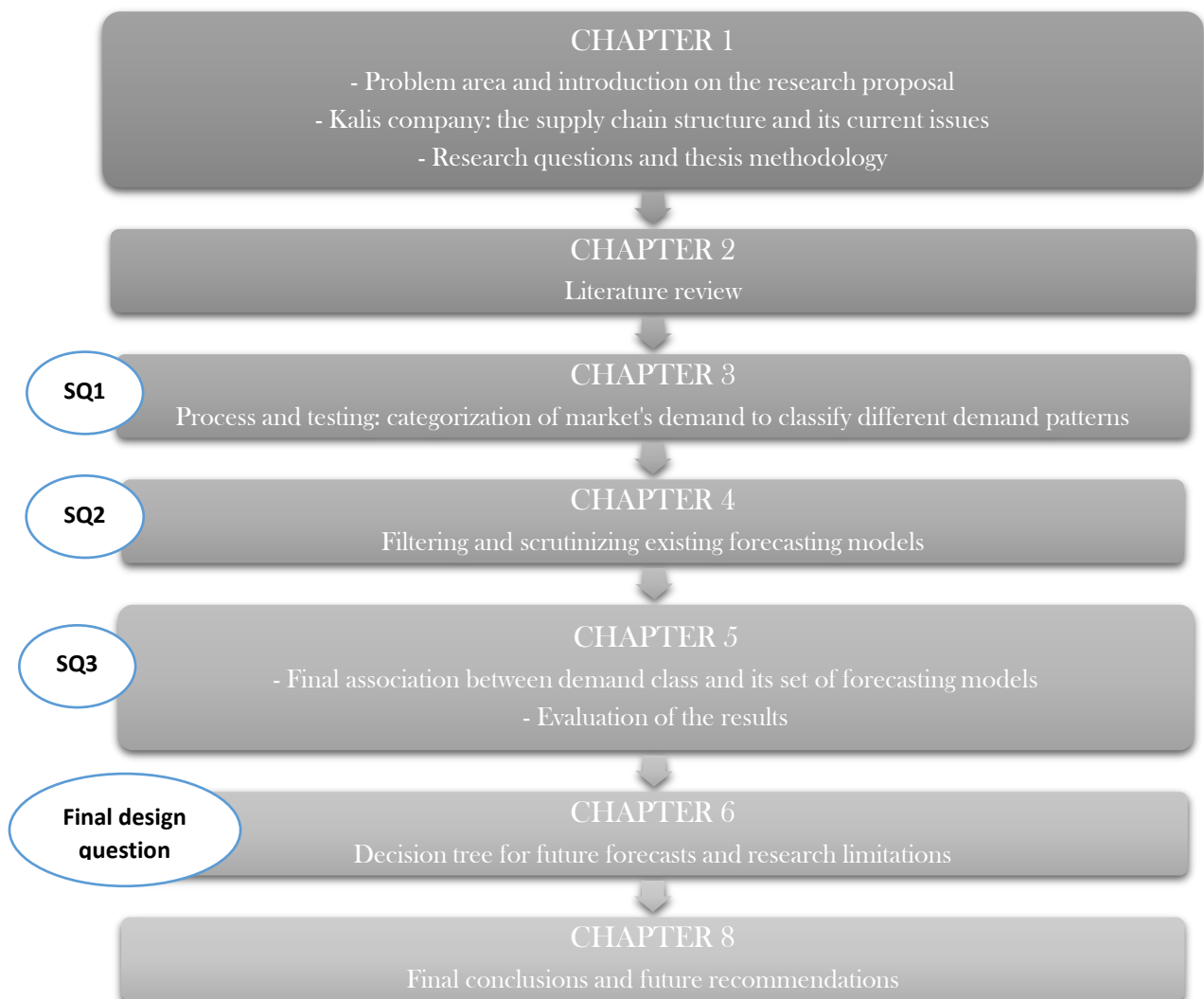
2 = the second research question will be led in parallel: stemming from past literature studies, an exhaustive list of up to date statistical models for future forecast will be established. Each model will be linked to a comprehensive explication about how and when to use it, and finally the current agenda of Kalis statistical models will be filtered and optimized

3 = results from these two first sub questions will be jointly linked to answer the third sub question: now that the guidelines on how to classify the market and the meaning of statistical models for future forecast has been highlighted, it will be possible to associate each demand pattern to its relative statistical model. This third step will be a natural implication of the previous results.

4 = finally, the overall procedure to follow while doing future forecast will be derived: the first step is to understand how to aggregate demand and its consecutive classification into different market categories will be explored. Next, the importance of statistical models during the decision making process. The final step will focus on learning how to associate different demand patterns to their most suitable statistical model.

1.7 Structure of the report

This initial chapter was essential to identify the research proposal, to understand the company's supply chain and issues and to finally have a global view on the specific research questions and research design. Following, during Chapter 2, a comprehensive literature review will be presented in order to highlight the current literature state of art and therefore derive the research gap. The first research question will be dealt in Chapter 3 where a deep analysis of the categorization of market's demand and its implementation in the industrial context will be done. In Chapter 4 an answer to the second research question regarding statistical models for future forecast will be given. The results from these two previous analyses will be gathered in Chapter 5 where a stable set of statistical models will be linked to each market class. Results will be validated and thanks to this, a final model for future forecast will eventually be realized. Chapter 6 will present and discuss the answer to the main research question concerning the creation of a supportive model for the forecasting process. The final chapter will be dedicated to conclusions and discussion of the final results, to the identification of future research lines together with future improvements to the current topic of research.



(Figure 13: Structure of the report)

Chapter 2

Literature Review

2.1 Forecast and inventory management: background history and current issues

In this section, past literature about demand forecasting and inventory management is reviewed and analyzed. First the literature concerning the forecasting process as a whole is presented then, more in detail the past studies concerning the market's categorization models are shown. Finally, the knowledge gap will be addressed together with the solutions proposed by this paper.

The state of art in the forecasting process

Junjun and Yongping in their work highlighted the erratic tendency of retailers in applying forecasting technologies (Junjun, G., & Yongping, H., 2008) to make future previsions. The topic of their study is subject of this research too: building a joint decision model that can simultaneously incorporate inventory control (IC) and product variety (PV) necessities. In order to achieve this, they analyzed the performance of different demand forecasting methods. In their assumptions multiple brands, promotion, sales price and seasonality are taken into account which is a positive starting point for concrete applications in a multinational context. The limits of Junjun and Yongping's work is their over simplification of reality as it comes to the demand modelling: only one dealer and one retailer are considered in the study and both are located in the same place, giving a resulting lead time of the transaction equal to zero. In addition to this, a centralized decision making process is assumed with all the information available when needed: this context is far away from the one experienced by real multinationals. As regards the forecast method analysis, they narrow their view on conventional statistical demand technique that cannot be generalized to all type of demand patterns.

Another remarkable work in forecasting and stock control research is presented by Strijbosch et al. (2008) that, also for the study at stake, represents an important starting point. Their study is an attempt to link theoretical knowledge to actual reality. In their analysis they use statistical models that will be discussed also in this paper: the single exponential smoothing (SES), the simple moving average (SMA). Even if their analysis contributes to an extension of the past knowledge to the spare demand topic, the results are still somehow too theoretical and simplistic. In the empirical dataset they retrieved from a Swiss software manufacturer, seasonality factor and trends of data where at least one zero demand was found have been excluded from the analysis. The transaction lead time was also taken as nil/zero. In addition, the statistical models analyzed might be too simple and out of date to be relied on. Nevertheless, they achieved important results for future research: a methodology to estimate both an optimal forecast parameter values and an optimal estimator for future demand forecast. In their conclusions, they suggested to future research to enhance the operational application of future forecasting technique, one of the goal of this paper.

Jha, A., et al. (2015) work brings an interested contribution by presenting an exhaustive explication of forecasting items in groups. The main contribution of forecasting groups instead of single items is that the final model will be more robust to outliers or missing values. Making forecast on the overall data set is not advisable since specificities of the set such as seasonality and trend could not be recognized. Thus, it is important to find the right level of detail in order to cluster the amount of historical data collected about past demand. Jha, A., et al. (2015) gave some rules to follow while clustering the data set: every item has to be related to only one group, that is to say that different clusters cannot overlap. Second, it is important to define both upper and lower bound with regards to the group size. The upper bound is needed to reduce computational times and cost whereas the lower bound helps to have a group's size which is

consistent enough to guarantee robustness to abnormal data. The work continues by presenting different techniques on how to estimate the similarities of different items and on clustering techniques. The reason why this work is not applicable in today's industrial sector is its technical specificities. Algorithms presented required high computational skills and specific software that are not always found in industrial contexts. These final results are not accessible by managers who would become even more diffident to apply the model.

It is relevant for the topic proposed in this research to analyze the work of Bacchetti and Saccani on the gap between research and practice (2012). They noticed that companies have recently started to give more attention to spare demand pattern and consequently to invest in it. The lack of a universal view on intermitted demand, pushed the two researchers to bring knowledge theory closer to everyday managerial practices. First, they recognize that the issue of classification is still in its infancy phase and strongly needed to be implemented in real case studies in order to determine each model practical applicability. Then they revised all the past literature about the most used statistical forecasting methods: even if they admit that recently more efforts are put by researchers in the study of spare parts demand, the optimal statistical technique has not been found yet. In addition to this when considering demand classification method, the past literature is never taking into account the different nature of items within an industrial context. Finally they highlighted one of the most important concept that is going to be the center of this analysis too: statistical models are nowadays considered as "black box" by companies because of a lack of technical knowledge, money, skills and the uncertainty behind several/multiple new techniques that still have to be proved. Bacchetti and Saccani reviewed that it is only a theoretical overview of the most urgent demand forecasting topics that need to be faced and considered by the current research.

(Table 3: past literature research)

Author	Contribution	Limits
G. Junjun & H. Yongping	- Joint decision model that simultaneously incorporates inventory control and product variety - Consideration of different brands, promotion, price and seasonality for the future demand	- Use of conventional statistical methods for future demand - One dealer and one retailer located in the same place - All information is available when needed
Strijbosch et al.	Realization of a methodology to estimate an optimal forecast parameter and an optimal estimator for future demand forecast	- No operational applications - Use of simple and conventional statistical models for future forecast
Jha, A., et al.	- Importance of forecast in clusters - Methods for estimating seasonality and clustering techniques - Low demand management	- Highly demanding from a computational point of view - Limited accessibility to industrial managers
A. Bacchetti & N. Saccani	Overall denounce of the nowadays gap between theory and practice: lack of an universal view, inefficient	Only theoretical approach, no concrete application

	demand patterns classification models, statistical models as a “black box”	
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Now that the main issues concerning the forecasting process from a global perspective have been identified, it is possible to go one step further and explain the literature state of art concerning the categorization of different market's demand.

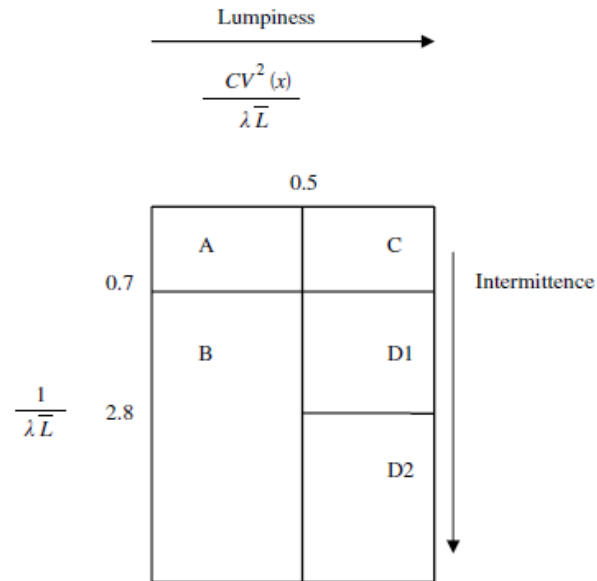
2.2 Past demand categorization models

In this section the previous literature regarding the categorization of market's demand is presented: concerning the classification of the market's demand, both Williams' and Syntetos' methods will be analyzed, based on the work of Syntetos A. A., et al. (2005). Then, Kalchschmidt et al. (2003) work concerning the alignment between the supply chain at stake and the different demand patterns will be presented. The little research that has been done around this argument only focuses on rough mathematical calculus without giving easy final operational guidelines to follow. In order to overcome this, the Syntetos A. A., et al. method (2005) presented will be concretely applied in an industrial context in Chapter 3 and then its results will be analyzed. The aim of this analysis is to prove that the final performance of an efficient market's demand categorization is “*successful when it is viewed in a wider system context, where constraints, interactions and market plans all affect the final forecast*” (Fildes et al, 2008). Results gathered from the literature will be collected (Chapter 2) and concretely applied (Chapter 3) and thanks to this first analysis, improvements will be then developed. The final deliverable of this analysis is to find a model for the categorization of the market demand that can be accessible from industrial managers.

Williams model

Williams' work (Syntetos A. A., et al. 2005) is one of the first model for demand categorization that can be found in the past literature, indeed it also represents one of the most simplistic work in this sector. Nevertheless, he contributed in identifying the two main attributes that are still needed to make the main distinction between stable and intermitted demand: the demand's variability and frequency along lead time periods. In his categorization scheme, he classifies demand into four different categories according to the two attributes (Syntetos A. A., et al. 2005) that have just been mentioned above:

- $\frac{1}{\lambda \bar{L}}$ indicates the demand intermittency (e.g. how often positive demand happens) where $\bar{L}$ = the mean of the lead time length and λ = mean demand arrival rate (Syntetos A. A., et al. 2005)
- $\frac{CV^2(x)}{\lambda \bar{L}}$ that describes the demand lumpiness (e.g. the spare nature of the demand) which varies according to both the demand frequency and variability; $CV^2(x)$ is the squared coefficient of demand size variability



(Figure 14: Williams' demand categorization, source: Syntetos A. A., et al. 2005)

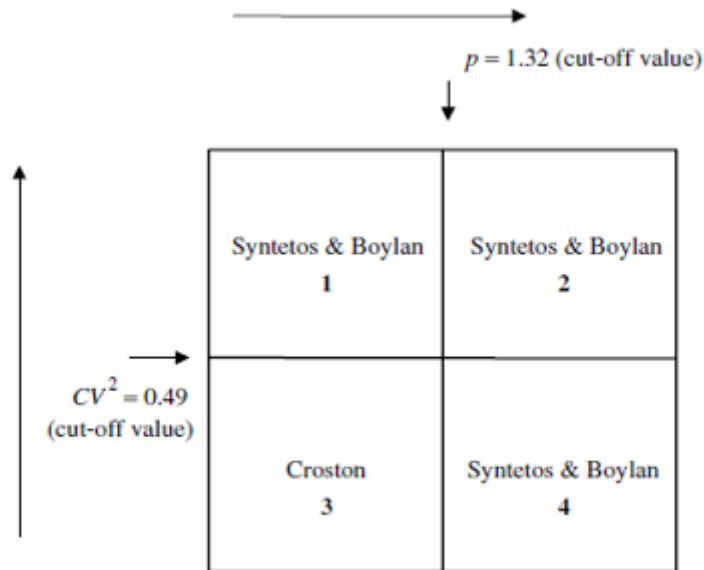
The four zones identified are classified according to their values of variability and lumpiness: D1 sporadic (erratic), D2 highly sporadic, that is to say markets characterized by irregular demand size and unpredictable timing. The zone B classifies slow demand and all the others, A and C, are smooth demand patterns always characterized by irregular demand transactions but in this case the demand intensity is always low (low variability of demand).

Williams' conceptual classification scheme was criticized not to adequately describe the real demand trend because of its simplicity in considering only two attributes; more in detail, the demand regarding the "slow" market was not sufficiently described because only its variability factor is analyzed.

Consequently, to try to solve this problem, Syntetos A.A. et al (2005) proposed a developed scheme that starts from Williams's basic work.

Syntetos model

The Syntetos A. A., et al. method (2005) to categorize specific demand pattern into different classes is now presented and afterwards implemented in an industrial context. In their work, the categorization of demand is driven by two principal metrics: the squared coefficient of variation (CV^2) that indicates the lumpiness of the demand, i.e. the variation in size of the positive demands (when the latter occurs); secondly, the average demand interval that indicates the frequency of demand so the time period between the occurrence of consecutive positive demand in the past. These two factors allow to divide the market in four main regions as it is shown below:



(Figure 15: Croston's method - Syntetos and Boylan method. Source: Syntetos, A. A., et al. 2005)

The corresponding four demand categories found are as follows: area 1—erratic (but not very intermittent); area 2—lumpy; area 3—smooth; area 4—intermittent (but not very erratic). Precise definitions of these 4 classes of markets will be given in Section 3.5 where this research question will be solved.

The problem with this final results is, as claimed before, the theoretical approach that has been adopted. In order to face this, the application in the industrial context of this model, with a few modification concerning variability and frequency cut-off values, will be described in the following sections concerning the first analysis of this research question.

Kalchschmidt model

The analysis of Kalchschmidt et al. (2003) represents a milestone for the final objective of this question because in their work they tried to link the supply chain to the demand pattern from a managerial perspective: they developed a specific solution for a specific supply chain structure which exactly corresponds to the group's multi echelon supply chain.

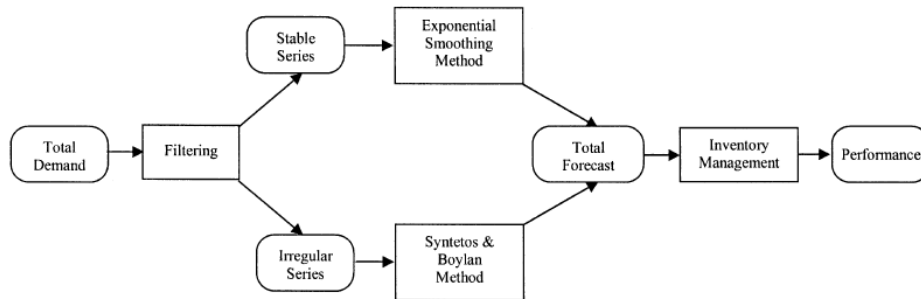
As it is stated in their article, nowadays one of the main causes of forecasts' inefficiency is that managers tend to simplify the forecast strategy that they choose to implement to their supply chain: even if managers recognize the existence of two main demand patterns, stable and irregular demand, analytically they do not distinguish them. Figure 16 represents the forecasting process that is always adopted by planners to no matter which demand pattern:



(Figure 16: traditional forecasting process adopted by managers. Source: Kalchschmidt et al. (2003))

Kalchschmidt et al. (2003) gave different alternatives to the model above which should be adopted nowadays by industrial managers.

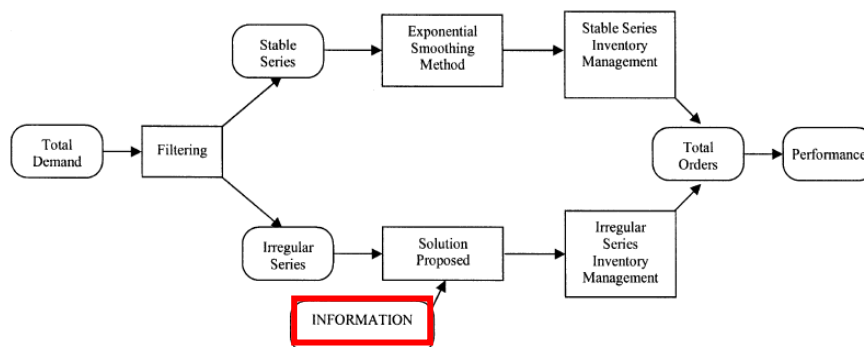
First, they urged to split the demand pattern in the two main categories that have been mentioned before: irregular and regular demand. According to them, different forecasting journeys have to be followed. They conceptualized this alternative into three different phases, first the filtering of the demand pattern, second the adoption of the right statistical model, lastly the consequent inventory management. The concrete representation of this option is given below:



(Figure 17: alternative supply chain design. Source: Kalchschmidt et al. 2003)

It is interesting to focus on the supply chain design proposed by the authors of the paper which is the contrary of the procedure offered by Syntetos A. A. et al. (2005) that has been previously illustrated: here the first step of the decision making process is the aggregation of the future demand. This is one of the few cases where research has adopted an industrial point of view, e.g. a concept that take into consideration the industrial mechanisms and complexities, since for the first time, customers and product's specificities are taken into account.

Finally, Kalchschmidt et al. (2003) give an ulterior suggestion to improve the supply chain performance: the consideration of the amount of information which is collected every day in a multi echelons supply chain structure such as Kalis. Unfortunately, the majority of this latter is not taken into account during the decision making process. A possible flow of information between consumers and the company could increase the final forecasting performance since managers will be aware of the order quantity before taking any decisions. Below a representation of the described alternative is shown:



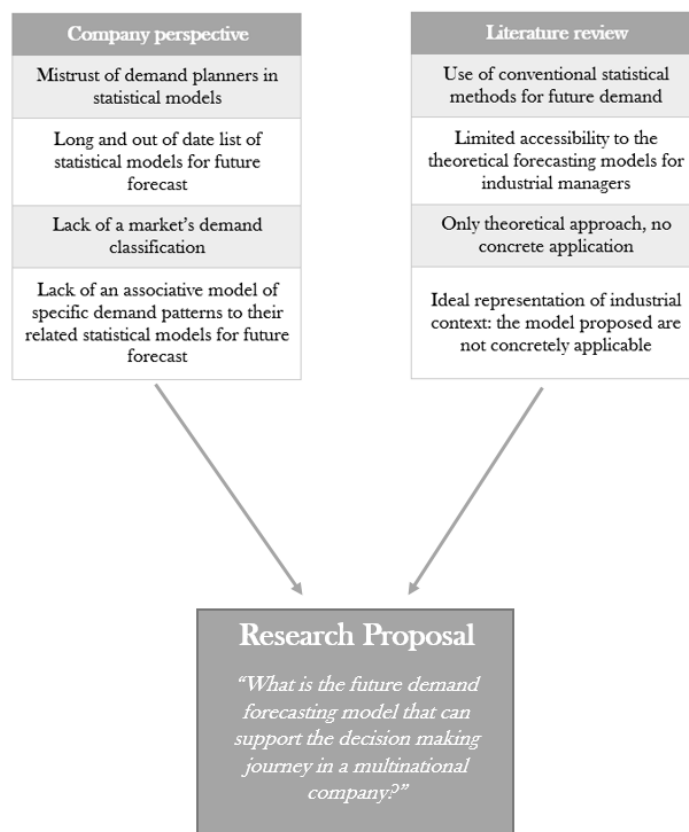
(Figure 18: alternative supply chain design. Source: Kalchschmidt et al. 2003)

This option of supply chain design is still impossible to be concretely implemented since it is not feasible to create a communication channel between multinational companies and their end customers. By the way, the subject raised by Kalchschmidt et al. (2003) is important to remind to managers that making forecast is not only a matter of mathematical issues but also the organization's and communication's structure highly influence the final results.

2.3 Research gap and intended deliverable

This paper aims to jointly study and gain more insight in the future demand forecast strategies adopted by multinationals as well as their inventory decisions. Today the two latter are strictly connected, as it is explained in Section 1.1, and represent one of the main source of profit for a company since they are impacting both its final customer satisfaction and its related costs. Unfortunately, there is no current rule in this domain, no theorem that can help managers along the decision making process because of the dynamic and unforeseen nature that characterizes the interconnection between forecast and inventory management. There is still not an indication on what is the best forecasting technique to apply according to different demand trends and market type as it has just been said in Section 2.2 of this chapter. In addition to this, both inventory control and future demand forecast managements are highly contextual, i.e. the number of external and unpredictable factors changes according to the case at stake.

What has just been claimed can be confirmed by both the company's issues highlighted in Section 1.2 and the past literature's gaps presented in this chapter concerning the issues of the forecasting process. It is easy to notice an interconnection between the theory and the industrial perspective around this topic: thus, next step is to put the literature and the multinational's issues one against each other and, by relating them, derive the main research aim, as it is shown in Figure 19.



(Figure 19: Identification of the research proposal given the company's and the literature gaps)

The above scheme shows how the main research proposal has been derived by the author of this paper both from the industrial context and the theoretical studies. In the diagram, the main research question has been highlighted in order to scope out the main driver of this analysis.

2.4 Research boundaries

In this section, in order to help understanding the context of the study and most of all to scope the final results aimed by the author of this article, some critical points that will not be taken into consideration during the analysis are listed below. Later, according to what is outlined in this introductory part, suggestions and advices for future research will be given.

First of all, Kalis' business concerns the luxury market therefore the final consequences and results application will not automatically be applied to other sectors, such as the mass production market (food and pharmaceutical industries), where goods' needs and constraints are different compared to the luxury sector. In order to be able to reach the highest level of external validity, so to have a final generalizable solution, only the so called "Basic" products will be study: these are "must to have" products that made Kalis popular all over the world. They are milestones for the Group's market share its establishment. In addition, still for a generalizability reason, no promotions or launch of new products will be considered. This is not to go too much in detail and avoid to lose time on not relevant argument. Research still lacks behind and there is the need of starting from the base, from the fundamentals.

Mathematical calculus is not sufficient to describe the future demands in its totality because it exists a series of external and unforeseen factors that can accidentally happen and this goes beyond statistical modeling. In this work, judgmental adjustments that can impact the future demand forecast is not analyzed. It has been chosen to leave this topic out of the scope because it requires another type of research approach.

Finally, the company provides past records from the last three years, 2015 2016 and 2017; no older demand patterns' data will be analyzed.

In the next chapter the first research question regarding the process and testing phase to understand how to categorize different demand patterns will be presented. The inputs for this first analysis will be the literature explained in Section 2.2 of this chapter concerning existing models of demand's classification and the company's real time data, as it has been anticipated in Section 1.5.

Chapter 3

Market demand classification

3.1 Introduction

In this section the first research question will be treated: *How can the markets portfolio of a multinational be classified?*²

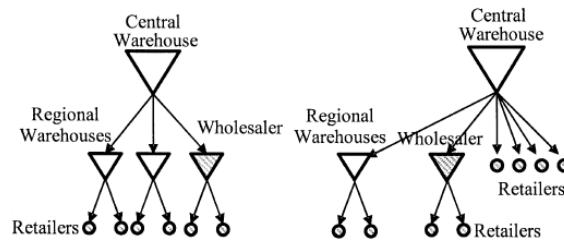
The basis of supply chain forecasting and planning system is the demand categorization of a broad spectrum of items from which the planning activity is derived. As it has been showed in the previous chapter, Section 2.1 and 2.2, past literature and research have not given the deserved attention to this topic, and the few researches that have approached the problem only from a theoretical perspective without adopting a concrete operational view and application. Furthermore, the few available models have been showed not to be complete and not suitable for the industrial sector.

The main challenge is nowadays represented by spare demand patterns, i.e. when there is a fluctuation between points in time of positive demands and large period of zero demand. In this kind of context, the number of data points in time will be greater than the number of positive demand occurrences (Syntetos, A. A., & Boylan, J. E. 2001). The frequency of this trend is unknown as well as the magnitude of the order. This is what makes intermitted demand (i.e. spare demand) difficult to deal with for managers. “*The stock value for spare parts may come for up to 60% of the total stock values in any industrial setting*” (Xu Q. et al., 2012). Demand variation is given by several factors, both internal and external to the firm’s boundaries: changes of customer’s tastes, arrival of new competitors in the market, transformations of the specific supply chain of the company, unforeseen changes in the economy of the country. From Xu Q. et al. (2012), these unpredictable events, bring managers and researchers to address two questions: when will the next positive demand happen? Once this happens, which will the demand intensity be? Stemming from this brief introduction to the case, “*intermitted demand patterns are built from two elements: demand size and the demand probability*” (or frequency of demand) (Teunter, R. H., et al. 2011). In addition to this, demand managers tend to estimate demand fluctuations according to their own feelings and personal judgments and by doing so they contribute to an increase of the bullwhip effect, i.e. the propagation of demand uncertainties in the whole network.

Following the research method chosen for the development of the study, the section is structured as follows: first, a brief explanation of the context and problems experienced by Kalis group is given; then, results retrieved by the literature review presented in section 2.2 are concretely applied and analyzed. This first analysis will be the input for the second analysis, where adjustments will be brought to the real time simulations done with Kalis data. In order to provide a better understanding on how the analysis has been conducted, the trial an error phase will be illustrated in detail. The real evaluation of this first answer will be done in Section 5.4 when also other research questions will be solved.

Context and Purpose of the question

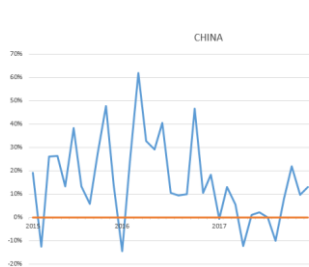
As it has been explained in Chapter 1 (Section 1.2), the company supply Chain has a complex structure. Indeed the group is serving both end consumers (direct delivery) and intermediate warehouses (e.g. Bangkok hub): this complexity is often the source of inefficient forecast management and of poor performance of inventory control. In this system, the control is centralized, i.e. decisions are not taken independently by separate subsidiaries but there is an effort to integrate the information flow in the all system. A nice comparison between a “pure”, simpler type of supply chain structure and a multi echelon organization, such as the one at stake, is given by Kalchschmidt et al. (2003):



(Figure 20: “Pure” multi-echelon vs. supply chains with various numbers of echelons
Source: Kalchschmidt et al. 2003)

The company has recently faced problems of future demand forecasting which is currently damaging both the company profit and customer service (as discussed in Chapter 2): given its multi echelons supply chain, it is not possible to adopt one single strategy for the categorization of demand patterns but different techniques have to be developed. For the purpose of the study, the company made available data from last three years, 2015 2016 and 2017. While the analysis has been done on all the 27 subsidiaries, only the most representative results will be showed.

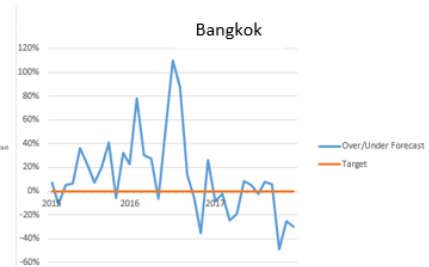
To give a clear idea of the problem at stake, a few examples of recent year’s performances of the company’s main markets are given in the graphs showing the data values relative to the evolution of last three years’ forecasts. More specifically, the graphs exhibit the percentage of under and over forecast with a target level equal to zero. Indeed, the ideal case would be to have the value of total forecast equal to the value of the observed demand.



(Figure 21: Chinese data values)



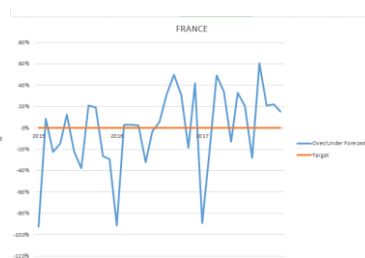
(Figure 22: Singapore data values)



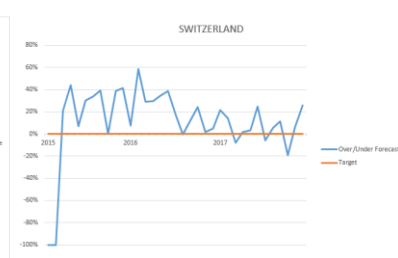
(Figure 23: American data values)



(Figure 24: Russian data values)



(Figure 25: French data values)



(Figure 26: Swiss data values)

While looking at the graphs, it is easy to notice the urgency of the problem: for the majority of the cases, demand forecast is heavily missing the real value of the actual order. Consequently, it is urgent to find a solution in order to help the company adjust its forecast strategy.

First requirements

Before going into the empirical section of data collection and data analysis, it is essential to underline some important guidelines that can be useful in this kind of research in order to help other company to apply the same framework in different context. In Table 4 below the most important requirements and their relative future benefits that it is possible to derive from the past literature and from the company's reality are highlighted:

(Table 4: guidelines for the categorization of market's demand)

Guideline	Future benefits
Avoid to make arbitrary choices when defining the main drivers of the analysis (variability's thresholds, cut-off values, etc.)	Model's generalizability to different contexts
Avoid the adoption of too simplistic models	Models for demand's categorization have to be realistic so that the actual demand can be represented without approximations
Avoid abstraction while modelling	Most of all in the literature, it is easy to find "ideal representations" of the supply chain structure without the considerations of concrete industrial bottlenecks. The adoption of a managerial perspective will facilitate both the implementation and the performance of the final categorization
Conduce the analysis not only from a mathematical point of view but remember to include the customers' specificities	The categorization of the market's demand has to be applied in industrial contexts where sometimes customers' specificities are creating more constraints compared to the mathematical issues. By considering both the aspects, the technical specificities and the market's properties, the validity of the model will be guaranteed

Under the light of the above guidelines to follow when trying to classify the market's demand in the industrial context, the Syntetos et al. (2005) model and Kalchschmidt et al. (2003) assumptions described in Section 2.2 are tested and evaluated during the first research's analysis.



(Figure 27: application of literature results)

It is important to remember that because of confidentiality reasons, the names of the company and its subsidiaries have been changed during the report.

3.2 Demand's clustering

First in this analysis, Kalchschmidt et al. (2003) guidelines concerning customers' specificities are applied. The first issue that needs to be tackled is "*the problem of managing the trade-off between the amount of information collected and the forecast accuracy*" (Kalchschmidt et al. 2003).

To address this trade-off, Kalchschmidt et al. (2006) introduced the concept of "customer heterogeneity" as one of the main driver of demand lumpiness. Indeed, even if demand size and frequency strongly affect demand variability, the specificity of different customers segment alter the final demand pattern. Heterogeneity in the demand can be given by both external and internal elements of the customers purchasing journey: the purchasing process, brand loyalty, utility, socio-cultural elements, the pricing conditions, promotional activities, distributional strategies and so on. Bartezzaghi et al; (1999) affirmed that heterogeneity and demand variability are positively correlated: "*as customer heterogeneity increases, demand lumpiness also increases*". At the same time, high level of heterogeneity requires high amount of information that needs to be collected in order to classify different customers' specificities. This is why in the following analysis, the customer heterogeneity has been considered as the main source of uncertainty and the main driver in the future demand categorization.

The goal is to develop demand categorization according to the specific customer's clusters that will be found at the end of the analysis of the company's past records.

Under the light of these assumptions, the main customers and product characteristics will be given through a list of the main attributes that characterized Kalis production lines. The main attributes are

- Active Code Name = The specific name of the product
- Brand = Contains the brand name associated with the item. Exemple : Kalis age, Kalis Men, Kalis make up, etc.
- Item Group Code = Financial classification of item
- Line Range Name = Product marketing and sales segmentation
- Life Style = it defines the production, forecast & stock coverage logics related to the warehouse information
- Family Name = fragrance, make up or skin care
- Shipped Quantity = the amount of shipped quantity from the central warehouse to the local subsidiary

These attributes are common to all the different industrial sectors, this is why the author of this paper decided to focus on them, in order to give the most generalizable possible results.

To proceed in the analysis, the same data collected for computing the graphs in the previous section have been used. It is again important to remember the filters that have been applied in the analysis:

- Basic products
- Years under study: 2015, 2016, 2017
- Most critical subsidiaries under study: Italy, Russia, Australia, America and China

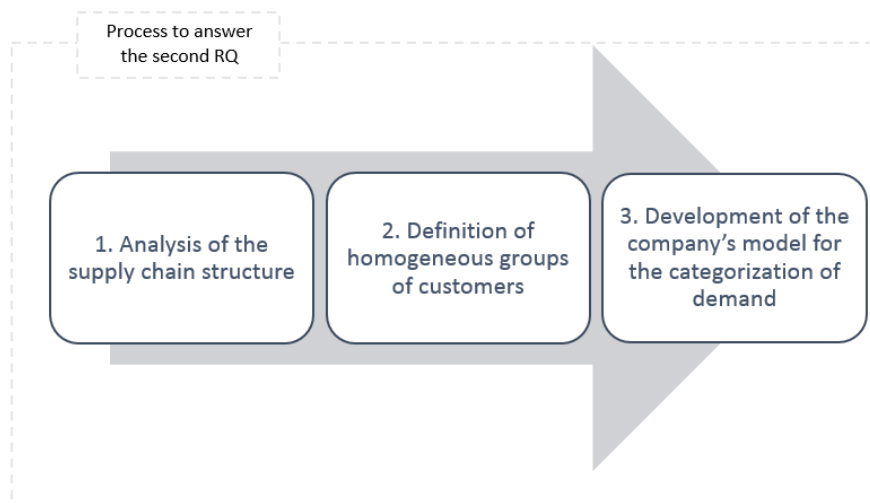
Data from more than 6000 products have been extrapolated from the data management platform (DPM) used by demand planners in every local subsidiary and then to conduct the analysis and data manipulation, information's have been converted to the Excel format.

3.3 Data analysis

Now that the importance of demand aggregation has been highlighted, in this section the analysis' phases are explained. In order to solve the mentioned trade-off between demand variability and customer specificity, customer demand will be cluster according to the most representative attributes found throughout the analysis. Indeed, as it is suggested by Kalchschmidt et al. (2006), the main analysis will follow the subsequent procedure:

1. Analysis of the supply chain structure, that has already been done in the second chapter of this paper
2. Definition of homogeneous groups: information will be aggregated and separately managed according to the main clusters that will be derived during the study
3. The company's model for the categorization of demand based on demand and frequency level will be adjusted

A schematic process on how the answer to the second research question will be derived is given below:

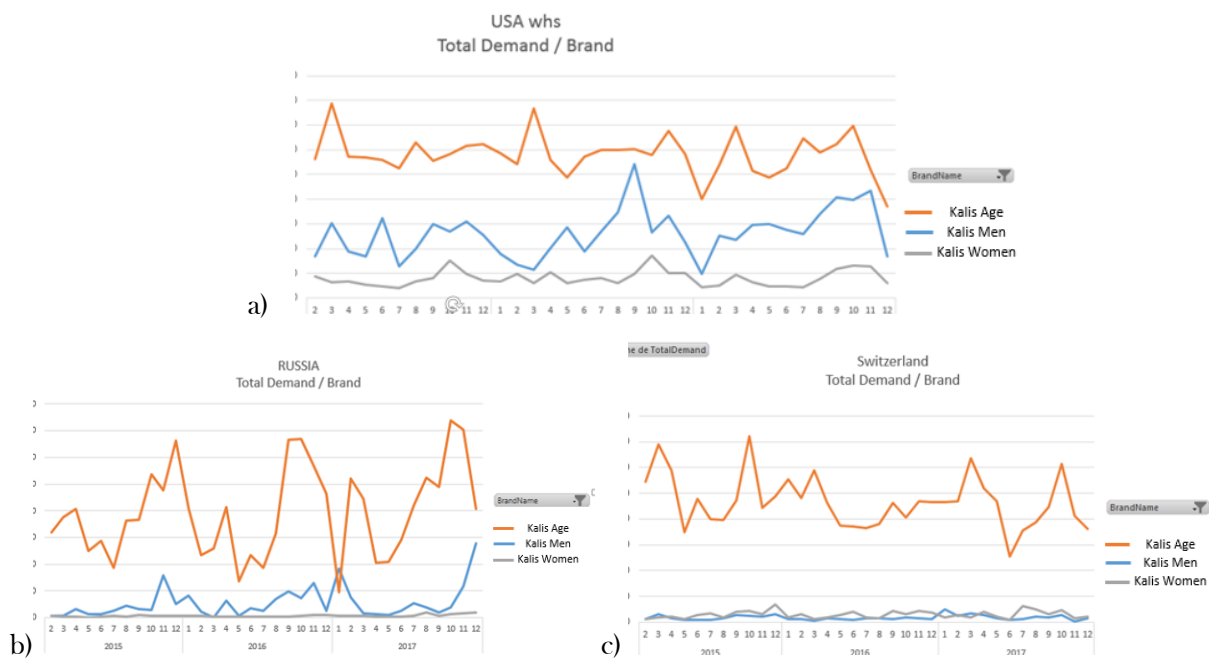


(Figure 28: second research question procedure)

As it will be shown in the following analysis, the main problem will be to decide the level of detail at which leading the clustering process. On one side, demand cannot be considered as a whole, otherwise both heterogeneity and variability information could not be studied. On the other hand, claiming to study demand too in detail, customer by customer, would be too expensive and risky since the amount of information gathered would not be enough.

3.4 Definition of customers clusters

To understand which attributes have to be considered as “filters” of the demand categorization process, for each critical subsidiary the actual demand of last three years has been graphically represented in relation to each attribute. Indeed, in order to understand data patterns, the first step is to plot the set of available data and to have a first glance on them. Figure 29 show the Brand's example: in this case, for each Brand in different subsidiaries it is possible to identify a specific trend of the evolution of the demand; more details concerning the other simulations done can be found in **Annex C.2**.

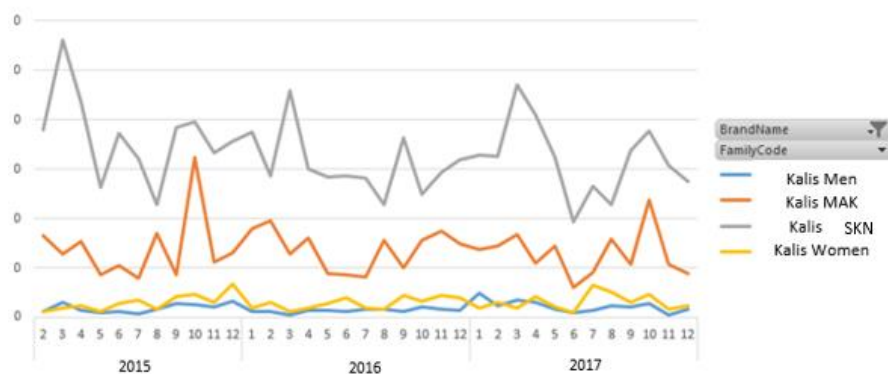


(Figure 29: aggregation of demand according to the Brand, a) USA b) Russia c) Switzerland)

From this first phase of the analysis done through the visualization illustrated in the Annex C.1, a first filter can be straightforwardly applied: it is clear that some attributes are not useful as concerns demand classification patterns, for instance the Item Group and the Line Range have too many different classifications that make the final demand interpretation impossible (Annex C.1).

The product life style is indeed clearer to be interpreted, by the way it would be more reasonable to consider it as an assumption of the analysis: since only basics products are taken into account, only those whose life style is permanent, i.e. with a stable production status, should be studied.

Finally, the most satisfying representations are given by using the Brand and the product family attributes (skin, make up and perfumes). Customers heterogeneity could be explained through the cross analysis of these two elements. According to this, the analysis can start to be narrowed to these two factors (Figure 30).



(Figure 30: application of the two filters for demand's categorization)

In order to give a universal explanation of the first finding mentioned above, the seasonality of each Brand has been computed for every local subsidiary. The seasonality can be a good indicator to identify which

attributes can be considered as filters to cluster all the data collected by industries: indeed, it indicates the repetitive pattern of demand from year to year (APICS, 2009) and when this pattern is constant throughout the years, all subsidiaries belonging to it can be considered part of the same group. In this way it is possible to evaluate whether each Brand has the same trend and pattern over the years, it therefore verifies the assumptions just made above. The importance of seasonality in demand forecasting will be later highlighted in Section 3.5.

The seasonality has been computed through the seasonality index (SI), defined by Kalekar, P. S. (2004), which quantifies how much the demand pattern deviates from the annual average: to compute this, past records from the last three years have been considered. In this case, the European market has been considered.

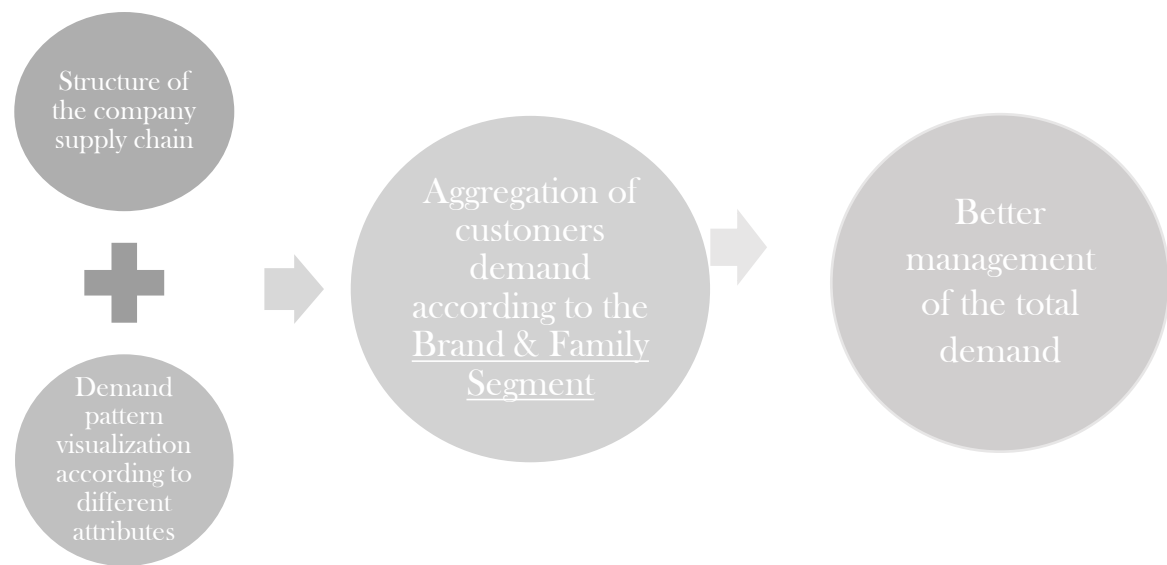


(Figure 31: evolution of SI during 2017 for the three different Brands, a) Kalis Age b) Kalis Men c) Kalis Women)

It is interesting to notice that indeed different patterns can be recognized according to specific brands. Kalis age shows a more stable demand compared to the other two cases. In particular, Kalis Men shows the most erratic trend with peaks in June September and November. Kalis Women Brand presents an overall increasing trend, except for the French warehouse. Therefore these two brands present a more irregular, spare parts pattern compared to Kalis Age which indeed is steady over the years. This observation will be of primary importance later in the paper when the association between different demand patterns with their statistical models will be done.

In addition to the seasonality index, another element that pushes to choose the Brand as a first leading attribute to cluster the customers demand is the supply chain structure: in some subsidiaries, especially for the most contributing subsidiaries of the group, demand planners organize their work according to the three different brands of the company, i.e. forecast for specific Brand are separately treated.

Thus, it is possible to conclude that the attribute corresponding to the product's Brand will be the main filter to manage customers' heterogeneity during the demand categorization process. Therefore, in comparison to the traditional strategy adopted by the company, it is now suggested to aggregate demand into three main groups that represent three specific category of customers.



(Figure 32: clustering procedure)

The second step of the process is therefore to understand how to use the most significant attributes found in the first step of the analysis to realize the final market classification and customers' clusters. In order to accomplish this, for each subsidiary the market share corresponding to each Brand has been calculated (main cluster). Then, for the Brand that contributes the most to the local profit, percentages of the Family segment have been computed (sub cluster). In this way, the demand pattern will be classified according to the most important Brand and if it is the case, the brand at stake will be filtered according to its family segment: skin care, perfume or make-up. Also for this second step of the analysis, related graphs can be found in **Annex C.2**.

In order to represent the clustering of the demand, based on Huber et al. (2017) work, it is interesting to introduce the concept of hierarchical forecasting which again is based on the principle that an aggregate time series does not represent the specificities of lower levels time series which is often the cause of inaccurate forecasts. There are two different type of hierarchical forecasting: the top-down and the bottom-up approach. The former one derives forecasting by splitting the aggregate level in sub clusters / lower time series. On the contrary, the bottom up method sums forecasts at lower levels to compute the aggregate total forecast (cumulative forecast).

Thanks to the findings in Section 5.7, it is useful to build a hierarchical structure to re construct the path of the final classification clusters. In the case at stake the top-down approach is adopted because groups' products at the lower level have different demand variabilities therefore they cannot be summed up to form a cumulative aggregate forecast.

The organizational structure of the items can be represented as a hierarchy, indeed articles are grouped into clusters and sub clusters representing different articles categories. Different hierarchies can be build but according to the results found we consider three main level of detail: the local subsidiary, the products' Brand and the Family segment. In Figure 33, a clear representation of the hierarchy at stake is shown where:

S = subsidiary

X = group of articles

B = Brand

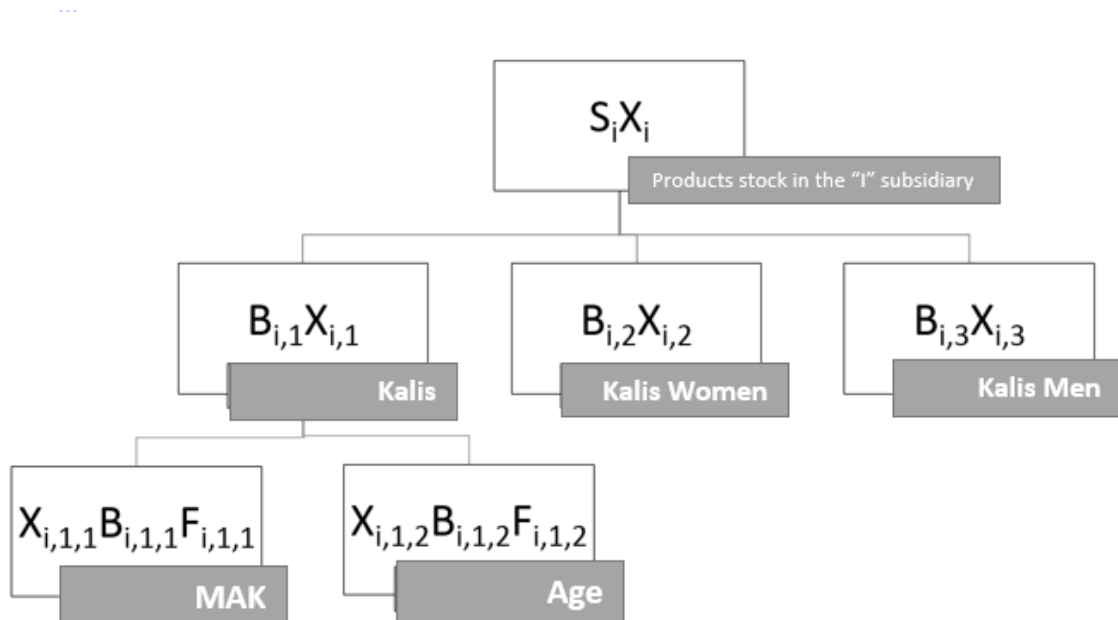
F = Family

Three indices:

i = [1:27] number of subsidiaries

j = [1:3] number of Brands

k = [1,2] number of Family segments



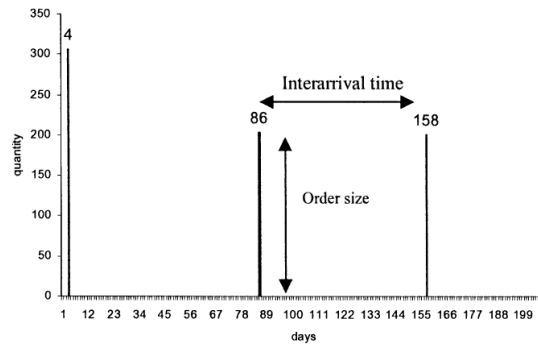
(Figure 33: top-down hierarchy)

Figure 33 gives the final representation of the main clusters found in section 5.7; thus, once the main filters to cluster the demand have been found, a visual representation of the final result can be shown through the hierarchical approach that has been explained in this section. Next, each demand cluster needs to be linked to a specific market class and this is what the following sections will treat.

3.5 Implementation of market's demand classification model

As stated in Section 5.1, results gathered from the literature review done in section 5.3, concerning the categorization of market demand can be concretely applied and evaluated. At the end of this first phase of the analysis, new adjustments will be brought to the final methods for the demand classification.

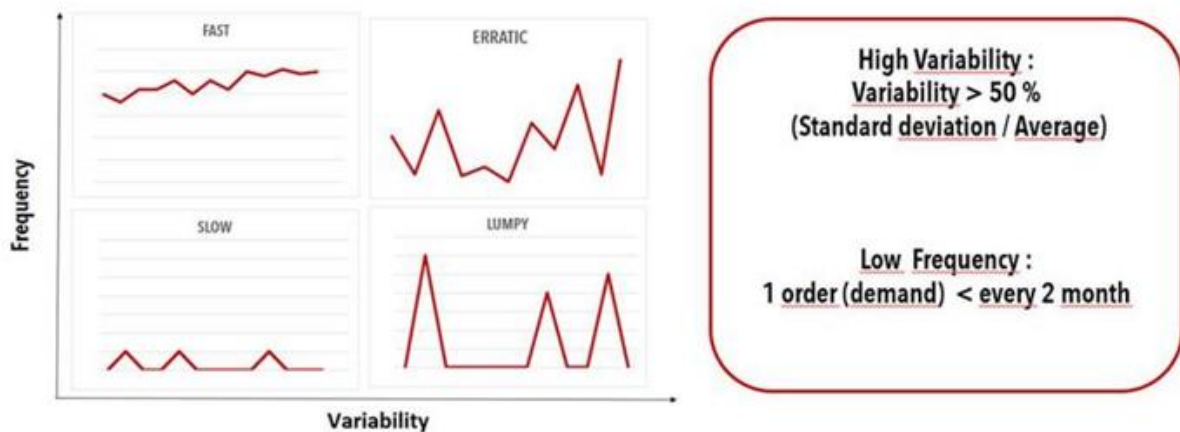
In this section, the Syntetos et al. (2005) model for market's demand categorization presented in section 5.3.2 is tested and evaluated. As it has been claimed by the authors of this work, "*demand estimates is built from constituent elements, namely, the demand size when demand occurs and the interdemand interval*"



(Figure 34: the dual dimension problem of forecasting
Source : Kalchschmidt et al. 2003)

Following this model, the first analysis starts by dividing the market into four main areas, as suggested by Syntetos et al. (2005): the slow, the fast, the lumpy and the erratic market. In a matter of keeping the model as simple as possible, the cut-off values chosen to classify demand are a variability's threshold of $CV^2 = 0,50$, and as it concerns the frequency value if positive demand occurs in more than five time periods (one period is equal to one month) along one year, the demand is considered as highly frequent

The basic diagram that shows this classification is shown below:



(Figure 35: material given by the company on the market classification scheme)

To help the reader in the graph interpretation, the four quadrants are explained with the help of past literature documentation:

- **Lumpy demand:** stemming from the literature, “a lumpy demand may be defined as a demand with great differences between each period’s requirements and with a great number of periods with zero requests“(Bartezzaghi, E., et al., 1999). In the current model used by Kalis, lumpy demand variability is negatively correlated with the frequency factor: indeed, when customers’ frequency of orders increases, the market’s demand trend become more stable and loses its lumpiness
- **Erratic demand:** as stated by Onyeocha et al. (2015), “demand profiles characterised by uneven transactions of variable demand sizes are often referred to as erratic demands. It is distinguished

by intermittent operations and occurs when demands are depicted with irregular sizes at different intervals.” In Figure 35, erratic demand has been classified with a respective high level of both variability and frequency:

- **Slow demand:** contrary to the previous two markets, slow demand is characterized by a low variability level. Products at the end of their life cycle could be placed in this category, because they are about to exit the market therefore only the most affectionate customers will purchase them and each sell will not be significant in quantity. Also luxury goods could be classified in this category: orders are exceptional and usually one finished product at a time is purchased (for instance luxury cars or jewelleries)
- **Fast demand:** it is easy to make future forecast on this type of markets thanks to its stability. Stables demand markets are here classified as positively affected by both high frequency demand level and a low variability of customers demand. The alimentary mass production could be placed in this quadrant: for instance beverages like milk have a low range of variability and are daily requested by the public.

In order to test the validity of the diagram in Figure 35, all subsidiaries’ demand from last three years have been classified against the two axes of frequency and variability with the cut-off values proposed, respectively 50% as the variability threshold and an assumption of low frequency when there is less than one demand every two months; accordingly to previous results, demand has always been considered clustered according to the product’s brand.

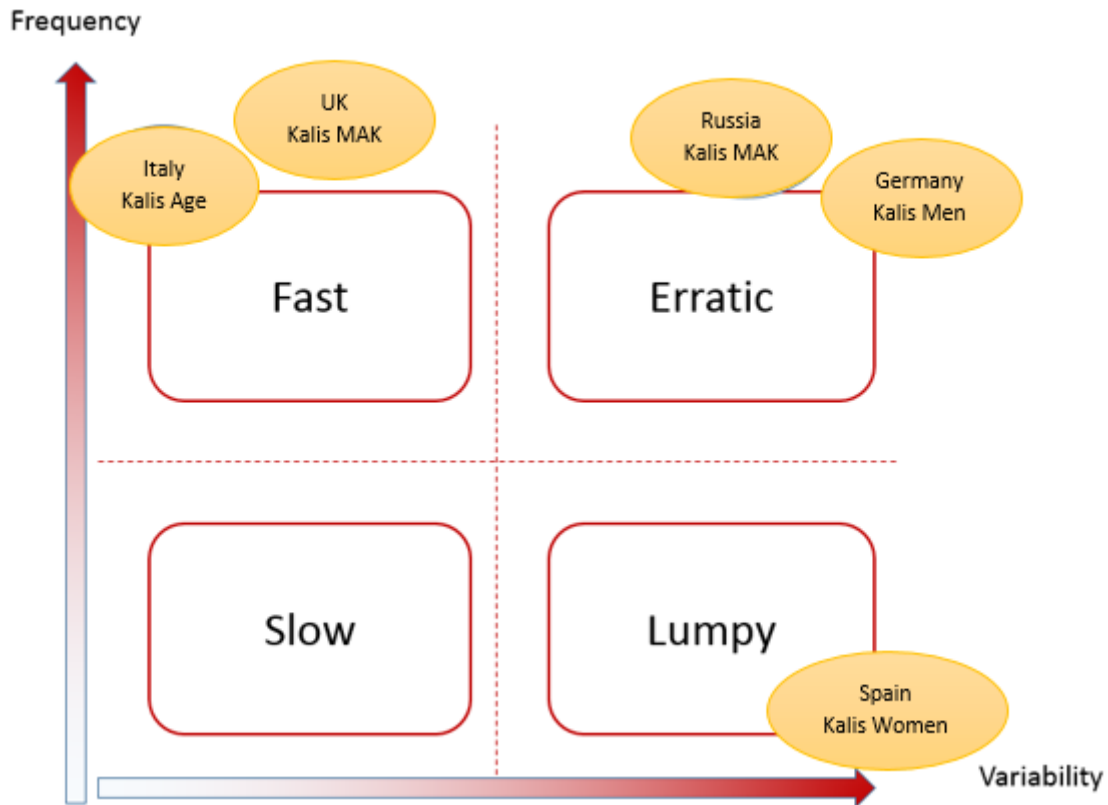
According to this, for each cluster the variability and the frequency along the three years of study have been computed. This allows to place each market in one of the four category presented in Figure 35: slow, fast, lumpy and erratic. Here below, some examples of the described analysis are illustrated:

(Table 5: example of results from the first data analysis)

Russian subsidiary	Variability	Variability classification	Number of month without demand	Frequency of demand	Type of market
Kalis Men	82,21 %	High	15	High	Erratic
PRF	82,21 %	High	15	High	Erratic
Kalis Age	18,36%	Low	0	High	Fast
MAK	20,11%	Low	0	High	Fast
SKN	21,12%	Low	0	High	Fast
Kalis Women	61,69%	High	0	High	Erratic
PRF	61,69%	High	0	High	Erratic
Total	20,46%	Low	0	High	Fast

In this way, the final demand categorization in four different categories (Fast, Erratic, Slow and Lumpy) can be finalized:

- High Variability + High Frequency = Erratic demand
- High Variability + Low Frequency = Lumpy demand
- Low Variability + High Frequency = Fast demand
- Low Variability + Low Frequency = Slow demand



(Figure 36: first categorization of market's demand)

After this analysis phase, the discussion of the results put under light the existence of some issues regarding the model adopted. Indeed, results from this first analysis clearly showed that the categorization of demand following this scheme is unsuitable in industrial multinational context such as the one at stake for three main reasons:

- Cut-off values chosen are too simplistic and not realistic: each brand presents specific proprieties in its demand pattern (different demand sizes, demand interval, class of customers) and it is not reliable to classify all the three different brands with the same variability threshold.
- The frequency of demand has been found to be high for all types of market: by looking at the dataset of results presented above, it is rare to find long period in time with zero demand values, i.e. the company sells a range of products that is everyday sold, almost without period of zero demand. Thus, it is necessary to put under discussion the relevance of the frequency axis in the model as a discriminant for demand pattern's categorization
- There is no differentiation between different subsidiaries: all warehouses are treated as a single identity which is not realistic compared to the contribution of each of them to the final turnover

In the next section, according to the model's limitations mentioned above, the new adjustments that need to be implemented in the second analysis are presented

Adjustments proposed for an improved model of market demand's categorization

Following from the findings of the first analysis based on the traditional model adopted by the company, three solutions are proposed to tackle the three problems derived:

- Division of subsidiaries into “Big” and “Small customers

The 26 subsidiaries do not have the same economics, the same demand size and therefore they do not contribute in the same way at the final total demand; thus, it is interesting to apply a first differentiation between those warehouses that have a major number of transactions during the years compared to those that are less influential on the final turnover of the company.

In order to find this, for each country the ratio between the average local demand and the total group's demand has been computed and considered in percentage:

$$\text{Contribution of the local subsidiary (\%)} = \frac{D_i}{\sum_{i=1}^{26} D_i}$$

Where

$D_i = \sum_{t=2015}^{2017} D_{i,t}$ = sum of the last three years demand for the i -th local subsidiary

$\sum_{i=1}^{26} D_i$ = total demand of the group during last three years

According to this, the following results have been derived:

(Table 6: contribution in percentage of each subsidiary to the total demand)

Countries %	Kalis Men	Kalis Women	Kalis MAK	Kalis Age
USA	37%	12%	8%	3%
Canada	1%	1%	4%	1%
Miami	11%	15%	2%	2%
Mexico	0%	0%	2%	0%
Poland	0%	0%	0%	28%
Bangkok	0%	0%	0%	0%
Malaysia	0%	0%	0%	36%
Honk Kong	0%	0%	0%	1%
Japan	0%	0%	2%	1%
China	0%	0%	0%	2%
Australia	0%	0%	2%	1%
New Zealand	0%	0%	0%	0%
France	15%	18%	10%	5%
New Zealand	0%	0%	0%	0%
Ireland	0%	0%	2%	0%
Netherlands	0%	0%	2%	1%
Germany	4%	9%	3%	2%
UK	1%	10%	13%	5%
Italy	3%	9%	9%	2%
Portugal	1%	1%	1%	0%
Spain	1%	6%	7%	2%
Switzerland	1%	2%	3%	1%
Slovenia	4%	5%	2%	1%
Austria	0%	1%	1%	0%
Russia	16%	2%	22%	4%
Dubai	4%	8%	5%	1%

As it is showed in the table above, the aggregation of the demand according to the products' brand and type (make-up and skin care) has been considered, coherently with the results previously found on the clustering of customers' orders.

It is interesting to notice that the average percentage of contribution of each Brand is equal to 4%; this will be the threshold to divide subsidiaries into Big and Small customers:

- Average demand in percentage $> 4\%$ $\rightarrow$ Big customer
- Average demand in percentage $< 4\%$ $\rightarrow$ Small customer

More coherently with the reality, subsidiaries are now classified according to their different marketing strategies.

- Adjustment of the variability level

Variability is the main driver in demand pattern categorization: it represents the first filter to apply in order to understand whether a market is stable or not and this is the reason why it has to be carefully studied. In the past literature, the variability issue is still representing a vivid topic that needs to find answers: indeed nowadays categorization models of market's demand are still not universally accepted and difficult to implement, given the high number of mathematical computations they require. On the other hand, it is not advisable to choose too simplistic representation of the demand, like the model that is nowadays adopted by the company where only one variability cut-off value is considered for the all group's brands, because too far from the reality and it is therefore source of error in the final performance.

Each brand has different market shares according to specific regions. Consequently, the average variability strongly changes according to the Brand and the local subsidiary considered.

For each Brand, Small and Big Customers are separately studied and it will be observed that for specific brand, the threshold level for variability changes together with the type of customers that the brand serves; if we considered for instance the Big Customers belonging to Kalis Women, the average variability found is equal to 54%, thus:

- Local variability value $< 54\%$ $\rightarrow$ Low variability
- Local variability value $> 54\%$ $\rightarrow$ High variability

This analysis of variability has been applied to all the three brand and it allows to have a clear mapping of the evolution of demand for all the group's subsidiaries

This test proves that the adoption of only one variability threshold for all the group's markets is unreliable because each Brand has its own characteristics of demand size. Indeed for the Big customers market, the one that contributes the most to the final turnover, the average variability level varies from a minimum of 33% to an extreme of 255%, which gives a totally different representation of the different Brand's market compared to the original model. In this way, the proposed model tries to give a more realistic representation of the three different Brand's markets according to their own market's properties.

- The frequency factor

The frequency element has shown to be not suitable for the analysis at stake: indeed, from the results of the first analysis, all different local market demands always show a high frequency in demand. Thus, all group's products will be assumed to belong to a high frequency market and as an assumption, the frequency axis will be canceled from the categorization model because not representative enough.

The frequency factor is substituted by another element that is determinant in understanding whether the demand pattern is stable or not in time: the seasonality index (SI). In the **Annex C.3** of this paper it is possible to find the simple passages to follow to compute the SI. This indicator is a measure of seasonality which can be said as "an intra-year movement, which is generally considered as a systematic component,

but it does not necessarily have to be systematic” (Koc, E., & Altinay, G. 2006). There are two different types of seasonality:

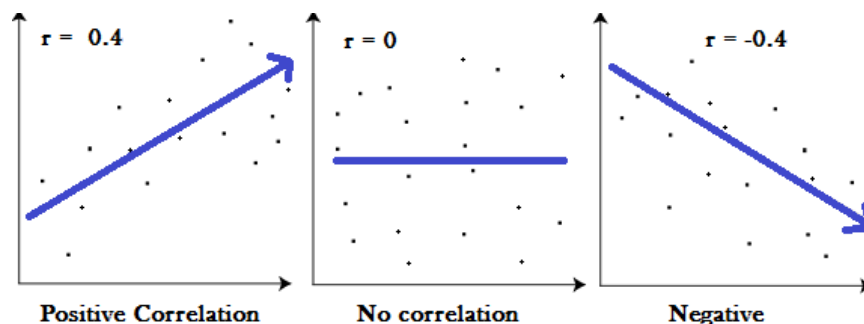
- Deterministic, when the seasonal fluctuation is the same over time
- Stochastic, when the seasonal variation is not stable over

In the case at stake, by assuming for all the products a high frequency in demand, the seasonality index will be useful to determine whether a market is has a deterministic seasonality or not: indeed when variability is high, if seasonality index relative to all the months in a year remains the same over time, this means that the seasonality pattern is following a recurrent path; on the other hand, when demand’s variability is high and the seasonality index relative to each month varies year by year, this means that the seasonal pattern is stochastic and cannot be handled by a statistical model.

In order to translate this concept into numbers, the correlation coefficient has been used: from a mathematical point of view, the correlation indicates the strength of the relation between two variables, in this case the two seasonality indexes relative to two different years. Its value is comprised between -1 and +1 where values below zero indicates a negatively proportional relation between the two variables and values above zero indicate a positively proportional relation between the two series. The extreme cases of the value’s interval are:

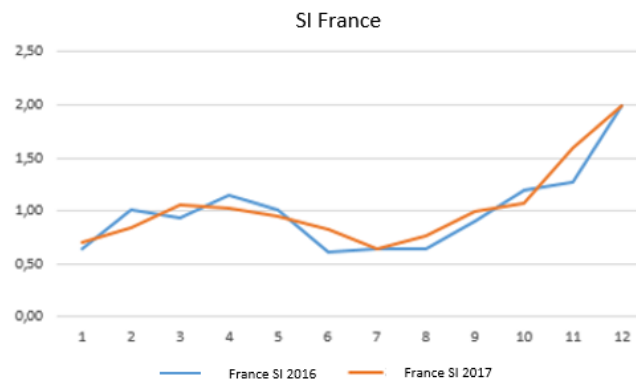
- +1 : perfect positive correlation between the variables
- -1: perfect negative correlation between the variables
- 0 : no relation between the variables

In order to give a concrete meaning of the correlation coefficient, below three different graphs show the three different patterns concerned with respectively a positive, a zero and a negative correlation coefficient:

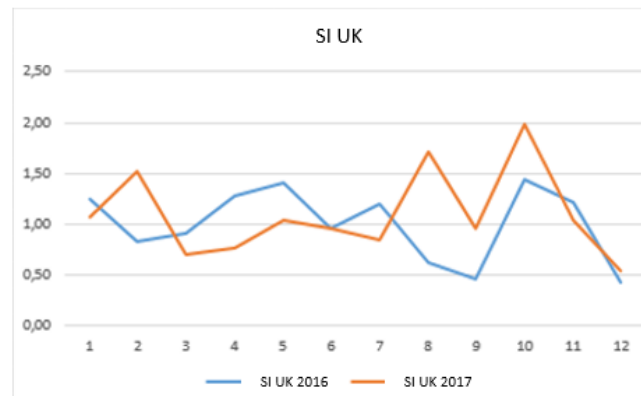


(Figure 37: graphs showing different types of correlation, Source: Statistics How To)

In this study, the interest was to understand the relation between seasonality indexes of 2016 and 2017, thus to compute the correlation between the seasonality factors of the subsidiary for a certain Brand. Following, examples for Kalis are presented relatively to a high positive correlation coefficient, i.e. where demand pattern is following a stable seasonality through the years and a low correlation coefficient, where demand is not characterized by a stable seasonality.



(Figure 38: Subsidiary 1 - Correlation coefficient = 0,92)



(Figure 39: Subsidiary 2 - Correlation coefficient = 0,20)

The two graphs clearly show the different relation between seasonality index along the years: in the former, the seasonality pattern can be defined as deterministic, indeed the two indexes are following the same pattern, thus the market is affected by a stable seasonality; for the second case, the correlation is low so the two patterns are almost independent one from the other, this is the case of a stochastic seasonality.

The threshold that has been chosen by the author of this paper to define whether a market is following a stable seasonality pattern is 0,5:

- Local correlation coefficient $> 0,5 \rightarrow$ Deterministic seasonality
- Local correlation coefficient $< 0,5 \rightarrow$ Stochastic seasonality

In order to highlight the importance of the seasonality factor, in the next section a brief theoretical explanations gained through the literature studies will be presented. In this way, the reasons why the seasonal factor has been chosen as the second driver of the demand categorization will be highlighted.

The importance of seasonality

The impact of seasonality on the variations of demand is an important theme not only in the past literature but in different domains such as policy making and the tourism management (Lewis, N. K., & Bischoff, E. E. 2005). By the way, the work on seasonality still needs to be developed: generally, seasonal variations are considered as a negative factor that needs to be removed and this is the main cause of a loss of important information about the demand pattern (Goh, C., & Law, R. 2002).

In Lewis, N. K., & Bischoff, E. E. work (2005) it is possible to find how seasonality has been used in past studies: for instance, different statistical measures have been used in literature such as the ‘Coefficients of Variability, Coefficient of Variation, Concentration Indices and Similarity Indices, which are applied to compare the acuteness of seasonality for different regions. The Seasonal Index, used in this analysis, has also been applied in the literature to estimate the seasonal monthly variation of tourism fluctuations at a national level.

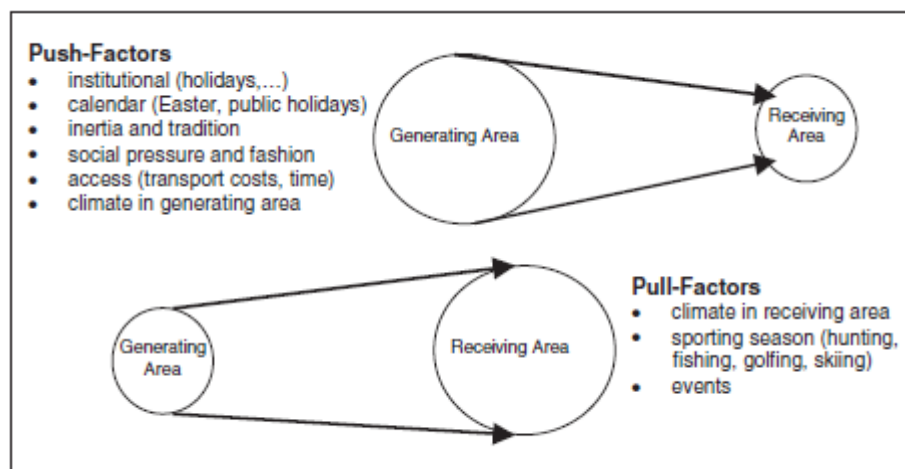
Certain studies have focused on developing refined method to correctly handle seasonality factor with the final goal of improving the forecast performance. For instance, Sichel, B. (winter 2008-2009) points out that thanks to the application of the seasonal indexes, the MAPE (Mean Absolute Percent Error used also in this research) indicators used to evaluate his forecast performance improved by 9.2%.

Koc, E., & Altinay, G. (2006) give an important example of application of the seasonality factor to segment the tourism in Turkey; by estimating the seasonal variations in tourist expenses, he manages to segment the tourist market into “*light and heavy clients*”. This study can be linked to what it has been done in this research: to classify different product lines according to their last two years of seasonal variations.

Koenig, N., & Bischoff, E. E. (2004) show a nice application of the seasonality component to study the tourism fluctuations in the Welsh region. They find out that the 75% of the overall variance can be explained by two main dimensions: the seasonality factor and the occupancy ratio. This is another reason why the seasonality and variability factors could be two essential drivers in the categorization of demand patterns.

Generally in the literature, it is advised to first compute seasonal factors and then to use different measures in order to understand the nature of the seasonal variations. For this latter, several techniques are adopted: regression models, decomposition models or statistical test such as the test for seasonal unit-root. An example of this latter can be found in Goh, C., & Law, R. (2002) study where the Augmented Dickey-Fuller test is used to model the tourist demand pattern. If the test results in a unit-root, it means that the series is non stationary and vice versa. The main distinction between stationary and non-stationary seasonal variations has also been adopted in the current study to classify different products.

There are three main causes of seasonality variations (Lewis, N. K., & Bischoff, E. E. 2005): the *weather* (e.g. temperature, changes in daily hours etc.), *calendar occurrences* (e.g. Christmas day, Valentin’s day, religious events, etc.) and *timing decisions* (e.g. school and industry holidays, tax years, etc.). These categories have been classified as push or pull factors in the generation of seasonality as it can be seen in Figure 40:



(Figure 40: push and pull factors that cause seasonality. Source: Lewis, N. K., & Bischoff, E. E. 2005)

According to Figure 40, several factors can be distinguished into push and pull elements for the Kalis Company:

- Push factors:
 - Christmas and Valentine's day are calendar events that always push people to buy kits of products of all Brands
 - Being a multinational company, Kalis has to satisfy needs from all over the world. This is why foreign traditions represent an important push factor for far away subsidiaries
- Pull factors:
 - Every summer solar products are pulled by the hot temperature that increase this line's sales
 - Sales promotions and discounts during the summer and winter seasons are as well contributing to motivate clients to buy products

In order to correctly handle seasonality it is therefore important to understand its causes and different components.

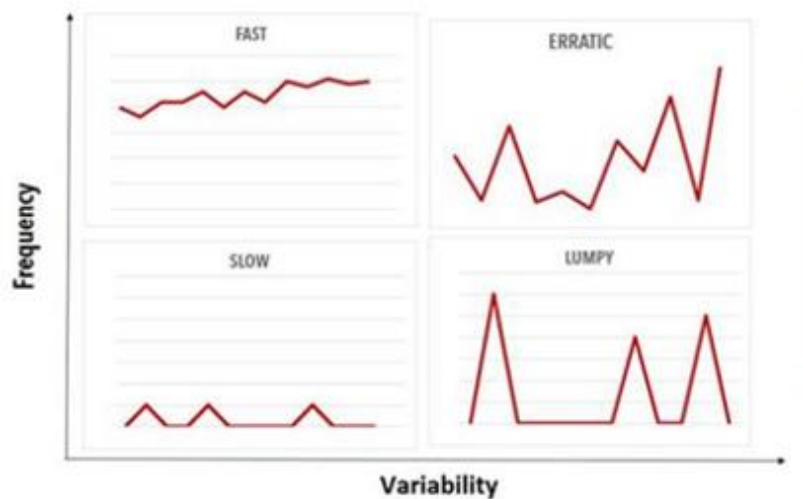
Finally, after this brief description on the importance of seasonality in market categorization, it is argued that in cases such as Kalis company, where the final classification model has to be used and implemented in an industrial context where a low level of technical knowledge is required, easy computational procedures are needed. This is the reason why the use of the correlation coefficient has been chosen to estimate the seasonality fluctuations and to eventually segment the market at stake. The use of regression models or some more complex statistical tests such as the unit-root one, have a too high technical complexity and they require users to have a refine statistical knowledge something that is not realistic in the multinational context.

By the way it is important to highlight some limitations of this way of measuring seasonality: it is required by demand planners to always have a critical judgment on the final classification of products seasonality. Since only two years of data are considered, it could be that some external factors influenced the pattern of some products that usually have an erratic pattern (belonging to the lumpy category) and that in the end result to have a stable seasonality along the two past years. These are exceptional cases since the analysis has been conducted on products that belong to the maturity phase of their life cycle and therefore they are supposed to have a stable market during consecutive years. In addition to this, the frequency factor is not determinant in the specific case of Kalis Company: this does not mean that frequency is not important for the demand categorization in other contexts; this issue will be discussed and solved in Section 7.5 of this paper where limitations and future adjustments will be presented.

In the following section, a summary of the final results will be presented in order to clarify the final achievements of this chapter.

Overview of the final results

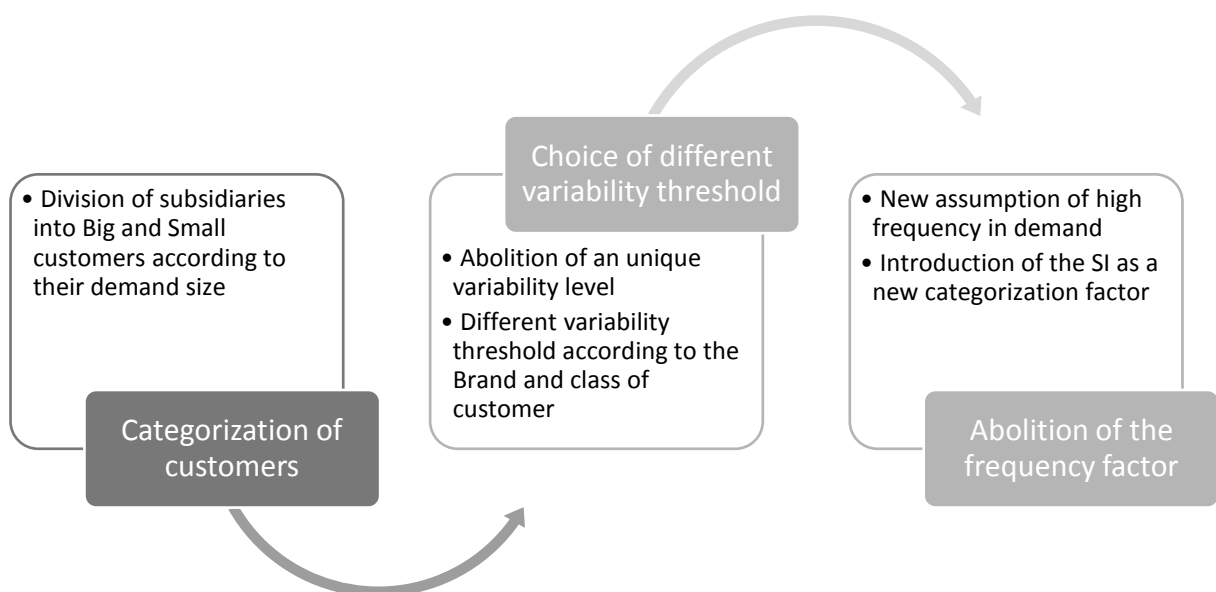
In Section 5.3.3, attention was given to the aggregation of the demand into meaningful clusters accordingly to the theoretical study of Kalchschmidt et al. (2003); once the representation of demand aggregation through a hierarchy approach has been finalized in section 5.5, the different clusters identified needed to be linked to a specific demand class. This analysis started by the study of the model proposed by Syntetos et al. (2005) work:



(Figure 41: original demand categorization diagram adopted by the company)

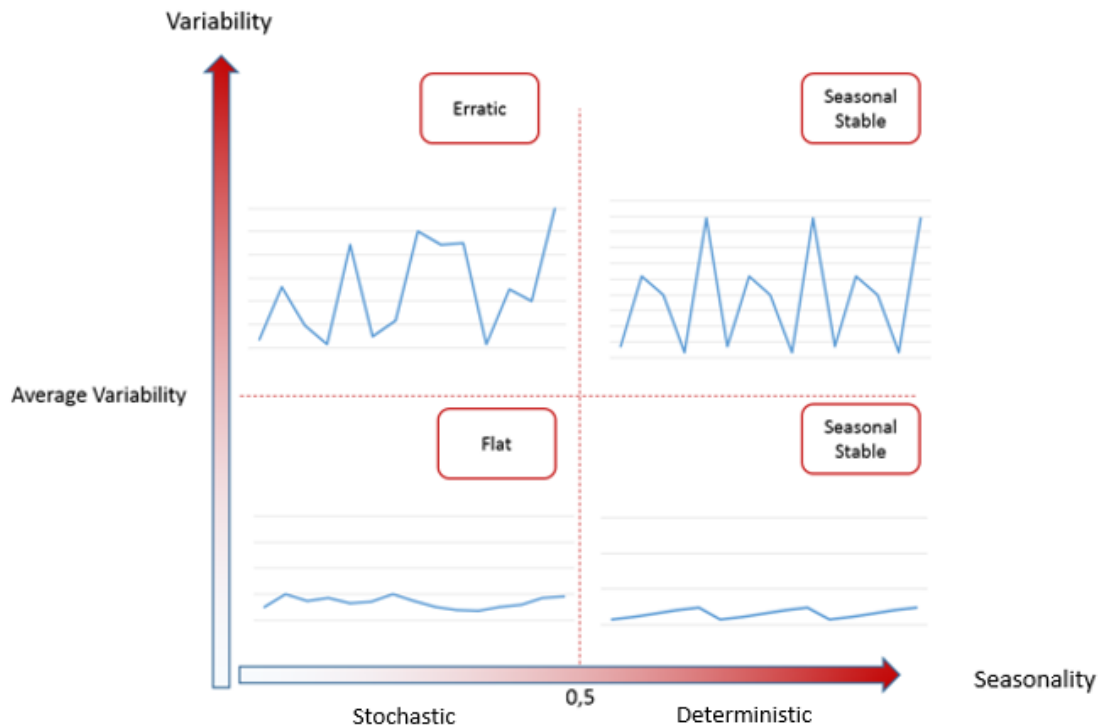
Three main adjustments have been brought thanks to the data analysis:

- 1) Local subsidiaries are not considered anymore as a whole but divided into Big and Small costumers, according to their demand size
- 2) Different variability levels have been distinguished according to specific markets that is to say relative to specific Brand and class of customers (big or small)
- 3) The frequency factor has been replaced by the correlation coefficient between seasonality indexes of 2016 and 2017 to control the stability of the demand



(Figure 42: procedure followed to answer the research question)

According to this, the new graph proposed by this study is given by:

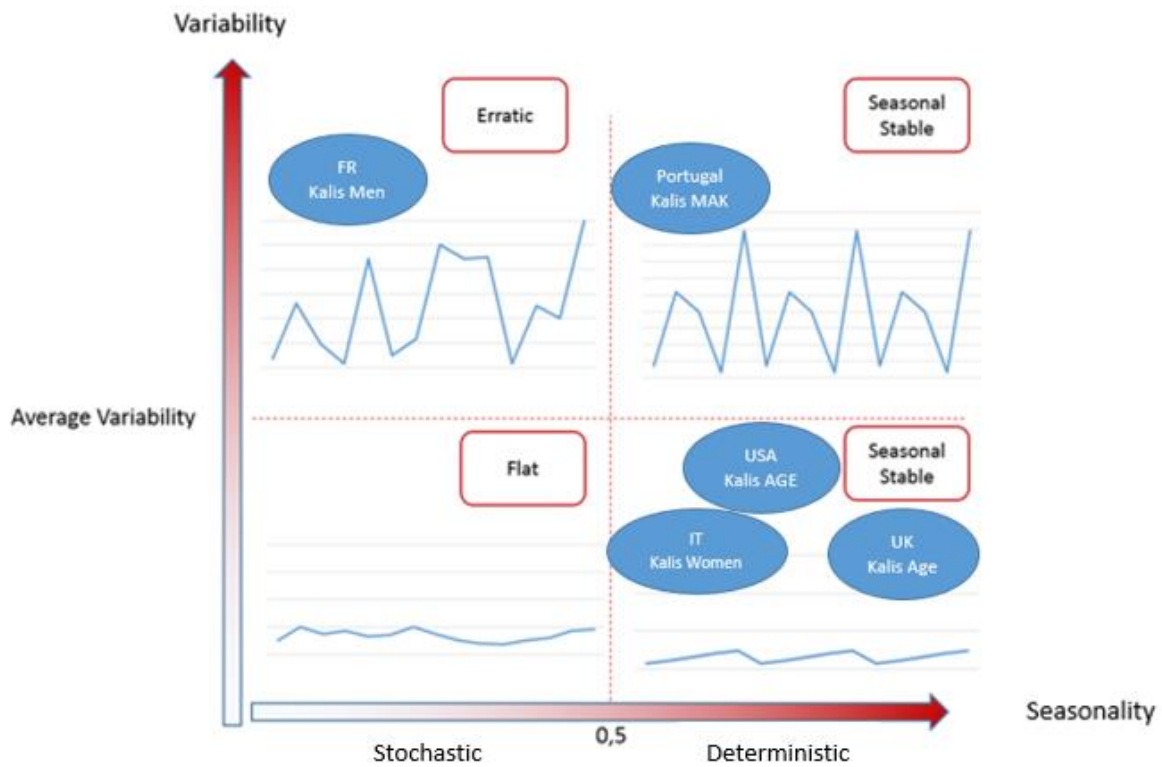


(Figure 43: new demand categorization diagram proposed by this study)

In the graph it is possible to distinguish three different demand's patterns category, always assuming a high demand's frequency:

- Erratic: high variability and stochastic seasonality, it represents those markets where demand is unpredictable and chaotic therefore not suitable for the use of statistical models for forecast
- Seasonable stable: High/Low variability and deterministic seasonality, those markets whose demand is highly variable but that is still following a defined pattern, thus it can be forecasted in advance
- Flat: Low variability and stochastic seasonality

Finally, clusters that have been formed in the previous steps of the study can be classified as part of one of the three main market's categories found in the paper. A final example that shows the attribution of different subsidiaries to their relative category is given in the following graph:



(Figure 44: new demand categorization diagram proposed by this study)

According to their variability levels defined for each market (per Brand and per demand size) and to the correlation between the seasonality factors in 2016 and 2017, markets demands from different subsidiaries have been placed according to their properties. For instance, the Russian market for Kalis Men brand presents a highly instable trend given by a high variability in demand and an instable seasonality factor therefore its demand would be difficult to forecast using statistical models. On the other hand, the French market for Kalis' make-up is highly variable but is following a defined variability thus it will be possible to associate its demand's characteristics to specific statistical models.

These examples represent just a few cases of the overall final view on the 26 subsidiaries but they have been used to give a practical idea of the final findings.

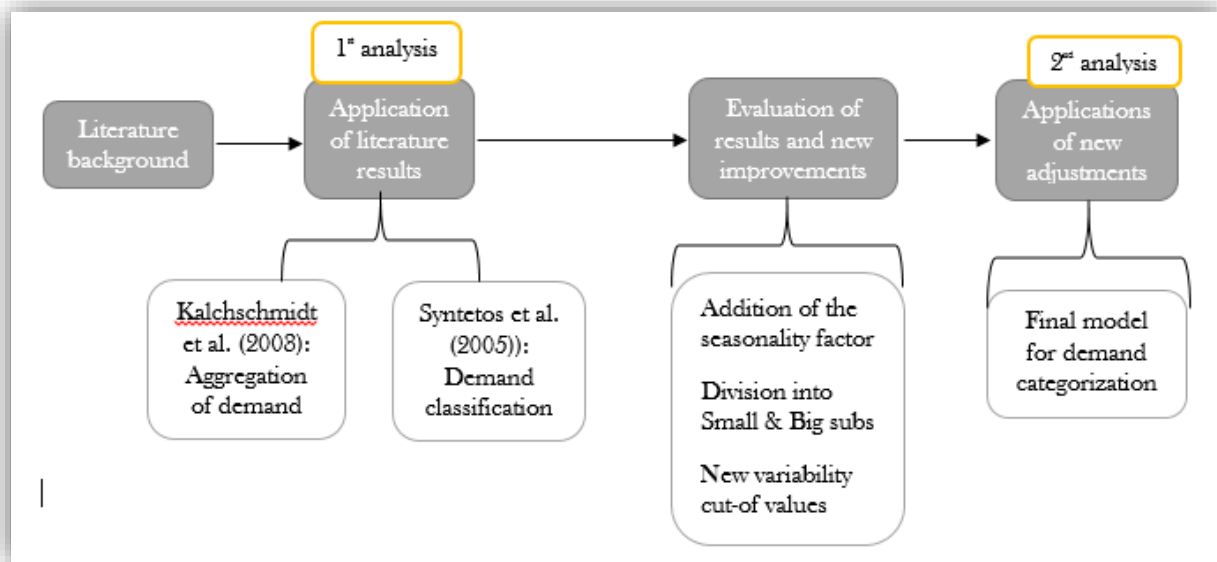
3.6 Final answers and future adjustments

Intermittent and erratic demand are difficult to forecast, this obstacle complicates the problem of managing future goods' orders and inventory in the industrial sector. When managers are confronted with the forecasts of thousands of items whose demand is sparse, it is essential to have a fast, accessible and automatic mechanism that can help them facing the forecasting process.

In the answer to the first question of this research, the initial step of the journey of the demand planner has been analyzed: the market demand's pattern classification. As it has been showed in the analysis of past literature, researchers have always focused on the mathematical aspects of demand without giving attention to the industrial implementation and managerial considerations that need to be taken into account. In this paper, this gap has been tackled thanks to the customers' clustering procedure suggested in the work of Kalchschmidt et al. (2006). The key finding to define the proper level of detail in the

demand classification is to use customers' heterogeneity: divide customers into homogeneous groups based on their specificity. By managing heterogeneity the final performance can significantly be improved and the trade-off between data accuracy and collection be solved. The overall results of this analysis give to managers a practical and accessible guide to follow while classifying demand.

The analysis followed the subsequent process:



(Figure 45: process to answer the second research question)

Figure 45 shows the different phases done during the analysis. Finally, according to the analysis and results found, it is possible to address a few concrete and easy guidelines that lead the first phase of the demand's planner journey, the market demand's categorization:

- *Identification of root causes of demand uncertainties*

In industrial sectors such as Kalis Group, where the market is internationally extended and customers' size and specificities change throughout the all countries, a big amount of information is everyday collected and stored in the digital platforms. To help managers to give sense to the data collected, a filtering procedure it is suggested. By plotting past records of the observed demand against each of the most meaningful attributes, a first glance at the data trend can be given. Some attributes can rapidly be removed from the list: those that produce confused and chaotic demand's patterns for sure will not be the drivers of the clusters division (in the case at stake for instance the Line Range attribute); in addition to these, personal judgment can play a part in the filtering process: by supposing that each demand's planner knows the company's context and local market, some attributes can deliberately be decided not to be considered as the main filter of the study (for instance in this case the products' Life Style). Finally, the list of elements that will work as filters for the customers' heterogeneity can be derived: here it is important to precise those attributes that will constitute the main clusters (in the case at stake the Brand of the product) and those that will be filters for the sub-clusters (the Family of the product)

- *Definition of homogeneous customers' clusters and sub clusters*

According to the filters found in the previous step, each subsidiary can start grouping the local market demand into clusters (in this case the Brand and the Family segment). In this way a clear map of the main customers' specificities will be drawn. Moving forward, each cluster of demand has to be classified along the two main axes of classification: demand's size and frequency: thanks to the clustering procedure, customers' demand can be easily classified. In addition to this, one of the main result of the study concerns the differentiation of local subsidiaries, for each Brand, into sub groups according to their specific demand

size: Big customers, those who contribute the most to the final company's turnover and small customers who contribute for a small part to the total demand. Thanks to this improvement, the study of the market becomes easier to manage and more representative of the real market's demand

- *Definition of demand's patterns*

Finally, a new demand categorization diagram has been realized: variability levels have been adapted according to the market at stake and the frequency factor is now considered as an assumption. A new element has been introduced as a market demand's determinant: the seasonality index thanks to which market can be classified into stochastic and deterministic seasonality. Thus, once the clusters have been formed and local subsidiaries have been divided according to their demand sizes, each cluster can be placed in one of the three markets presented in the section: seasonal stable, fast and erratic.

It is important to underline the managerial contribution of this research in considering the customers' specificities: mathematical calculus it is indeed not enough to deal with concrete industrial issues such as the erroneous nature of customers' demand and their social perspective. Past research has always suggested new path to further develop the technical analysis without taking into account the actual implementation in the industrial sector and causing mistrust and discouragement in demand planners. With these three guidelines managers will still feel in possess of the decision making process thanks to the concrete application of their personal organizational knowledge that will allow them to simplify the demand categorization procedure through the customers clustering in homogeneous groups.

Chapter 4

Statistical models

4.1 Context and Purpose

This section will address the second research question "*How can statistics model future demand trend?*". The main goal of the following analysis is two folded, both analytical and managerial.

First, it is essential to derive an exhaustive list of nowadays most innovating statistical model for future demand forecast applied in the industrial context. As it has been claimed in in Chapter 1, the majority of multinationals as Kalis group are making use of a long list of statistical models are either not optimized or out of date. It is urgent to filter this list in favor of a new synthetic version: the updated models will be replaced by their new versions and those that are not used anymore will be removed from the agenda.

It could be of help for the reader to repeat again the future forecast process adopted by the company: the Demand Planner builds his future forecasts based on the past demand observed of each product, the total demand is composed by three different elements, as it has been already explained in the initial chapter:

$$\text{Total Demand} = \text{Regular Demand} + \text{Promo Demand} + \text{Free Demand}$$

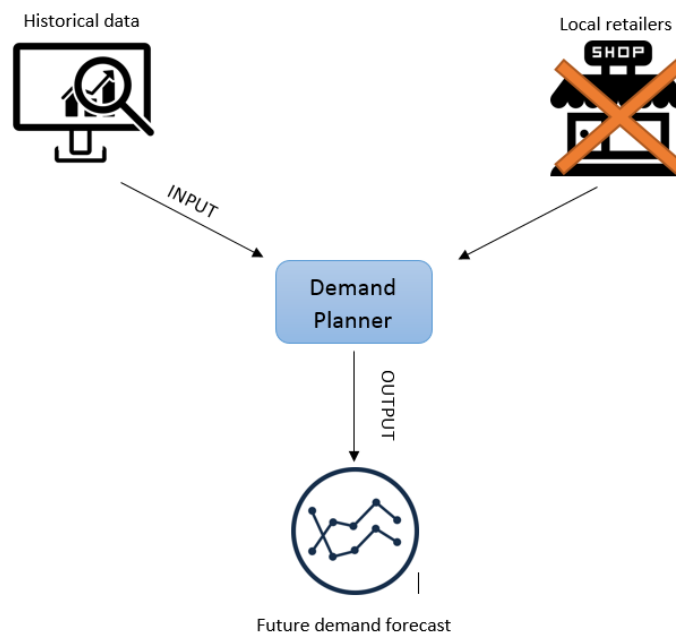
The demand planner follows a precise journey: at the beginning of the month, the demand planner receives on his digital platform DMP the actual demand of the previous month. Thanks to past data analysis, the demand planner will be able to make future forecast. Here is where the Demand Planner has to act: according to the month at stake, he can decide to change the automatic demand generated by the computer with the so called "Modified Demand", which is indeed manually computed;

$$\text{Modified Demand} = \text{Regular Demand}$$

The changes that the demand planner can bring to the Modified Demand consist in adding to the regular demand the promo and the free demand, according to what he is expecting from the next months.

During the analysis, only those products that are in the maturity phase of their life cycle have been taken into account. Those products are hence named as “basic” because the most representative and the ones generating the greatest sales volume. It is important to carefully understand the main concept behind the main research problem: future demand forecast of basic products is only based on past records; demand planners are not receiving order from the individual retailer but the statistical model they use to compute future forecasts is based on times series analysis which means that future estimations are derived from historical data. Therefore, according to the composition of the Modified Demand chosen by the local demand planner, the mathematical model will give different results on future previsions. It is the demand planner’s choice for every month whether to decide to compute future forecasts based on the regular demand or to add the promo and free factors, according to his expectations for the future.

Thus, the problem which is nowadays faced by the company is at the demand planner’s level, since there is no input given by the single retailers to calculate future forecasts.



(Figure 46: process to calculate future demand forecast)

According to this process, the problem falls on the demand planner when he has to use the statistical models to automatically compute future forecasts: indeed, every time the Demand Planner opts to use this automatic procedure, they have to choose among 29 different Statistical models available on the software. Nowadays, this choice is randomly made by the demand planner because there is a lack of knowledge on the mathematics behind all the different statistical models, therefore the deviation between the actual demand and the previous forecast is too big and this can be one of the main cause of future sales loss and therefore of a decreased final profit.

4.2 The problem at stake

In order to better visualize the problem, a list of the nowadays statistical models for future forecast used by the company has been conducted: an up to date list of real time data concerning the use of the 29 different statistical models adopted by the company is presented below. Together with the number of

times each model is used, the relative percentage has been calculated. The most popular models, those that have a percentage of use above 5%, have been highlighted in red.

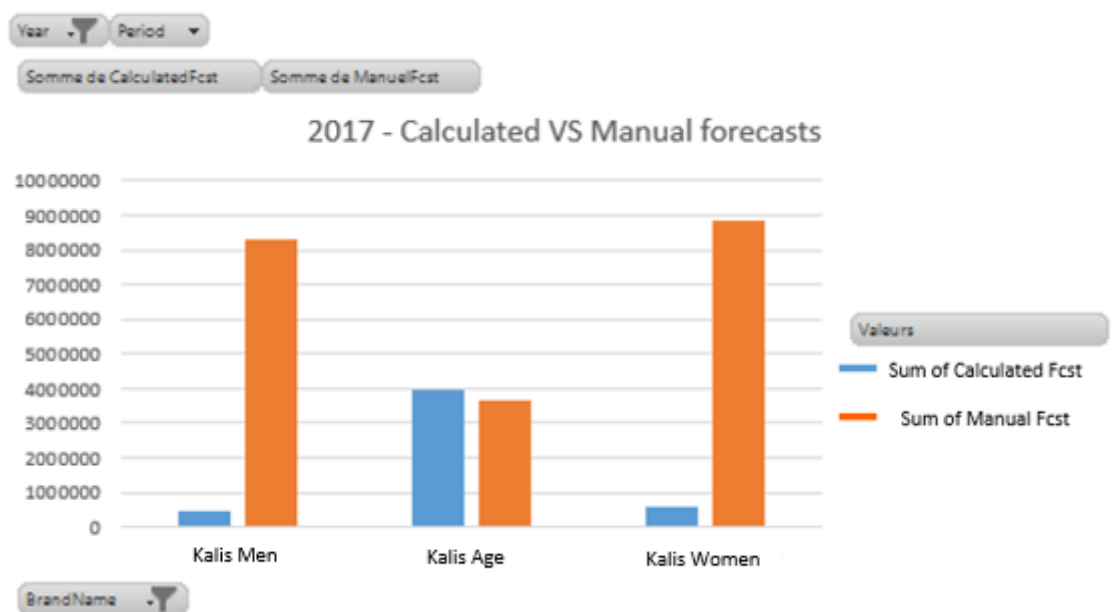
(Table 7: list of statistical models for future demand)

Statistical Model	Number of usage	Percentage on the total	Reason
Basic Moving Average Season 12 months	4509	42%	Low technical difficulty Easy to implement
Basic Moving Average 12 months	1430	13%	Low technical difficulty Easy to implement
Basic Moving Average 3 months	1343	12%	Low technical difficulty Easy to implement
As preceding year 1 YEAR	556	5%	No technical knowledge required Stable markets
Exponential Smoothing 0.2	584	5%	Medium technical difficulty Easy to implement
Exponential Smoothing 0.5	473	4%	Medium technical difficulty Easy to implement
Holt Winters 1	279	3%	Difficult to implement High technical difficulty
Holt Winters 2	201	2%	Difficult to implement High technical difficulty
Holt Winters 3	199	2%	Difficult to implement High technical difficulty
Moving Average Season 12 months	263	2%	Managers do not know the math behind
As preceding year 2 YEARS	70	1%	Demand cannot be the same as 2 years ago
Exponential Smoothing 0.3	145	1%	Similar to Exponential Smoothing 0,2
Exponential Smoothing Test1	149	1%	Test model
Holt Winters 4	93	1%	Difficult to implement High technical difficulty
Moving Average 3 months	85	1%	It considers the demand from two years ago Managers do not know the math behind
Moving Average 6 months	55	1%	It considers the demand from two years ago Managers do not know the math behind
Moving Average Season 3 months	88	1%	Managers do not know the math behind
Croston Method 0.2	31	0%	The worst performing model of all High technical difficulty
Croston Method 0.4	10	0%	The worst performing model of all High technical difficulty
Croston Method 0.6	47	0%	The worst performing model of all High technical difficulty
Croston Method Test2	19	0%	The worst performing model of all High technical difficulty
Exponential Smoothing Test2	12	0%	Test model
Holt Winters 5	6	0%	Wrong parameters Difficult to implement High technical difficulty
Holt Winters 6	15	0%	Wrong parameters Difficult to implement High technical difficulty
Holt Winters 7	17	0%	Wrong parameters Difficult to implement High technical difficulty
Holt Winters Test1	17	0%	Test model
Holt Winters Test2	9	0%	Test model
Moving Average 12 months	14	0%	Managers do not know the math behind
Moving Average Season 6 months	45	0%	Managers do not know the math behind
Total general	10764	100%	

From the Table 7, three main issues can be identified in the company forecasting routine:

- Demand planners are not relying on the mathematical calculus, indeed the average percentage of use of the models during last 3 years is only equal to 3%; the use of personal knowledge and manual calculus is one of the main causes of time and cost waste during the forecasting process: an increase in trust of the software's computation could avoid managers to spend time writing on paper their own predictions and adjustment for next period forecasts. In addition to this, by the use of their personal experience, managers from different subsidiaries are not following the same universal procedure to make forecast which results in confusing and often wrong estimation of future demand.
- The list of statistical models used by the company is out of date: this can be explained by the excessive number of models, 29, that is now available in the managers' software and that needs to be optimized. In this list, the same model can be represented five distinctive times because of the use of its different parameters' values: today, the impact of the models' parameters value is unknown. This is the reason why during the analysis a detailed study of the latter will be undertaken in order to give a meaning to them; other models are never used because they are out of date and unreliable
- Managers do not know the technical meaning of the model: the most used models are those based on "basic averages" which is the only case where demand planners can more or less understand the model's structure, in this case an average of the past data, as it will be explained in the next sections of this chapter.

The second aim of this study is, stemming from what it has just been claimed, to help managers to trust the mathematical computation. As it is evident from the graph below, demand planners are more and more using their personal knowledge and experiences to make forecast.



(Figure 47: Calculated forecast versus Manual forecast)

This picture from 2017 clearly displays the considerable number of time when the Manual Forecast (the orange column) was chosen over the Calculated Forecast (blue column); this is a result of the managers' mistrust in the mathematical calculus, mainly because they do not know how it works and consequently how to use it.

Finally, to summarize the problem that will be tackled during the chapter a list of the issues found in the company forecasting strategy is given below:

(Table 8: issues concerning the use of forecasting methods faced by the company)

Problem	Description
Long and out to date list of statistical models	29 is the total number of statistical models that demand planners can find today in the company software: the list need to be updated and filtered
Use of simple and conventional statistical models	A general lack of technical knowledge about the mathematics behind the models. Models proposed by theory are considered too complex and not accessible by industrial managers
Lack of a common forecasting procedure to follow	The lack of guidelines to follow during the decision making process causes that problems arise only after the gap between actual and forecasted demand are compared, that is to say only once the sales lost has already happened
Demand planners are not relying on the mathematical calculus	The low average use of statistical models, 3%, is cause of time and cost waste during the forecasting process

First, in order to help the reader to get familiar with the statistical forecasting domain, an overall review of forecasting terminology will be given (Section 4.3); next, the main statistical models suitable for nowadays future demand forecast found in past and current research will be presented (Section 4.4). Finally, stemming from the list of ideal statistical model found in the background history, Kalis group's agenda of models will be filtered and optimized (Section 4.5). Results will be evaluated by comparing the simulations results against the results found in theory.

4.3 Forecast terminology

As it is shown in the APICS guide, forecasting follows four main principles; these letters are listed below together with a concrete example from Kalis group:

- 1) **Forecast are almost always wrong**
Because of future uncertainties and unforeseeable factors, it is impossible to exactly forecast events in the future; thus, under certain limits, it is acceptable to have a small margin of error. However, this margin cannot reach high levels: Kalis group has recently experienced strong deviations between future forecast and the actual demand that pushed the company to reevaluate its forecasting strategies.
- 2) **Forecasting should include an estimate of error**
Performance indicators are essential to monitor and keep under control the final performance of companies' forecasting techniques. Thanks to its monthly performance indicators, Kalis group has been able to detect the gap between their calculated forecast and the observed demand
- 3) **Forecast are more accurate for groups than for single items**
In Chapter 3, the topic on how to group demand according to specific product's attributes has been shown; indeed, finding the level of detail according to which the overall data set is one of the main issues of today's research

4) **Forecasts of near-term demand are more accurate than long-term forecasts**

It is evident that the more the actual demand is approached, the more information are collected by the demand planner about the possible future customers' order. According to this, it is essential for companies to periodically update their future forecasts both on the long and on the short term. In order to face this last principle, the group is monthly updating its forecasts for the next eighteen months.

The analysis will be based on **independent demand** (demand for finished products) because even in case of necessity, the demand for product's components can be easily derived from the overall demand of the finished goods.

The approach adopted during the study is a **quantitative approach to forecast**: quantitative strategies rely on the collection of historical data. Indeed, future forecasts are based on the evaluation of past records and then they try to reproduce the past trend of data in the future.

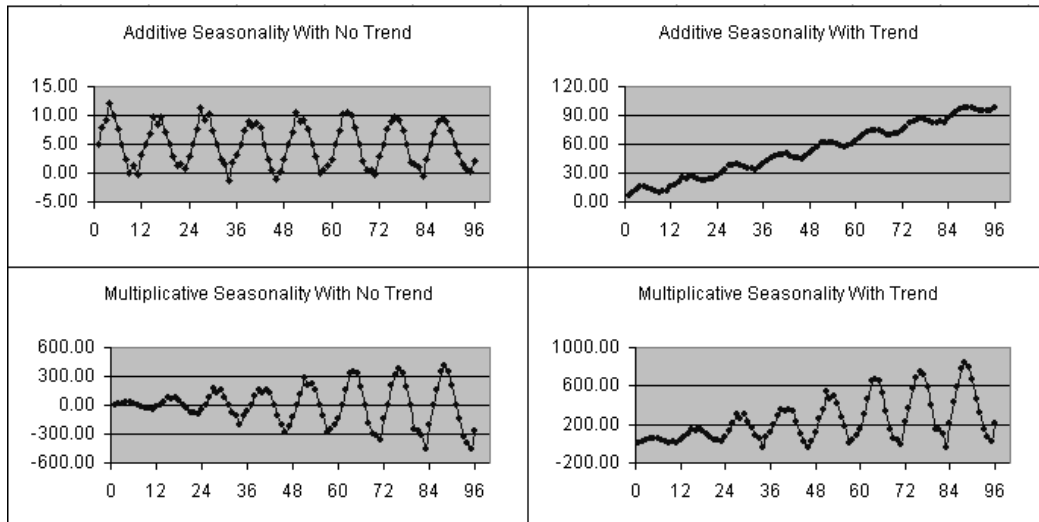
Two different types of quantitative approach to forecast can be recognized: extrinsic and **intrinsic**. The latter is the one on which the following analysis will be based upon because its forecasts are made according to the company's internal factors which is exactly what time series model are based on: demand's past records.

The four main variabilities that characterize demand patterns and could be ideally recognized thanks to statistical time series are (APICS, 2009):

- **Trends** = the long-term steady tendency of the demand pattern that can be either up (if the slope of the line crossing the average demand pattern is positive) or damped (if the slope of the line is negative). Kalekar P. S. (2004) also recognizes the exponential trend when sales steadily increase by a factor of 1.3 every year
- **Seasonality** = it refers to changes that occurs periodically every year such as Christmas, summer time, St Valentine's Day, etc. At the end of the total seasonal cycle, i.e. the year, a new cycle begins with the same seasonality occurrences. The sum of the individual seasonality's periods usually has to be equal to the overall cycle: e.g. if the overall cycle is made of 12 months (one year), the total number of seasonality periods has to be equal to 12.

It is possible to distinguish between two types of seasonality: additive and multiplicative (Kalekar, P. S. 2004). For instance, during July when summer comes, solar sales' increase by a certain amount of money every year. Therefore the demand planner knows that every July, the same amount of orders has to be added to the monthly forecast. In this case the seasonality is additive. On the contrary, when sales for a certain product increase every July for a stable factor, for instance they increase by 30%, the seasonality is multiplicative (in this case, forecasts in July have to be multiplied by the constant number 1.3).

From a graphical point of view, the additive seasonality can be distinguished because seasonal movements are stable no matter which is the level of the series whereas in the multiplicative seasonality, the intensity of the seasonal variation is not stable but varies according to the level of the series. The figure below clearly shows what it has been just said both in the case of series with and without a trend:



(Figure 48: Additive and multiplicative seasonality, Source: Oracle)

- **Cycles** = the interval of time during which a system or process, such as a seasonal demand, periodically returns to similar initial conditions
- **Chance** = those unforeseeable external factors that happen by chance and that cannot be previously forecasted (strikes, economy crises, etc.)

To have a concrete visualization of the basic terminology that has just been exposed, a summary picture is presented below

	Nonseasonal	Additive Seasonal	Multiplicative Seasonal
(SIMPLE)			
Constant Level	 NN	 NA	 NM
Linear Trend	 LN	 LA	 (WINTERS) LM
Damped Trend (0.95)	 DN	 DA	 DM
Exponential Trend (1.05)	 EN	 EA	 EM

(Figure 49: representation of different seasonality and trend typologies in time series. Source: Gartner E. 1985)
Figure 49 gives a visual representation of different combinations of time series' properties (seasonality and trend) according to their different values and typologies

4.4 Statistical models for future demand forecast

In order to simplify the analysis, it will be divided in two parts: first, according to past and current literature on the topic, an exhaustive and synthetic list of the most innovative and suitable statistical models will be derived. Secondly, the list of statistical models used nowadays by Kalis' group will be evaluated against the models found in the first part of the analysis and consequently improved. Finally, managerial implications of the results found will be explained in detail.

More details about the theory behind statistical models for future forecast, can be found in the Annex B at the end of this paper.

Naïve method

This statistical method is the simplest and oldest among all models. Indeed, it simply consists in considering the next future forecast equal to the most recent data available. For instance, in the given list of statistical models presented at the beginning of this chapter, the models "As preceding years 1 Year" and "As preceding year 2 Years" are examples of naïve methods, where in the first case the forecast for the next 12 months is equal to the observed demand of the previous year whereas in the second case the forecast for the next year is equal to the actual demand observed two years before the current one.

Moving average

The single moving average represents one of the most popular and used method by industrial companies. The model computes future period's forecasts through an arithmetic average of data gathered over a certain number of the most recent past time periods; normally at least two or three periods are considered in the average (United States Government & US Army (2012); A first distinction can be done between "basic moving average" and the "moving average method", the difference is simple: in the former one, the average considered to compute future forecast is fixed in time and never updates, whereas in the second one, the attribute "moving" comes from the fact that for each new forecast, the average is updated accordingly. It could be said that the average is "moving" with the new forecasts.

The main method's advantages are:

- Thanks to its smoothing nature, the moving average can decrease the importance given to unusual occurrences that are misleading the general trend (United States Government & US Army (2012))
- moving average is useful when the market is supposed to be stable thus for stationary time series.

The main method's limitations are:

- If demands patterns present cyclical seasonality, a trend or cases of irregularity, the moving average methods smooth out the real entity of the pattern. (Hyndman, R. J., & Athanasopoulos, G. 2013).
- When the market presents a stable up ward trend the choice of the moving average model could cause an under forecast of the demand because of its tendency to soften the general trend of the demand; viceversa, when actual demand is constantly decreasing (Chiang, T. C. n.d.)
- Since no weights is given to past time periods, e.g. all periods are considered of the same importance, it is not possible to give more relevance to those moments in the past that are considered critical for future demand (Chiang, T. C. n.d.)

Exponential smoothing

The exponential smoothing technique is an updated extension of the weighted moving average: it is a parametric model where weights are exponentially decreasing as the observations get older (Hyndman, R. J., & Athanasopoulos, G. 2013)., that is to say that as the observation gets old, less importance is given to it. Recent observations are considered more important for future forecast thus they receive more weight in the computation (Kalekar, 2004). This method is particularly significant when only a few observations are available for predicting future forecast. Also for this case, different model's types can be found according to the trend and seasonality of the demand pattern.

Holt Winters method

Compared to the previous models, the Holt Winters version can easily adapt to irregular occurrences such as changes in consumers' behavior (Goodwin, P. 2010). Generally speaking, the method further enriches the exponential smoothing model by considering both the trend and the seasonality of the demand pattern (Chatfield, C. & Yar, M. 1988).

In order to handle the seasonality and the trend component, in the HW method two more smoothing parameters are added; accordingly, in total there are three equations: one for the level, one for the trend and one for the seasonality (Hyndman, R. J., & Athanasopoulos, G. 2013) with the corresponding parameters α (level) γ (trend) and β (season).

Generally speaking, the Holt-Winter's method is suitable for regular demand whose pattern is dominated by seasonality and trend properties; however, the choice of this model is not advisable when the time series is showing exponential growth or several discontinuities during time periods.

Croston's method

The Croston's method is based on exponential smoothing and tries to answer the two main questions that managers face every day: when is the next demand occurring? What is going to be its volume (Xu, Q. et al. 2012)? Thus, Croston's method separately deals with the two main elements mentioned above: the demand is decomposed into the size of zero-demand and the probability, in other words the time interval between the occurrences of consecutive demand. Globally, each of these two parts is then applied to the simple exponential smoothing method separately and then the forecast for the next period consists in the ratio of those two estimates (size/interval) (XU, Q. et al. 2012).

Croston's method has shown two main limitations:

- 1 The two separate forecast of demand size and inter-demand interval are correctly computed but their combination under the ratio form is not an accurate estimation of the demand per time period: this is the reason why the method has been shown to be positively biased by Syntetos study (Syntetos, A. A., & Boylan, J. E., 2001).
- 2 The method does not update after periods with zero demand so if the pattern presents several periods of zero demand, the forecast results are not up to date (Teunter, R. H. et al. 2012).

Because of these two main limitations, model's variations have been developed and carried on during last years of research.

It is possible to have a deeper explanations of the statistical models that have just been explained in the **Appendix B** where their mathematical equations together with their variants are presented.

Global view on statistical models for future forecasts

In order to give a synthetic view on what it has just been explained from a theoretical point of view, a sum up table is given below where each model's advantages and disadvantages are showed:.

(Tables 9: statistical models' characteristics)

Statistical Model	Advantages	Disadvantages	Type of Market
Naïve method (as preceding year)	Easy to implement Easy to understand	1 No consideration of real demand changing factors 2 Well performing only in ideal stable demand patterns	Ideal static demand pattern
Basic moving average	1 Easy to implement 2 Easy to understand 3 No use of parameter	1 Too simplistic interpretation of demand 2 Historical data are not updated for each new forecast	Stable market with a specific representative period of past time data
Moving average	1 Easy to understand and implement 2 Control of outliers thanks to its smoothing nature, it can decrease the importance given to unusual occurrences that are misleading the general trend 3 Historical data are updated every new iteration	1 Smoothing out the real entity of the pattern: tendency in softening the general trend and seasonality of the demand 2 No weights id given to past time periods: no possibility to give different priorities to past time data	Stationary time series: useful when the product reaches its maturity phase
Exponential Smoothing	Possibility to prioritize current and past data: different weights are given to past data	1 Estimation of the smoothing parameter 2 Seasonality and trend are not taken into account	For markets where is not present a significant historic of data / when recent data need to have more importance compared to the past
Double Exponential Smoothing	Extension of the simple exponential smoothing: seasonality is taken into account	1 Estimation of two smoothing parameters 2 Trend is not taken into account	For markets that present a stable up ward trend with the presence of seasonality
Holt Winters	1 Accurate representation of real demand pattern 2 Level, trend and seasonality are taken into account	1 Difficult to implement 2 Estimation of three smoothing parameters 3 Estimation of initial values	Markets that present both seasonality and trend factors

Croston's method	1 Different study of demand size and demand interval 2 First attempt in dealing with erratic time series	1 Difficult to implement 2 No estimation of the level of obsolescence when demand is slow: the method does not update after periods with zero demand Results for future forecasts are positively biased	Slow moving and irregular demand pattern
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Thanks to this theoretical introduction on statistical models, it is now possible to optimize the forecasting methods used by the company both through the application of literature concepts and the concrete simulations conducted in the company context.

4.5 Optimization of statistical models for future forecast

The main goal of this section is the optimization of the long list of statistical models that is nowadays adopted by the company: every statistical model which is today available on the company's list of forecasting models has been tested on products belonging to different class of demand which have been identified in Chapter 3; thanks to these simulations, it is possible to rank the model and to understand which are the most recurrent and at the same time the best performing models

Two main assumptions concerning the Croston and the naïve methods can be done stemming from the literature study presented in this chapter:

1. The model "As preceding Year 2", where to forecast next periods of demand the observed demand of two years ago is copied in the future, is not giving a reliable idea of the real future demand. Even in the most stable markets, a fix pattern of previous actual demand risks not to consider the properties and specificities of the real demand pattern.
2. Croston's method for future demand is not considered, given the long list of researchers that proved its unreliability about forecasts. New versions of this model have been realized, the SBA and the Teunter approach that improved the two main disadvantages of the Croston's procedure (see **Annex B.6**): the positive bias present in its results and the not updated estimation of demand when this latter is equal to zero. The Croston's method is also one of the most difficult to understand from a technical point of view. Indeed from the table of percentages of usage of statistical models presented in Section 4.2, this model is never used by demand's planners because of its too complicated mathematical nature;

In order to have an accessible and efficient list of forecasting models for future demand, two main improvements are expected for the company's list of forecasting models:

- Optimization of the models' parameters: today the list contains several times the same type of model because of a lack of a selection of the best parameter to use; for instance, on the list it is possible to find the Exponential Smoothing model 5 times because linked to five different values of the parameter alpha: $\alpha = \{0,1 ; 0,2 ; 0,3 ; 0,5 ; 0,8\}$

- To filter the best performing models and take off from the list the worst found: forecasting models that are nowadays inadequate both from a theoretical and a practical perspective, need to be removed from the forecasting procedures

Optimization of the models' parameters

The simulations done by the author of this article on all the statistical models belonging to the company's list, allowed to understand which was, among the different versions of the same model, the best performing parameters for each of them. The results have been linked to the literature findings in order to have them validated.

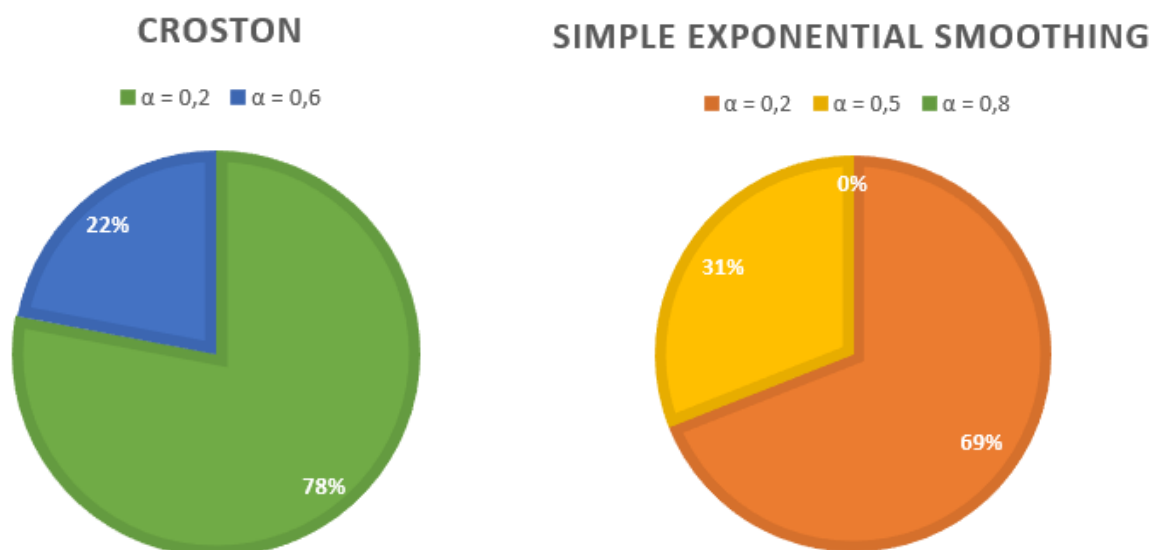
Starting from the **Simple Exponential Smoothing (SES)** and the **Croston's** model, it is interesting to first introduce the table of results concerning the best models' parameters found in past studies such as the Master Thesis of Schraven, M. M. (2015):

(Table 10: Selected smoothing parameters in past studies)

Study	Method	Selected constant	Type of data
Croston, 1972	Croston	Alpha = 0.1 ; 0.2 ; 0.3	Simulated
Syntetos, 2001	Croston	Alpha = 0.1, 0.2, 0.3 1 included	Simulated
Teunter, 2009 Teunter, 2011	Croston & SES	Alpha = 0.1 ; 0.2 ; 0.3	Royal Airforce United Kingdom & Simulated
Eaves, 2004	Croston & SES	Alpha = 0.1 ; 0.2 ; 0.3 included	Royal Airforce United Kingdom
Romeijnders, 2011	Croston & SES	Alpha = 0.2 selected	Fokker Services Netherlands

As it is clear in the past literature and as it is stated in the work of Chatfield, C. & Mohammad, Y. (1988), in general it is advisable to choose a smoothing parameter smaller than 0,5 which can vary according to the length and type of time series under study.

In agreement with the literature findings, the same results have resulted during this research analysis:

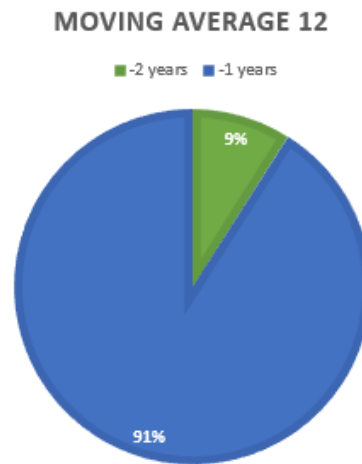


(Figure 50 : best smoothing parameters analysis results)

The results retrieved from the analysis of the company's past demand records are in line with what has been found in the theory: smoothing constant whose value is smaller than 0.5 are the best performing methods.

After the best parameter selection for both the Croston and the SES models, attention was given to the **Moving Average** method, one of the most used models nowadays by the demand planners.

All the versions of the model that the company is using nowadays are all considering computing future demand based on the past observation from two years ago: the improvement suggested by the author of this paper was to reset all the moving average models on the last year of observed demand records; results are clear: as concerns both the Moving Average with a period of 6 months and 3 months, both of them show better results in all the simulations done when they base their forecast on last year data; As concerns the Moving Average with a length period of 12 months, the results are as shown below:

*(Figure 51: performance results for the Moving Average method)*

As it is easy to see from the Figure 51, the model's performance significantly improves when more recent data are considered; in general it has been concluded that the most recent observations have to be chosen for forecasting models based on historical data; an explanation of this finding is given once again by the nature of the market that has been taken under analysis: the luxury market that is more variable and therefore needs to be more reactive compared to the mass market; to guarantee its reactivity, it is essential to give more weight to the most recent observed demand's observations.

Second best criteria to choose is which length of period's time to prefer as concerns the Moving Average of 12 months. Generally in the literature it is stated that the more historical data available the more precise the forecasting based on time series. In the case at stake, the company uses statistical models that compute their forecasts by using 12 of historical data (e.g. one year); a possible improvement would be to extend the period's length to 24 months. Unfortunately, because of the company's software limitations, it is not possible to implement this new adjustments that could be essential for the final results. This limit will be later reminded as a suggestion for future research.

The last model to analyze is the **Holt Winters** method: as explained in chapter 4, this method is potentially one of the best performing model that exists for forecasting because it can take into account several demand's specificities such as the Seasonality and Trend. However, in the simulations done with the company it has resulted to be the worst performing of all. That is to say, it was always been ranked as last for all the test done in all the different market categories; an explanation of this result is given by a likely

badly parametrization of the model which is based on 3 different smoothing constants that require a long and expensive computational study and consequent implementation. Thus, in this last case it was not possible to make a selection of the best model's parameters.

Selection of the best performing models

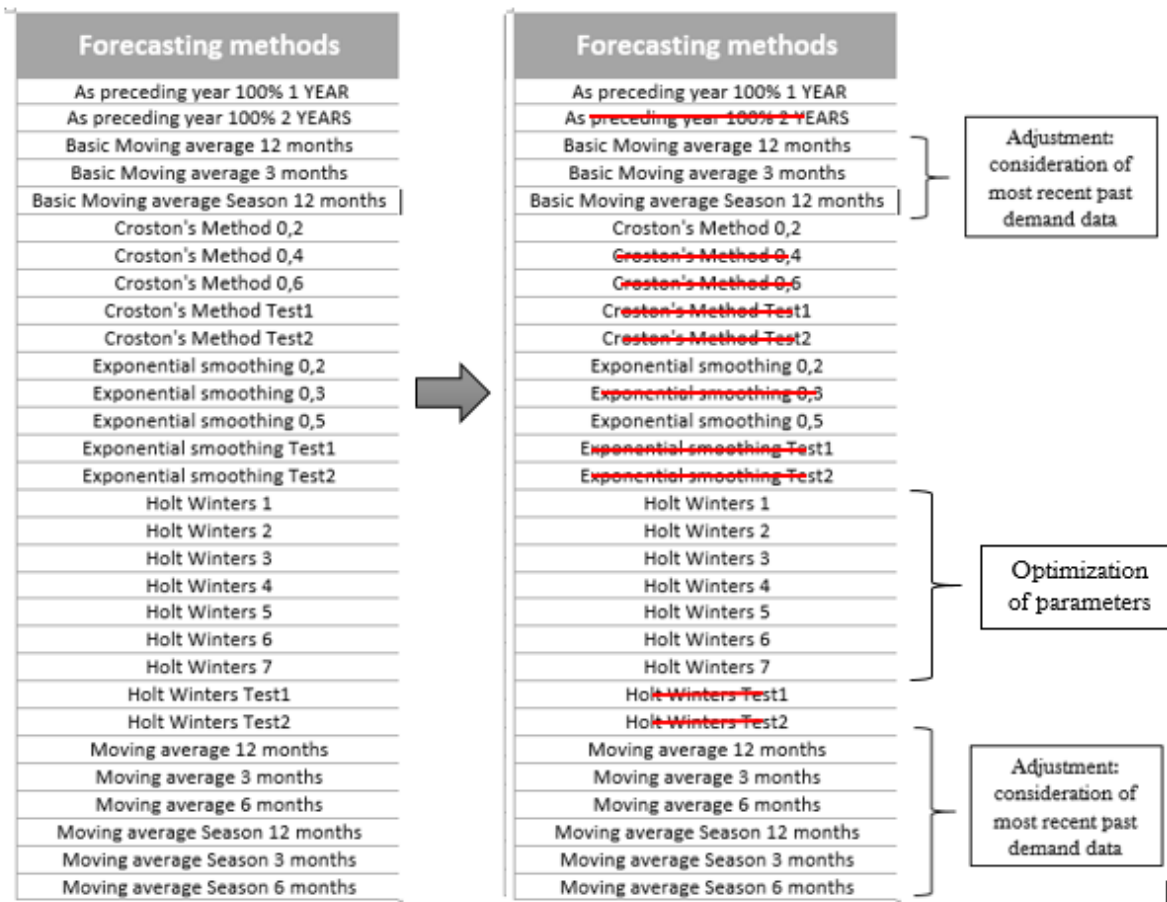
In order to acquire more knowledge concerning statistical models and to validate the choices taken at the end of the analysis, a new source of information was involved during the final changes: experts of forecasting methods, the owners of the company's software for future forecasts, have been interviewed and questioned. Thanks to their collaboration, it has been possible to verify the reasoning and the results derived during the analysis.

Stemming from both the analysis' results and the experts' interviews, it is now possible to filter the old list of 29 models for future forecast into a shorter and optimized one.

Five main families of methods have been identified: the naïve method (As preceding year), the Moving/Basic Average, The Exponential Smoothing, the Croston's method and the Holt Winter's method. Thanks to the data analysis, for each of them the following adjustments have been chosen:

- **As Preceding Year:** from the two available versions of this method, the one that takes into account the most recent data (last year's demand) is kept in the list
- **Moving/Basic Average:** in both of the cases, parameters are changed in order to consider the most recent historical data and no more demand observed ages ago. Ideally, it would be useful to test a longer historical (24 months of past demand data instead of 12 months) but because of an instrumental constraint, this was not possible to be done
- **Exponential smoothing:** according to the theory, the best performing models among the five versions present in the list are those with a small value of alpha. This is the reason why models with a smoothing constant of value $\{0,2 ; 0,5 ; \}$ are conserved in the current list of methods.
- **Croston's method:** confirming the initial assumptions made in Section 5.5, this method showed to be one of the worst performing. Indeed, in all the simulations results, it never ended up to at the top of the ranking. For this reason, all the three versions of the model will be taken out from the list of statistical models for future forecasts
- **Holt Winters:** to be optimized in future implementations

Summing up, the tables below shows the changes brought from the initial list of models adopted by the company, to the new one suggested by the analysis during this research:



(Figure 52: optimization of the list of statistical models for future forecasts)

Now that it has been shown how statistics can be used to improve the forecasting process, the next step is to understand how the market's demand can be categorized. This topic will be dealt thanks to the second research question in the following chapter.

Chapter 5

Association of statistical model with the market demand

5.1 Introduction

In this chapter, the results given by the first two research questions will be linked together. Thanks to the first question, the adopted model by the company for market demand's categorization has been tested and proved to be inadequate and unreliable (Chapter 3); from the results found, a new model has been created in order to give a more reliable and realistic classification of market's demand. Three different market's classes have been found according to their variability and seasonality levels: erratic, flat and seasonal stable. Following, in the second question an overall mapping of statistical models for future demand has been realized together with their managerial implication, advantages and limitations. In this first phase (Chapter 4) a detailed explication on how statistics can model future forecast has been presented. The aim of the current chapter is to link the knowledge accumulated throughout the last two chapters to find a final model for future demand forecasts.

Context and Purpose

Nowadays no model or series of guidelines have been found to help demand planners to link different markets' demand to their relative statistical model to make future forecast. The company at stake is facing severe problems caused by this issue because the absence of a clear process to follow during the decision making process is translated into a strong incoherence between the observed demand and the forecasts made which in the extreme cases means a loss of sales and an increased mistrust in statistical models. This paper is then trying to give a first resolution to improve its future forecasts' management in order to help the company to progress and to adopt new innovative solutions instead of being stuck to manually forecast the future demand.

Once again, in order to highlight the urgency of the problem, the future benefits that the company could retrieve by the given analysis are listed below:



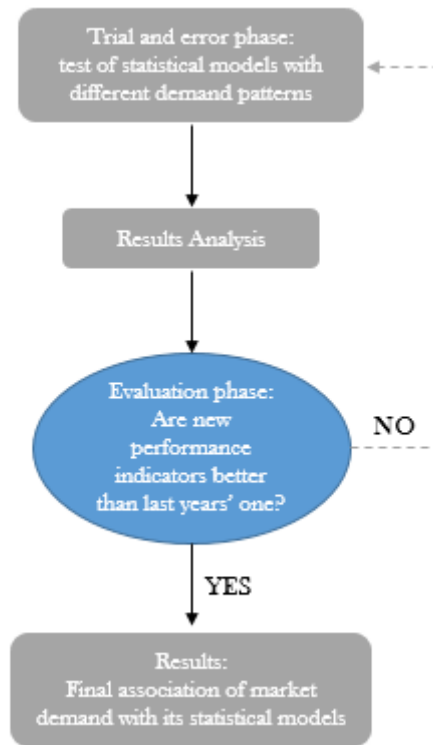
(Figure 53: future benefits given by a supportive model for future forecast)

As shown in Figure 53, the final goal is an overall increase of the company's competitive advantage. These future benefits have been retrieved by two main sources of information: the company and the past literature.

- Increase of managers trust in statistical models: company's need highlighted in both Section 1.2 and Section 4.2, as well as in Becchetti, A., & Saccani, N. (2012) article
- Decrease of sales loss and time waste: company's statements discussed in Section 1.5 during the analysis of the Quality Function Deployment (QFD) matrix
- Realization of a universal language for future forecast: this is the most important wish of the company that has been highlighted several times in this paper (Chapters 1, 3 and 4) as well as in the past literature (Jha, A., et al. (2015), Syntetos et al., (2004) and Becchetti, A., & Saccani, N. (2012)) discussed in Chapter 2
- Increase in final performance: both the company demand planners and past studies agree on the importance of the forecasting process since it directly impacts the final industrial performance. All the articles presented in Chapter 2 are indeed showing that a wrong forecasting strategy is the main cause of the final underperformance.

To tackle these issues the analysis will follow different phases: first, the statistical models will be tested for the three different demand patterns that have been recognized in the previous chapter (erratic, flat and seasonal stable). Models will be judged and ranked according to the performance indicators adopted to evaluate their performance. Thanks to this evaluation phase, the performance of the new model will be compared to the old one thanks to the analysis of the old and new indicators' values. If the new model results to be underperforming compared to the adopted one, a new trial and error phase will be started again. The generalizability to other companies of the final list of statistical models retrieved will be given by the final association of these latter to a specific market's demand category and this relation will be shown to be easily adaptable to any industrial sector.

A schematic view on the steps through which this chapter will answer the third questions can be visualized in Figure 54:



(Figure 54: structure of the third research question)

Initially, the assumptions of the following analysis will be identified in the next section, afterwards the trial and error phase will start with the description of the data collection method and finally the actual analysis together with its evaluation phase will be presented in detail.

5.2 Assumption of the analysis

It is important to highlight the main assumptions considered for the analysis at stake:

- 1) As it has been done until now for the data analysis, records from the last three years of the company's performance will be studied. In particular, the statistical models will be tested on the observed demand in 2017 and during the evaluation phase, the performance indicators' values of the company during the year 2017 will be compared to the new results of the analysis.
- 2) The subsidiaries that contribute the most to the turnover in 2017 are taken into account
- 3) The statistical models used during the simulations are the one derived from the analyses led in Section 4.4, so only the best performing models will be taken into account

5.3 Trial and error phase

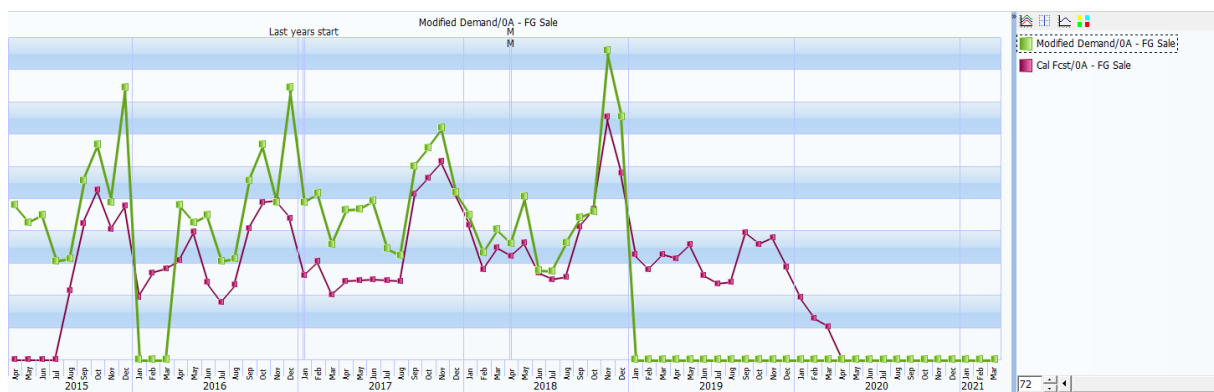
Given the market classification exhibited in Chapter 3, now each product of the group can be placed in one of the three different market's class according to both the variability and the seasonality values of its Brand and the type of subsidiaries (big or small customer). In this phase, products from different market's

categories are tested against all the different statistical models adopted by the company and these latter are ranked according to the company's performance's indicators.

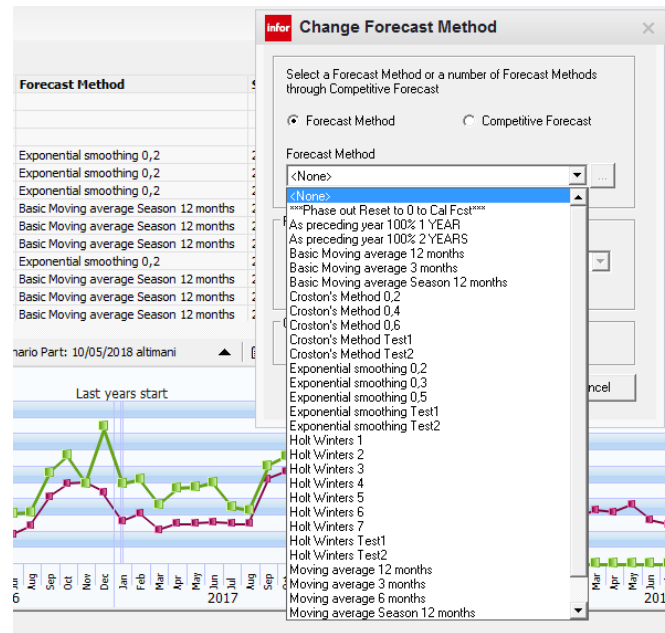
Data collection

Data have been retrieved from the DMP (data management platform) of the company where all past records of both past demand and past performance are collected. In this software every month the demand planner of each local subsidiary publishes his future forecast for the next 18 months and it is here where month by month he chooses his forecast strategy. As explained in Chapter 1, the demand planner has a main choice to make: whether to compute future demand forecast through the use of his manual calculus and personal knowledge (through the Manual Forecast) or to trust the statistical models presented in the software (Calculated Forecast). The aim of the analysis is to have the majority of choices for the calculated forecast reducing both the time and the cost waste. Thus, during the forecast simulation done during the analysis, the Calculated Forecast has always been chosen as a strategy of forecast for basic products in their maturity phase.

In the two figures that follow, a plot of example is shown to give a visual idea of what it has been just said. The first image represent the trend of the Modified demand during the years and the trend of the statistical model chosen, in this case the Exponential Smoothing. In the second figure, the detail of the list of 29 statistical models presented in the software is represented.



(Figure 55: example of simulation of demand forecast, source: DMP software)



(Figure 56: list of the 29 statistical model for future forecasts, source: DMP software)

In Figures 55 and 56 it is easy to recognize the Modified demand in green and the Calculated forecast in pink;

For every statistical model selected, so for every simulation of future forecasts, data are then extracted into an Excel format in order to calculate their specific performance indicators. Following, a representation of the Excel analysis is shown for a given product, during the year 2018:

(Table 11: extrapolation of past company's records in Excel format)

Year	Month	Data	Data Value	Monthly SFD
2018	Apr	Modified Demand	xxx	
2018	Apr	Cal Fcst	xxx	4%
2018	May	Modified Demand	xxx	
2018	May	Cal Fcst	xxx	24%
2018	Jun	Modified Demand	xxx	
2018	Jun	Cal Fcst	xxx	60%
2018	Jul	Modified Demand	xxx	
2018	Jul	Cal Fcst	xxx	40%
2018	Aug	Modified Demand	xxx	
2018	Aug	Cal Fcst	xxx	20%
2018	Sep	Modified Demand	xxx	
2018	Sep	Cal Fcst	xxx	15%
2018	Oct	Modified Demand	xxx	
2018	Oct	Cal Fcst	xxx	185%
2018	Nov	Modified Demand	xxx	
2018	Nov	Cal Fcst	xxx	4%
2018	Dec	Modified Demand	xxx	
2018	Dec	Cal Fcst	xxx	212%
2019	Jan	Modified Demand	xxx	
2019	Jan	Cal Fcst	xxx	217%
2019	Feb	Modified Demand	xxx	
2019	Feb	Cal Fcst	xxx	225%
2019	Mar	Modified Demand	xxx	
2019	Mar	Cal Fcst	xxx	18%

For confidentiality reason, raw data concerning the actual demand and forecast are not shown in Table 11. Thanks to this extraction, the monthly SFD is calculated according to the data values gathered in the software. This indicator has been manually calculated for every simulation that has been done, indeed this procedure has represented a limitation of the research process because of the long-time waiting.

Data analysis

Even if this analysis procedure takes a long time to be done, it allows to have the most detailed final results concerning the different market's class and thanks to this today's list of 29 statistical models will be filtered and optimized.

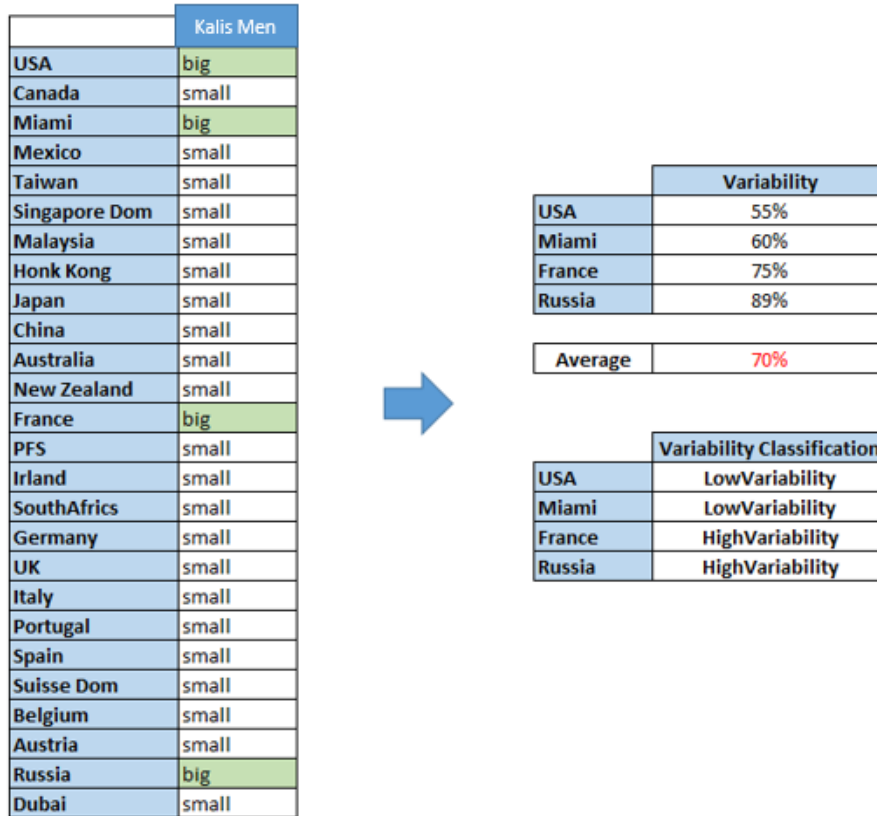
Next, two different analysis will be presented; the aim of these two is the same: to find a final association between a demand class and its statistical models. The first analysis is an initial attempt to solve the problem at stake therefore from it a few adjustments will be derived; the latter will be then applied in the second analysis which can be considered as an evolution of the first one: same goal, same data but improved procedures.

The main issue of these analysis is to understand the level of detail of the study: a trade-off between the quality of results and the computation time. On one side keeping it simple allows to do more simulations but it impacts the final quality of results. On the other hand, choosing a deeper level of analysis gives more precise and performant results but it incredibly increases the computing cost. In the first following analysis, as a first attempt, a more general level of analysis has been taken into account to measure the variability's cut-off value.

First Analysis

In this initial trial and error phase the variability levels needed to classify the specific product's demand has been computed at the group's subsidiary level i.e. that the variabilities of the big customers identified

for each brand has been compared in order to choose the cut off values.



(Figure 57: example of variability's classification in the First Analysis)

In the case above, only the big customers of the specific Brand have been taken into account, once again this choice has been done because these subsidiaries are considered as more representative of the group's market demand. Once the Big customers are identified, the variability of each of them is computed in order to finally obtain the variability's cut off value given by the average of all big customer's individual value. In this specific case, the average (or the cut off value) chosen for the Brand will be 70%.

An example of simulation is given for Kalis Age brand and for one of its big customer, the French subsidiary. In this context, a product with high correlation and high variability i.e. belonging to the Seasonal Stable market's class has been considered as subject of the analysis. All the 29 statistical models have been tested on the product as concerns the forecasts of the past year, 2017, and the sales forecast deviation related to each model has been calculated for each month of the year.

(Table 12: test on Moving Average
Season 3 months)

(Table 13: test on Exponential
Smoothing 0,5)

(Table 14: test on naïve
method 1 year)

MA Season 3		SES 0,5		Naive method 1 Year	
Month	SFD	Month	SFD	Month	SFD
jan	8%	jan	8%	jan	8%
feb	7%	feb	7%	feb	7%
mar	6%	mar	6%	mar	6%
apr	100%	apr	6%	apr	20%
may	42%	may	7%	may	31%
jun	52%	jun	56%	jun	46%
jul	25%	jul	55%	jul	44%
aug	6%	aug	37%	aug	21%
sep	17%	sep	51%	sep	38%
oct	9%	oct	47%	oct	32%
nov	23%	nov	55%	nov	42%
dec	18%	dec	32%	dec	42%
Average	28%	Average	31%	Average	28%

Above, only three examples of test on statistical models are represented, to give an idea of the test that has been done. Each model is evaluated from the average sales forecast deviation (SFD) indicators given by the average of the 12 indicators linked to each month:

$$\text{SFD (\%)} = \frac{|\text{Demand} - \text{Forecast}|}{\text{Demand}} * 100$$

And the final average value is given by the average of the twelve monthly forecast indicators. Thanks to the final average value computed, it is possible to rank the models according to their performance. Because of a limitation given by the company's software, the performance of the eldest months considered in the dataset has not been computed: indeed the software does not allow to consider periods that happened more than 15 months ago.

Results and limitations of the analysis

The results of this first analysis have not been satisfactory enough because no clear association between each market's class and its related statistical model. In other words, for each demand's category it has not been possible to find a stable set of statistical models to forecast its future pattern.

At this first stage of the analysis, two main issues have been identified as main bottlenecks of the research:

- 1) Because of a software problem, several months have not been taken into account during the test phase which does not give the opportunity to have a broad spectrum of data to evaluate and derive the final conclusions
- 2) The level of detail of the analysis. The main reason why the first results have been underperforming is that the level of detail that chosen to compute the variability's index was too general. On the one hand, comparing different subsidiaries from different regions can be useful to have an overall idea on the market compositions and to identify its most important actors. On the other hand it is not appropriate to compare demand's patterns of markets that have totally different proprieties and customer's specificities, therefore the level of the analysis chosen to find the variability's threshold has to be changed

Second Analysis

In this second stage of the analysis, according to the limitations previously found, adjustments and correction will be adopted in order to have better performing final results.

In the first analysis the amount of data to be analysed was not enough to derive final solutions about the best statistical model to use according to each market demand: indeed, only the period from April 2018 to December 2018 was considered. In order to solve this issue, the simulation was adapted in order to have estimation of future demand until 2019. In this way, the researcher has been able to have more data available to derive final solutions:

First Analysis (2018)				Second Analysis (2018-2019)			
Year	Month	Model	SFD	Year	Month	Model	SFD
2018	Jan	Modified D		2018	Apr	Modified D	
2018	Jan	Cal Fcst	0,0452489	2018	Apr	Cal Fcst	37%
2018	Feb	Modified D		2018	May	Modified D	
2018	Feb	Cal Fcst	0,0436782	2018	May	Cal Fcst	3%
2018	Mar	Modified D		2018	Jun	Modified D	
2018	Mar	Cal Fcst	0,0421053	2018	Jun	Cal Fcst	31%
2018	Apr	Modified D		2018	Jul	Modified D	
2018	Apr	Cal Fcst	0,4051724	2018	Jul	Cal Fcst	86%
2018	May	Modified D		2018	Aug	Modified D	
2018	May	Cal Fcst	0,0387597	2018	Aug	Cal Fcst	119%
2018	Jun	Modified D		2018	Sep	Modified D	
2018	Jun	Cal Fcst	0,2169118	2018	Sep	Cal Fcst	115%
2018	Jul	Modified D		2018	Oct	Modified D	
2018	Jul	Cal Fcst	0,1348315	2018	Oct	Cal Fcst	52%
2018	Aug	Modified D		2018	Nov	Modified D	
2018	Aug	Cal Fcst	0,2509804	2018	Nov	Cal Fcst	37%
2018	Sep	Modified D		2018	Dec	Modified D	
2018	Sep	Cal Fcst	0,0916031	2018	Dec	Cal Fcst	2%
2018	Oct	Modified D		2019	Jan	Modified D	
2018	Oct	Cal Fcst	1,6050955	2019	Jan	Cal Fcst	17%
2018	Nov	Modified D		2019	Feb	Modified D	
2018	Nov	Cal Fcst	1,3605263	2019	Feb	Cal Fcst	18%
2018	Dec	Modified D		2019	Mar	Modified D	
2018	Dec	Cal Fcst	0,1204082	2019	Mar	Cal Fcst	5%

(Figure 58: changing of period of time considered from the first analysis to the second analysis)

Regarding the level of detail of the analysis, this time the variability level has been computed more in depth, by considering each product's marketing specificities. Indeed, in perfume's and cosmetics luxury companies such as the one at stake, each product has its own range of sub products. For instance that a face cream is linked to its specific line composed of: anti age cream, day cream, night cream, cream for the young, etc. This time, the variability cut off value has been computed considering each product's line specific to each different subsidiary as the below example shows:

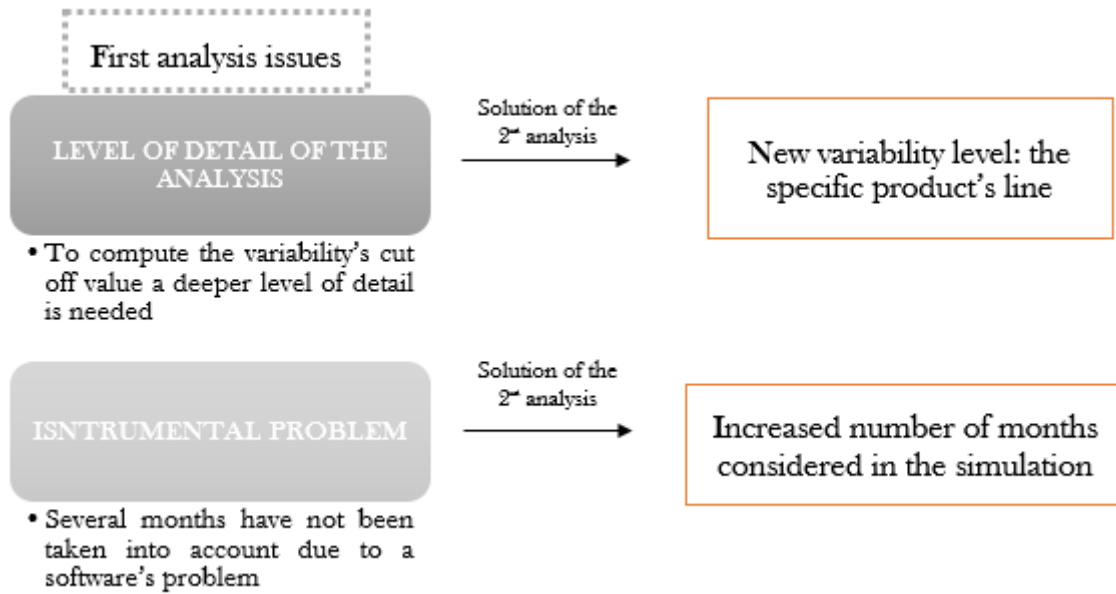
(Tables 15: New variability cut-off values)

MAK	VARIABILITY	Classification
Blush Powder	38%	LowVariability
Mascara volume	46%	HighVariability
Red lipstick	42%	LowVariability
Mascara 3D	52%	HighVariability
Blush cream	42%	LowVariability
Lip pencil	33%	LowVariability
Lip base	45%	HighVariability
Lip perfecter	50%	HighVariability
Mascara waterproof	48%	HighVariability
Mascara color	56%	HighVariability
Eye pencil	41%	LowVariability
Eyebrow	37%	LowVariability
Eye base	49%	HighVariability
Eye liner	48%	HighVariability
Average		45 %

In this case, the make-up line for a specific subsidiaries has been considered. As it is easy to see, the variability concerning the last two years of past demands has been computed for each product belonging to the line and then the average variability of the line has been derived and therefore considered as the variability threshold to classify the specific product in the market. In this case the threshold found was equal to 44% so all those products with variability bigger than 44% are considered as highly variable whereas those whose variability is below this level found are considered as having a low variability.

As it has been explained at the beginning of 5.1, both analyses have the same goal: to find a final, reliable association between different demand classes and a stable set of statistical models. The first analysis was an initial attempt to find a solution to the problem and stemming from its limitations, a new analysis has been implemented thanks to the implementation of the adjustments derived from the previous phase: a deeper level of detail linked to the product's specificities and the solution adopted to overcome the instrumental issue given by the company's software

Following, a sum up of the issues found in the first analysis and the related solutions adopted in the second study are explained by Figure 59.



(Figure 59: evolution between the first and the second analysis)

The next and last step of this chapter is to evaluate results derived on the association between each demand's class and the statistical models to apply. This will be done in the next section through the evaluation of the analysis' results and its related discussion.

5.4 Evaluation of final results

In the current chapter an evaluation of the final results concerning the association between each specific demand's class with a stable set of statistical models is presented.

The main goal while making forecasting is to minimize the residual between the actual demand and what was forecasted; forecast error measures are grouped in two main clusters: relative and absolute error indicators (Ghobbar, A.A. & Friend, C.H. 2004). It is generally suggested to consider more than a single accuracy indicator to evaluate the final error (Ghobbar, A.A. & Friend, C.H. 2004); two of the most conventional measures used in literature to evaluate forecast errors are the Mean Absolute Deviation (MAD) and the Root Mean Squared Error (RMSE) (Teunter, R.H. & Duncan, L. 2009), this is why these two indicators have been used during this analysis:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (Demand - Forecast)^2} , \quad MAD = \frac{1}{n} \sum_{t=1}^n |Demand - Forecast|$$

Together with these two latter, the main performance indicator used by the company to assess the monthly forecast performance has been considered: the Sales Forecast Deviation (SFD); this indicator explicitly shows, in absolute value, the gap between forecasted and actual demand. It is one of the most important to be analyzed at any level of the chain.

$$SFD = \frac{100}{n} \sum_{t=1}^n \frac{|Demand - Forecast|}{Demand}$$

Low values of the SFD are linked to a good forecast performance; it is important to notice that values that approach zero can have negative consequences since forecast should always be bigger than the actual demand in order to guarantee a safety stock in case of emergency; this indicator correspond to the so called Mean Absolute Percentage Error (MAPE) in the literature (Ghobbar, A.A. & Friend, C.H. 2004).

All the statistical models used by the company have been tested for each market category identified in Chapter 3; the best performance was considered to be the one with the lowest value of the error indicator. The new simulation results suggest the following association between market's demand and forecasting methods (that have been optimized according to results presented in Chapter 4):

(Table 16: performance indicators for *HIGH* variability and *HIGH* correlation demand)

HIGH variability HIGH correlation					
Forecasting methods	SFD	Forecasting methods	RMSE	Forecasting methods	MAD
MA12_Season	95%	MA12_Season	2230,81	MA3_Season	1683,167
PrecedingYear1	96%	MA3_Season	2255,98	MA12_Season	1690,000
MA3_Season	96%	ES_0,2	2342,22	ES_0,2	1759,750
BMA12_Season	97%	ES_0,5	2738,00	ES_0,5	2134,750
ES_0,2	98%	MA6_Season	2936,35	MA6_Season	2239,417
MA6_Season	99%	PrecedingYear1	3377,22	PrecedingYear1	2539,500
ES_0,5	119%	HW3	3433,58	BMA12_Season	2608,583
HW3	158%	BMA12_Season	3494,32	HW3	2755,250

(Table 17: performance indicators for *LOW* variability and *HIGH* correlation demand)

LOW variability HIGH correlation					
Forecasting methods	SFD	Forecasting methods	RMSE	Forecasting methods	MAD
MA3 Season	99%	PrecedingYear1	1424,14	PrecedingYear1	1152,33
MA12 Season	101%	MA3_Season	1587,49	MA3_Season	1224,42
MA6 Season	102%	MA6_Season	1628,50	MA6_Season	1288,50
PrecedingYear1	103%	ES_0,2	1697,13	MA12_Season	1329,08
ES_0,2	103%	BMA12_Season	1703,36	ES_0,2	1338,92
BMA12_Season	105%	MA12_Season	1704,92	BMA12_Season	1345,17
ES_0,5	109%	ES_0,5	1948,94	ES_0,5	1543,42

(Table 18: performance indicators for *LOW* variability and *LOW* correlation demand)

LOW variability LOW correlation					
Forecasting methods	SFD	Forecasting methods	RMSE	Forecasting methods	MAD
ES_0,2	129%	MA12	600,72	PrecedingYear1	472,83
PrecedingYear1	132%	PrecedingYear1	601,75	MA3 Season	485,67
BMA 12 season	136%	MA3 Season	611,80	BMA 12 season	488,42
MA3 Season	148%	MA6	619,39	MA6 Season	499,92
MA6 Season	154%	BMA 12 season	622,82	MA12 Season	520,17
ES_0,5	161%	MA6 Season	626,29	ES_0,2	525,58
BMA 12	163%	MA12 Season	653,44	BMA 12	568,00
MA12 Season	171%	ES_0,2	661,45	MA12	585,08
MA3	180%	BMA 12	683,27	MA6	597,67
MA6	183%	MA3	736,04	MA3	601,75
BMA 3	191%	ES_0,5	752,78	ES_0,5	606,33
HW 3	191%	BMA 3	801,61	BMA 3	662,83
MA12	192%	HW 3	865,19	Croston 0,2	750,33
Croston 0,2	195%	Croston 0,2	891,15	HW 3	756,42

Models have been ordered according to their performance: the best ones can be found at the top of the list. As it can be noticed from the tables, a set of statistical models has been associated to each market's class except for the category with low correlation and high variability (concerning products with atypical life cycles): given its erratic nature, it was not possible to find a coherent and stable set of forecasting methods. For this class it is suggested to keep on making manual forecast

The results presented in Tables 16, 17, 18 can be explained as follows:

- *High variability and High correlation* class: overall, the results show that the best performing methods are the MA seasonal 12, MA seasonal 3 and the SES 0,2. The least results are given by the Holt Winters and the MA seasonal 6 methods
- *Low Variability and High correlation*: contrary from the previous case, the best methods that are suggested for this market category are the MA with seasonality 3 and 6 and the naïve method (As preceding year); the BMA 12 and the SES 0,5 have the worst performing results
- *Low variability and Low correlation*: according to Table 18, the majority of the error measures indicates as best methods the naïve method, the BMA 12 with seasonality and the MA seasonal 3. Once again, the lowest values of the accuracy measures belong the Holt Winters and the Croston's method.

As it is easy to notice from the Tables 16, 17 and 18, the final ranking of the forecasting methods' performance is coherent concerning the RMSE and MAD indicators while a few more differences can be found while looking at the SFD (MAPE) measure; this incoherence is caused by the MAPE asymmetry issue explained by Goodwin, P. & Lawton, R. (1999): over forecasts have a heavier penalty than those that are lower compared to the actual demand. This is the reason why the authors of this paper suggest to carefully use the MAPE indicator and they blame the lack in the literature of a coherent system of indicators that can render the evaluation phase less difficult and confusing. The same observation has been done by Ghobbar, A.A. & Friend, C.H. (2004) at the end of their paper where they remark that the difference between forecasting accuracy measures is given by the demand variability which, in the case at stake, is particularly significant in the SFD indicator whose values is indeed relative, i.e. divided by the actual demand.

The final ranking of the model has been done by summing their position in the three different final evaluations. The example for the “deterministic correlation & LOW variability” is shown in Figure 60:

Forecasting method	SFD results	RMSE results	MAD results	SOMME
ES 0,2	1	8	5	14
PrecedingYear1	2	2	1	5
BMA 12 season	3	5	3	11
MA3 Season	4	3	2	9
MA6 Season	5	6	4	15
ES 0,5	6	11	10	27
BMA 12	7	9	6	22
MA12 Season	8	7	4	19
MA3	9	10	9	28
MA6	10	4	8	22
BMA 3	11	12	11	34
HW 3	11	13	13	37
MA12	12	1	7	20
Croston 0,2	13	14	12	39

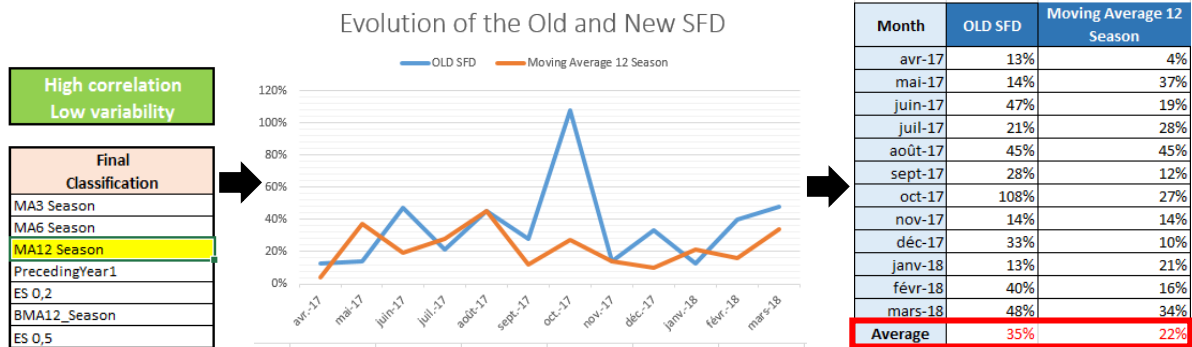


Final Classification	
PrecedingYear1	1
MA3 Season	2
BMA 12 season	3
ES 0,2	4
MA6 Season	5
MA12 Season	6
MA12	7
BMA 12	8
MA6	8
ES 0,5	9
MA3	10
BMA 3	11
HW 3	12
Croston 0,2	13

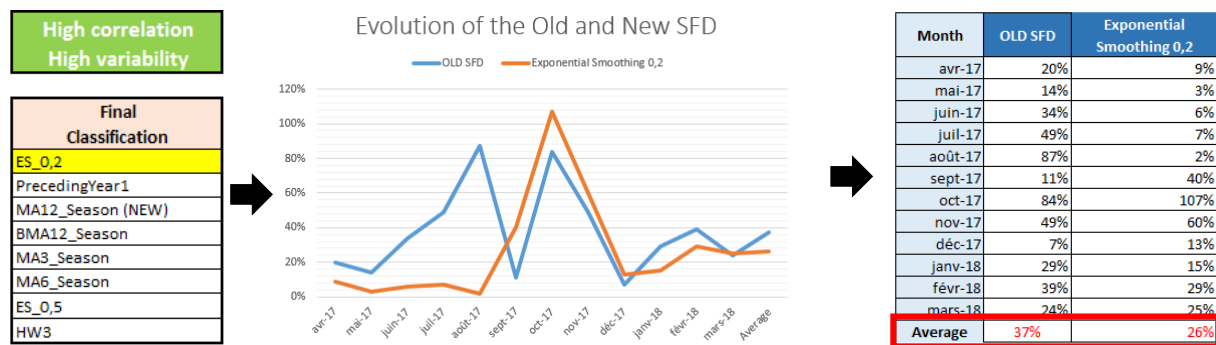
(Figure 60: final model classification for stochastic seasonality and low variability)

For each item that has been tested, the old results of the monthly evolution of the SFD during the year 2017 has been compared to the one given by the analysis' results. According to this new association, the

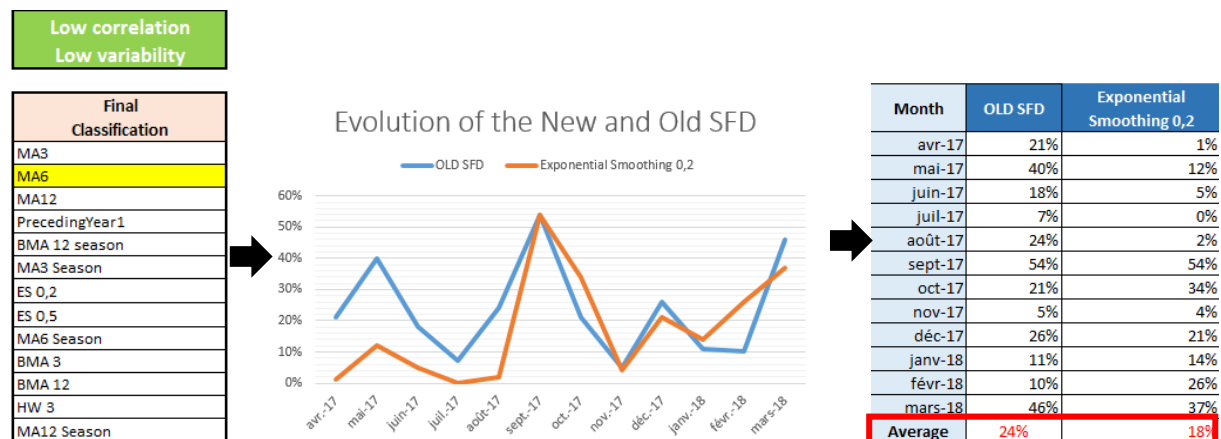
evolution of the Sales Forecast Deviation indicators for each product has been compared against each other. In the following Figures, the old SFD of an item chosen from the three market's categories identified in Chapter 3 and the new values derived by one of the forecasting methods proposed above for this class, are plotted against each other:



(Figure 61: comparison between old SFD values and new model's ones for the market class with Low variability and High correlation)



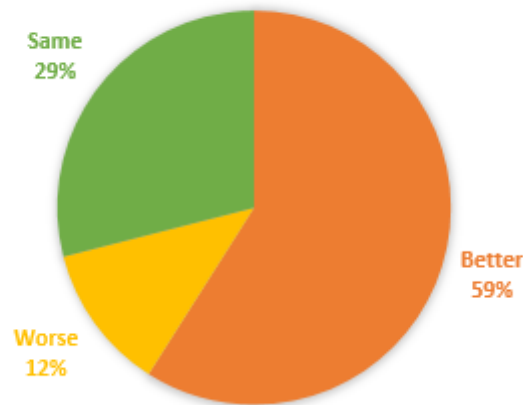
(Figure 62: comparison between old SFD values and new model's ones for the market class with High variability and High correlation)



(Figure 63: comparison between old SFD values and new model's ones for the market class with Low variability and Low correlation)

As one can notice from the figures above, the statistical method suggested performs better compared to last year's results. All evaluations have been done by following this procedure and finally, the overall results showed that the new association between each market's class and its set of statistical models proposed outperforms the old technique adopted by the demand planners last year as Figure 64 shows:

PERFORMANCE OF THE NEW VS OLD SFD



(Figure 64: evaluation results' for the new method proposed)

In 59% of the cases, at least one forecasting model chosen from the list proposed outperforms the forecasting strategy chosen last year by the local demand planner; only the 12% of the cases show a worse performance.

This first results allows the analysis to go one step further: the final realization of a decision tree to support the decision making during the forecast journey. All of this will be discussed during the next chapter.

Chapter 6

Final supportive model: the decision tree

This chapter is dedicated to the realization of the final model to support the forecasting decision making which represents the final deliverable of this research. First, the model's requirements gathered both from the company's demand planners and from the literature studies, will be identified. Secondly, both a visual representation and a theoretical explanation of the decision tree for future forecast will be presented. Finally, the research limitations will be highlighted at the end of the chapter.

6.1 Model's requirements

In this sections the requirements of the model's final design are explained together with their references. The main sources used to collect all of them have been the past literature presented in detail in the previous chapters, the company's demand planners and managers and the author of this paper who had the opportunity to jointly analyse both the company context and the past researches.

These requirements can be divided in two: on one side the "Need to have" requirements i.e. those that are strictly required in the final model that can be considered as the main driver of the analysis without

which the model cannot subsist; then the “Nice to have” requirements, those that can be taken into account but with a different eye: indeed they are not essential for the final design because sometimes they can be special desires or needs that are asked by the company’s or by the literature but that are not realizable in the actual practice.

(Table 19: classification of the analysis requirements)

Requirements	Typology	Reference	Why
Universal procedure: the model has to be adopted by different subsidiaries around the world	Need to have	Local demand planner	Usability: the company’s subsidiaries are spread in 27 countries in the world: they need to communicate with the same language
The demand planner has to have control on the overall procedure : avoid the creation of a total automated process	Need to have	Author of this paper	During unstructured interviews held inside the company, managers admitted that they do not trust the today’s forecasting software
Short list of statistical models for future forecast	Need to have	Company’s demand planner	As presented in Chapter 4, managers need to have the list of best performing statistical models to choose from
Understand how to estimate demand’s seasonality during time	Need to have	Jha, A., et al (2005)	In past literature presented in Chapter 2, the seasonality factor has never been considered
Reliable decision tree stable in time	Need to have	Company & Syntetos et al. (2004)	Except for a few details, the company needs to have a tool that is not subject to periodical adjustments
Low level of technical complexity in the final statistical models chosen	Nice to have	Company’s demand planners	For a matter of accessibility, managers would like to have a tool with the lowest level of technical complexity
Low time cost to set up the model	Nice to have	Company’s demand planner	Demand planners do not want to spend too much time for the installation of the new model
Consideration of product’s specificities	Need to have	G. Junjun & H. Yongping (2008)	In chapter 6 it has been highlighted the importance of the detail of the analysis that needs to reflects the products characteristics
Low cost for the model’s set-up	Need to have	Company’s demand planner	The company is giving a sum of money to invest in the project
Realisation of a model that can be applied in a concrete industrial context	Need to have	Bacchetti & N. Saccani (2012)	The users of the final deliverable are demand planners working in industrial contexts
Change the company’s software for future forecast	Nice to have	Author of this paper	The today’s software requires a long computational time to make simulations
Efficiency: better performance compared to 2017	Need to have	Company and the author of this paper	In Chapter 5, the underperforming results of year 2017 have been discussed

Accessibility: the model has to be readable and usable by everyone	Need to have	Author of this paper	The knowledge required to use the model has to be the ones possessed by industrial demand planners
Final real time demonstration on how the model works	Nice to have	Author of this paper	Communication of the final model: the final deliverable should be communicate to all the company through both and oral and a written demonstration

The requirements listed in Table 19 are translated in the final deliverable of this research: a supportive decision tree for demand planners' forecasting decision making. In the next section, it will be shown how these needs have been used to build this final model.

6.2 Decision tree for future forecast

One of the most important step after results have been analyzed, is to find a way on how to communicate them in an accessible and exhaustive way. In this specific case, a tool that can reconstruct the classification procedure studied in this research thanks to which when demand is not known a right class can be linked to it, is needed.

Because of its superiority in modelling the decision making process, the scope of this section is the creation of a decision making tree that can support managers during their forecasting journey. Since this tool is needed to show how to take the best decisions during the forecasting journey, this tree is going to be prescriptive. The main advantages of decision trees are (Quinlan, J.R. 1990):

- **Clarity and conciseness:** decision makers need to have an accessible tool to use every day to support their decisions. Thus, they prefer to have a lower level of precisions in the final outcome but to have a clear path to follow that is linked to their own knowledge.
- **Context sensitivity**
- **Flexibility:** decision tress allow to represent both continuous and discrete attributes

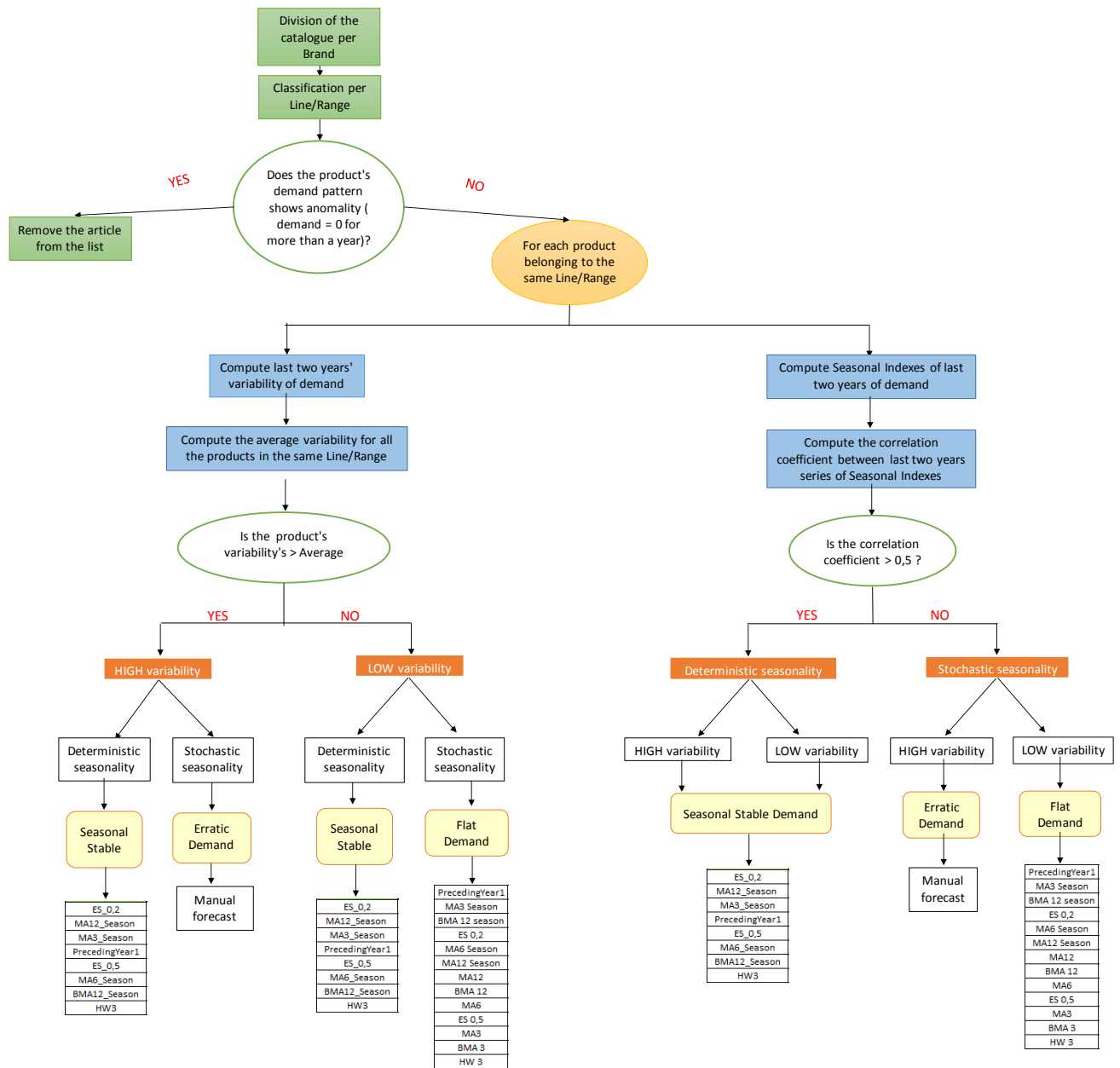
Compared to statistical tools where classification's rules are represented by a group of numbers and formulas, decision trees gives a symbolical reproduction of the decision making journey; indeed, each group of unknown objects will be identified with a Nominal class: in this specific case, unknown demand patterns will be classified into different pre-defined categories.

Before showing the final tree that will reproduce the classification results explained until now, it is important to explain the main terminology which characterizes it (Quinlan, J.R. 1990):

- The *object* of the tree are product's future demands
- Each object belongs to a specific *class*: in this case, three main classes are recognized corresponding to three different market's classes
- The proprieties of objects are called *attributes* and in this case they are the main drivers that categorize the demand: the variability and seasonality of demand's patterns

Noisy data, that is to say those products that for exceptional reasons had the demand equal to zero for more than a semester, are managed through a stopping criterion: if demand is equal to zero for more than 6 consecutive months, the item is removed from the list.

Figure 65 gives a representation of the final decision tree that will help demand planners to classify different demand's patterns:



(Figure 65: final decision tree to support future forecast)

Final company's remarks

The final decision tree, together with the guidelines to follow for its implementation, has been communicated to all the group's subsidiaries. Because of time's limitations, it was not possible to test the results once all the subsidiaries could concretely use the model. By the way, several interviews have been done to some of the region's coordinators and to the central coordinator of the company's demand planners. As a result, different feedbacks concerning the supportive model have been retrieved:

- **Future owner of the model:** in the imminent future, the central coordinator of demand planner's will be responsible for sensitize the subsidiaries on the topic. In a second moment, the group's demand planners will be in charge of testing the model and bring possible future adjustments

- Concerning the **detail of the analysis**, it would be of interest for the company to go more in detail, e.g. not to stop the level of the analysis at the product's line but try to go one step further to the single product.
- **Level of knowledge** required: stemming from the managers' opinions, through the simple explanations of statistical tools used to categorize the demand given and an oral explanation of the forecasting methods selected, all demand planners will be able to understand the steps to follow
- **External experts** analysis' results concerning the optimization of the Holt Winters are still pending
- In order to refine the model, it would be of interest in the future to expand it not only for the products in the maturity phase of their life cycle but also those that are up to other stages (i.e. decline, installation, new launch, etc.)
- **Usability** of the model: since, to classify demand patterns, last two years of demand data are needed, planners will have to update the classification at least once a year. From the company's side it would be of interest and also a gain of time to have a software that could automatically do the calculations instead of being obliged to make them manually on an Excel file. By the way, this model can be used by all subsidiaries around the world since its specificities are linked to the product and not to the local market at stake
- **Model's communication**: for now the communication has been done at a global level, in the future several meetings will be organized for smaller groups of subsidiaries at a time (i.e. divided by region: European, American, Asian, etc.) in order to have a more effective communication concerning specific markets
- **Forecast at the shop level**: during the interviews it has been faced the option of extending the model at the individual customer level. For instance, instead of receiving the orders of the Chinese subsidiary as a whole, which could be the improvements of receiving the individual Chinese retailer future forecast? From the company's point of view this option is not of interest since the demand planners and the whole supply chain are organized by "regions" and it would not be feasible to reorganize the entire chain in the imminent future. By the way, thanks to the experience had inside the company, a few suggestions regarding this topic for the future can be given by the author of this paper:
 - For those markets depending on just a few customers, it would be of interest of linking the forecast to the single retailer. In this way it would be possible to verify whether the forecasting problem is at the subsidiary level or at the single clients' one.
 - The company's hubs, such as Bangkok (see Section 1.2), serve also all those countries that do not possess their own stock. For instance Thailand, Korea, etc. In this case, if the orders' quantities are considerable, forecasts could be distinguished among those different countries instead of having one single order coming from the hub.
 - If the forecasts could be linked to the single customer, it could be possible to prioritize among different clients: in case of emergency, when the stock cannot cover all the subsidiaries orders, it could be an advantage for the company to be able to establish priorities for the stock allocation not at the regional level but at the individual customer one in order to have a closer relation with the final end client.

Overall, this model has been considered by the company as a first milestone in its forecasting process contributing both to build a new forecasting strategy for the group comprehensive of all the different steps of the decision making process (from classifying the demand pattern until the choice of the forecasting method related to it) and to improve the "forecasting culture" inside the company by involving all the subsidiaries during the studies.

In the next section of this chapter, the final model's limitations are highlighted in order to be able in a second moment, Sections 7.4 and 7.5, to give future recommendations both for the company and for future research.

6.3 Research limitations

During the course of the analysis, several factors, both internal and external, hampered the research and consequently the achievement of the ideal objectives prefixed at the beginning of this article. The main limitations faced during the study are listed below:

- **Optimization of the Holt Winters' parameters**

As it has been explained in Chapter 4, the Holt Winters method has a high potential as concerns future forecast thanks to its capacity to separately consider the seasonality, the level and the trend of demand's patterns through three distinctive smoothing constant. The only drawback of this model is its computational complexity which requires time to be optimized. During the research, external experts have been interviewed in order to understand the model in detail and to find an algorithm that could optimize the model's parameters present in the offset of the company's software. Unfortunately, even if the method's working principles have been understood, the optimization of its smoothing constant requires more time than expected preventing the author from ending up with the best performing version of the method

- **Software constraints**

The Data Management Platform (DMP) used by the company has presented two main issues during the leading of the analysis: first, it did not allow to consider a long historical of past demand data because of its short database memory; this did not allowed to test models whose performance theoretically improves as more past data are considered (i.e. the Moving Average method); in addition to this, because of the software's slowness in computing new simulations, the whole analysis resulted to be highly expensive from a timing / computational point of view

- **Communication among different actors**

Even if they were involved to understand the main problematic concerning the forecasting strategies, the physical distance from both the local demand planners and the experts in statistical models, has certainly been a weakness for the analysis. Even if data was available from all the subsidiaries of the group, the reactivity in receiving answers and in communicating the final results slew down the all process. Moreover, communication via mail and / or Excel's documents has often be susceptible to the beneficiary's misinterpretation of the proposed results and questions

- **Luxury business**

The research has been done in collaboration with a company that belongs to one of the four categories (Amatulli, C. et al. 2018) of the luxury market: the perfumes and cosmetics sector. Compared to the mass market, luxury markets present a different supply chain's configuration both at the up-stream and at the down-stream end (Brun, A. et al. 2008); indeed, products are the results of a complex solution of quality, innovation, and retail-control attention. From a generalizability point of view, having led the analysis in a luxury context could hamper the final model to be applied in several sectors belonging to the mass production but at the same time, the luxury market has faced an important demand growth during the last years (Amatulli, C. et al. 2018) in countries all over the world which urgently asks to be studied and controlled. Indeed results have not been severely impacted by the market at stake: even if Kalis is placed in the luxury business as concerns the cosmetic sector, the frequency of demand has been found to be always high. It could be supposed that, in contrary to the past, nowadays the customers buying power in developing countries such as in Asia, is increasing and this could be a reason why the demand of luxury business such as Kalis is increasing year by year. The only factor that could have been not important if the research was done in a mass market, is the seasonality factor. In fact it could be hypothesized that in

business such as the food market or the pharmaceutical one, people are buying not according to the current season but to their daily need (e.g. every day we need to buy water no matter the season at stake).

These limitations will be addressed in the next chapter where suggestions and future recommendations both for the company itself and for future research will be provided. In Chapter 7, the final answers to the three research questions and the relevance of this study will be given.

Chapter 7

Conclusions

This Chapter will help to highlight the relevance of the current study and to sum up the results finally found. In order to accomplish this, the research questions will be answered with clear references to the text, afterwards the importance of this research's achievements will be under lighted.

The research will be concluded with some final reflections of the author of this paper and future recommendations.

7.1 Research questions

In this section, the answers to each research question is given in order to precisely define the final guidelines to follow during the forecasting journey.

- **SQ1:** *“How can the markets portfolio of a multinational be classified?”*

The forecasting method chosen during the future demand planning strongly depends on the market's nature. Nowadays, research has still not succeeded in determining a reliable classification method to help demand planners understanding the nature of their market. The answer to this question has been the most delicate analysis during the research. Based on the past works of Syntetos et al. (2005) and Kalchschmidt et al. (2003), the final solution allows managers to classify whatever demand pattern by following some simple steps:

- 1) **Analysis of the supply chain structure.** The first step is to understand the organization of the supply chain at stake based on which the all categorization scheme will be realized.
- 2) **Aggregation of the global demand into meaningful clusters:** the analysis of a group of articles that shares the main properties simplifies and improves the final forecast performance. In this study, a top-down hierarchical approach has been used as it consents to gradually cluster demand according to different articles' specificities. The aggregation of the demand has to reflect as much as possible the supply chain structure identified in the previous step in order to guarantee its concrete applicability in the industrial context.
- 3) **Choice of the main demand factors with relative cut-off values:** this crucial step allows to determine which will be the main drivers of the classification. It is important to choose factors which are significant for the classification of the products demand; for example, even if in the literature the frequency of demand is always considered essential in categorizing the demand, here it has been removed since all the articles have found to be characterized by the same level of frequency. According to this, the seasonality and variability of demand have been found to be the main axis of the categorization scheme.
- 4) **Selection of the cut-off values.** To find the relative cut-off values, the main trade-off that needs to be solved is the conflict between the level of the analysis detail and the quality of the final forecast. It is suggested to privilege a deep level of detail during the analysis in order to find the best cut off values for each categorization factor in order to have the most realistic representation of the actual

demand. In addition to this, the more historical is considered, the best the final results will be since time series analysis is based upon past data

- **SQ2:** *“How can statistics model future demand trend?”*

Nowadays statistical models for future demand forecasts are considered by managers as a “black box” (N. Saccani, & A. Bacchetti, 2012), that is to say that they represent something unknown and therefore hard to rely on. In order to overcome this issue, the most conventional statistical models for future forecasts have been explored and explained from a managerial perspective: their advantages, limitations and their industrial applicability have been identified. The main goal of this part of the analysis was to establish demand planners’ trust in statistical models that can represent a future gain both in the time and performance of the overall process.

- **SQ3:** *“Which statistical forecasting models must be used to forecast the demand of different markets?”*

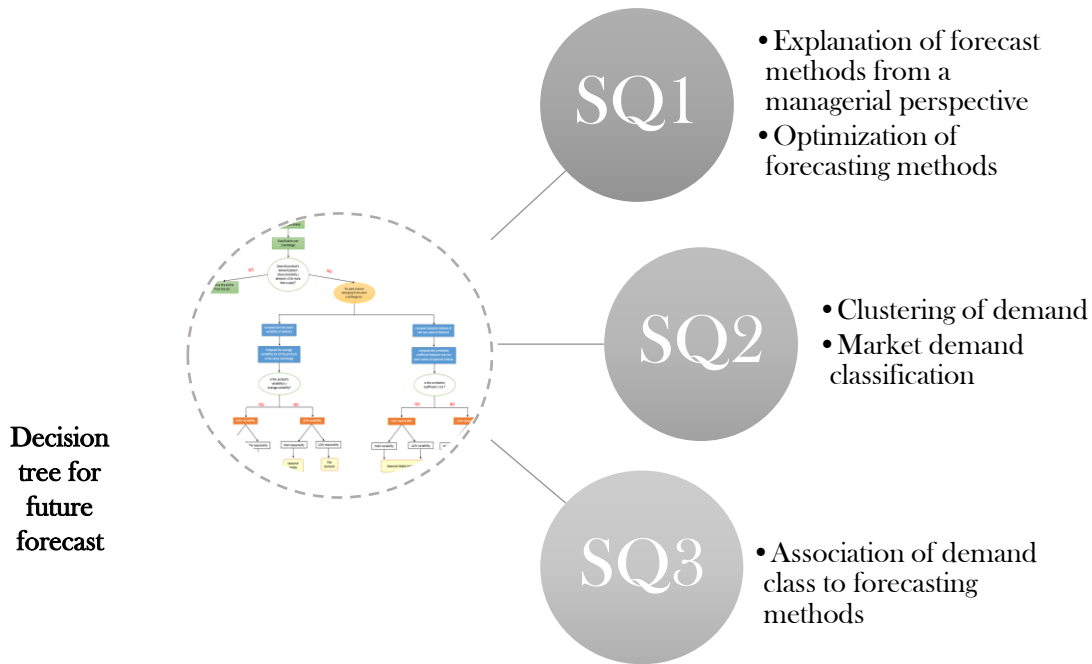
Thanks to the results given by the SQ1 and SQ2 the final decision tree to support the forecasting journey can be finalized. This can be realized through the following last phase of research: the association between specific market classes and a stable set of forecasting models

Evaluation of the results found has been done through three different accuracy measurement, which clearly showed the performance improvements compared to last year one.

The solution to this final question is strongly based on the last two questions results’: if these latter are not reliable, it is not possible to find a stable set of statistical models for each demand pattern. If this is the case, the all demand categorization scheme will have to be put under discussion again (as it has been done in the two different analysis of chapter 5).

- *“What is the future demand forecasting model that can support the decision making journey in a multinational company such as Kalis Group?”*

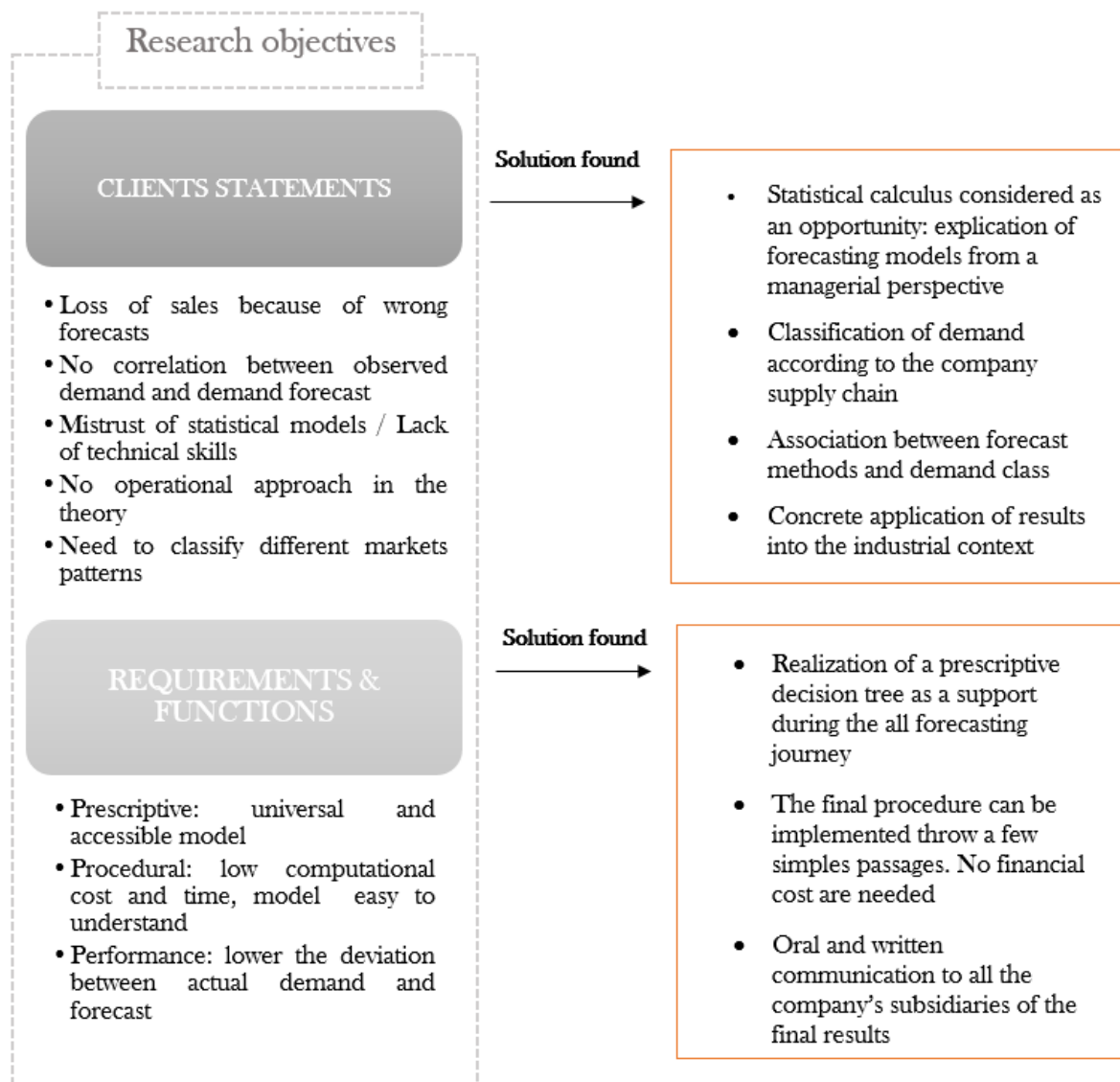
As said in Chapter 1, the main question that drives the all analysis is a design question; indeed the final support is an accessible, prescriptive tool that can help managers from the beginning until the end of their forecasting journey: the decision tree for future demand forecast. Figure 65 in Chapter 6, gives the final representation of the tree that has been sent to all the subsidiaries of the company under analysis. Managers find this tool easy to access, exhaustive and concretely applicable in an industrial context. This decision tree is the final result of all the decisions taken in the previous sub question, a coherent sum up of all the forecasting solutions proposed to the group to improve their strategies.



(Figure 66: steps to answer the final design question)

7.2 Contributions of this study

In Section 1.5, both the client's, Kalis company, statements and the requirements asked from this study have been identified; following, to highlight the contributions of this study, it will be shown that these latter have all been solved and answered.



(Figure 67: research final achievements)

From Figure 67 it is evident to notice that all the initial requirements and the clients' statements that have been tackled, only a few adjustments need to be brought in the upcoming future in order to improve its final design (see Section 6.3). The concluding deliverable is a prescriptive decision tree that entirely covers the forecasting process, it is an easy and accessible tool that can be used in different industrial contexts. Together with it, a series of guidelines have been given in this Section 7.1 while answering to the research questions, in order to help managers to implement the results found.

The final model solutions have been communicated both orally and through a written presentation to all the subsidiaries of the group in order to sensitize the all company about the urgency of the topic. This work has been considered essential since it is touching every single aspects of the forecasting process.

The current research has brought four main contributions to the past literature discussed in Chapter 2 especially by Bacchetti and Sacconi work (2012) whose review has been presented in Section 2.1:

- 1) The knowledge theory concerning the forecasting process has been brought close to the everyday managerial practice: thanks to the involvement of demand planners during the analysis, problems have been solved under an industrial perspective in order to guarantee the concrete

implementation of their solutions (contrary to the over simplification of reality done by Junjun, G. & Yongping H. (2008) and Strijbosch et al. (2008) in their works)

- 2) The issue of demand classification is still lacking behind in the literature state of art: this work strongly contributed to the categorization of the market demand not only from a theoretical perspective (as it is done in Junjun, G. & Yongping H. (2008) and Strijbosch et al. (2008) articles), by creating a new scheme for the demand pattern classification, but also from a practical perspective by implementing it in a real industrial case
- 3) Thanks to the clustering of the demand according to the product's characteristics and the creation of a top-down hierarchical approach, this research has taken into account the different nature of items within the industrial context, something that the past literature has rarely considered during its discussion (in answer to the problem highlighted by Jha A. et al. (2015) in their article)
- 4) Forecasting methods are not considered as a "black box" anymore by demand planners: thanks to both the managerial explanations concerning statistical models and to their optimization, demand planners are now more confident to include them in their forecasting routine (A. Bacchetti, & N. Saccani 2012)
- 5) Universal approach for the forecasting decision making process: this research created a holistic support that can help managers during their entirely forecasting journey. In contrary to other studies in the past that were focused only on a specific topic of the forecasting procedure, this work now addresses a whole range of topics simultaneously.

7.3 Personal reflections

This research has been a great opportunity to challenge myself in an unfamiliar academic field: the forecasting journey in a multinational context. For instance, I did not know all the specific factors that impact the final decision making and the theoretical contribution concerning the topic. Furthermore, I had the opportunity to experience this abroad, in a foreign company with specific needs and requirements. It was therefore the occasion to escape my comfort zone and develop my ability to adapt to a different working environment and new technical concepts. As the project progressed, I became more and more passionate about the practical significance of each part and their impact on the final performance.

More generally, the project was demanding because innovative and unprecedented, and involved multiple external variables. For example, the involvement of external experts or the needs of faraway subsidiaries. Working on this project was a mix of advantages and disadvantages: on one side it was useful because I took benefits of prior experiences through both documentation and design reviews with Kalis' managers. On the other hand, since this project sets the base for a universal forecasting process, it is dependent on others' opinion and on the available company's software. This eventually slowed the research down and forced me to accept that some of the final deliverables would not be completed on time, in spite of myself.

Overall, I believe that project success was achieved thanks to effective organization and time management. Also, the conflicts encountered during time, caused by the unknown context and different cultures, played a significant role in making the project rich in variety. This project was thus not only a technical challenge, but also a management and social challenge.

Besides being fully responsible for the realization of a final supporting tool for the forecasting decision making, I was in charge of communicating the project in the best possible way, which involved an oral presentation, report formatting and layout, and images and graphs quality. In future projects, I should

become more open to improvement suggestions which drive the project forward, instead of blindly focusing on task achievement.

Under the light of the research limitations identified during the analysis, in the following sections future adjustments and suggestions will be addressed accordingly. First, specific suggestions will be given to the company at stake for future improvements; second, the generalizability of the model to other contexts will be treated thanks to specific recommendations to apply when using the model in different situations.

7.4 Recommendations for the company

In the future, in order to further improve the model realized during the course of this research, the company should:

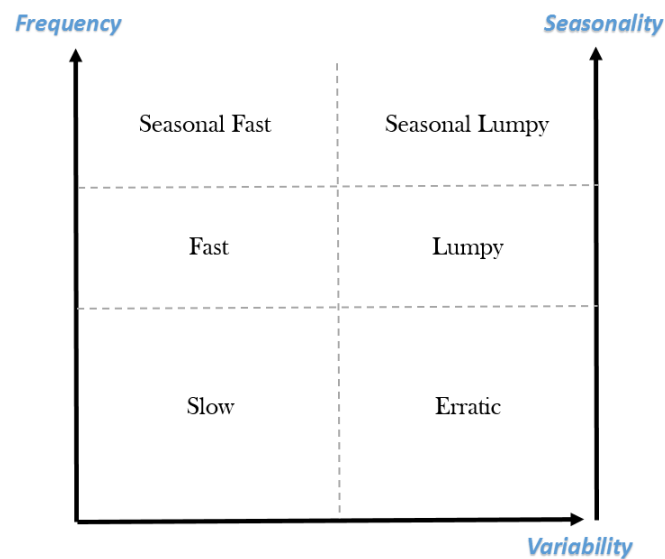
- **Optimize the Holt Winters method:** despite its theoretical potential in making future forecast, the Holt Winters' method requires computing time in order to find the optimal values of its smoothing constant α , β and γ . Stemming from the literature, two main guidelines should be followed in order to find the best parameters:
 - Adoption of an adaptive technique (Kalekar, S. 2004) (Williams, T. M., 1987): this technique consists in adjusting the parameters every two years in order to guarantee the parameters' adaptivity to the changing behaviour of the underlying time series
 - Selection of the best performing parameters through the minimization over a past period of time whose historical demand data are known. The performance of a grid of parameters values can be tested and evaluated through the minimization of forecasting errors such as the Mean Square Error (MSE) (Chatfield, C., & Yar, M. 1988) or the of the mean squared forecast error (MSFE) (Gelper, S. et al. 2010):. Generally, it is suggested to choose values between [0,1 : 0,3] or higher when the series presents an exponential growth (Chatfield, C., & Yar, M. 1988)
- **Sensitize the subsidiaries:** during the research, subsidiaries have been mostly involved only at the beginning of the project, in order to identify the problems they are facing concerning the forecasting strategy. In the future, it would be of help to define a routine inside the company in order to collaboratively find new solutions. For instance, through monthly meetings that could improve the interactions between the central hub and the faraway subsidiaries
- **Improvement of the company's software for forecasting:** time series analysis improves as more historical data are taken into account; one of the major constraint during the analysis was the impossibility of considering a long historical during the simulations because of an instrumental limitation: this is an adjustments that urges to be done in the current algorithm of the company's software
- **Improvement of the "forecasting culture" inside the company:** the implementation of a forecasting team composed by professional experts could build an in depth forecasting culture within the company: this latter could invest in training its demand planners on forecasting methods and evaluate the future impact of this initiative on the Return on Investment (ROI)

7.5 Recommendations for future research

Kalis places itself in a specific, premium market segment as it has been explained in Section 6.3 when the research limitations have been addressed. In order to guarantee the generalizability of the model proposed

to other contexts, several guidelines can be identified that can help to adapt the model according to the context at stake:

- **Aggregation of demand.** In this research, demand was grouped according to the Brand and to the family segment (skin, make-up or perfume); stemming from the lessons learnt during this analysis, it is recommended to cluster demand according to both the product's properties and the specific supply chain structure; as it has been shown in this research, clustering demand according to characteristics that do not concern the product itself (e.g. Big and Small subsidiaries) directly impact the final classification by not giving a realistic representation of the demand linked to the specific product
- **Forecasts' time period length.** In the company at stake, forecasts' computation happens on a monthly base; all the calculus that have been explained needed to compute the variability and the seasonality levels of the demand have to be adapted according to the specific time period length adopted: weeks, years, semesters; day, etc.
- **Classification of demand: the frequency factor.** For the company at stake, demand was found to be always defined with a high frequency: zero demand hardly never happens. In other markets, such as niche markets, characterized by slow demand (where positive demand occurs after a long period of zero demand) the frequency factor should be reintroduced into the categorization scheme. A possible idea of how the new scheme could look like is given in Figure 68:



(Figure 68: integration of the frequency axe in the demand categorization scheme)

Figure 68 suggests a possible visualization of a future introduction of the third frequency axis; in this scheme, seasonality is playing a role when demand's frequency is high since it is not coherent to compute a seasonality index if demand is either often zero (slow demand) or characterized by an instable pattern (erratic demand). In this way, six demands classes could be identified and as concerns the slow and erratic classes, new simulations should be done to have more insights concerning the best performing statistical models linked to them.

- **Cut-off values.** Stemming from the previous point, also cut-off values of the three main axis will have to be adapted according to the market at stake. For the three factors the same procedure adopted during this research is suggested:

- Seasonality: the cut off value concerning the correlation between the SI of last two years of demand has always to be considered equal to 0,5
- Variability: the cut-off value will be the average variability of the last two years of demand computed among all the article belonging to the same cluster
- Frequency: the cut-off value will be the average frequency level of the last two years of demand computed among all the article belonging to the same cluster

Thanks to their easy implementation, cut-off values used in this model will be easily found for articles belonging to no matter which context

Once the model's generalizability has been guaranteed, suggestions for incoming research can be addressed. Indeed, future research could highly contribute in the improvement and development of this study. Nowadays, literature is still lacking behind in finding new solutions concerning the forecasting process together with all its aspects and this is why future studies should be focused on this area. Possible line of future research should address the following topics:

- **Machine Learning:** nowadays multiple optimization algorithms can solve multi-objective optimization problems. These high-performing computing codes could be used to find the desired extremum, which in the case of this research would be the minimum of the difference between forecasted demand and real demand. This could be achieved very accurately using genetic algorithms or the Newton's method, although both of these methods would lead to great computing costs. Easier and faster approaches such as linear programming, Lagrange multipliers, the gradient-descent method could also be very efficient at solving forecasting problems with multiple objectives and constraints
- **Accuracy measures.** One of the most critical decision concerning the forecasting process, is the choice of the forecast error measures; nowadays research has still not found a clear explanation about what are the best indicators to use in different situations, there is not a universal agreement about the efficiency of all these measurements. Table 20 shows the amount of indicators discussed by authors cited in this paper:

(Table 20: error metrics, Source: Schraven, M. M. 2015)

Error Metric	Full Name	Definition	Used in comparative study
ME	Mean Error	$\frac{1}{n} \sum_{t=1}^n (y'_t - y_{t+1})$	Ghobbar & Friend, 2004 Syntetos & Boylan, 2005 Teunter et al., 2011
MSE	Mean Squared Error	$\frac{1}{n} \sum_{t=1}^n (y'_t - y_{t+1})^2$	Ghobbar & Friend, 2004 Syntetos & Boylan, 2005 Teunter et al., 2011 Teunter & Duncan, 2008
RMSE	Root Mean Squared Error	$\sqrt{\frac{1}{n} \sum_{t=1}^n (y'_t - y_{t+1})^2}$	Ghobbar & Friend, 2004 Syntetos & Boylan, 2005 Teunter & Duncan, 2008
MAE (MAD)	Mean Absolute Error	$\frac{1}{n} \sum_{t=1}^n y'_t - y_{t+1} $	Ghobbar & Friend, 2004 Syntetos & Boylan, 2005 Teunter et al., 2011 Teunter & Duncan, 2008

MAPE	Mean Absolute Percentage Error	$\frac{100}{n} \sum_{t=1}^n \left \frac{y'_t - y_{t+1}}{y_{t+1}} \right $	Ghobbar & Friend, 2004 Syntetos & Boylan, 2005 Teunter et al., 2011 Teunter & Duncan, 2008
SSE	Sum of Squared Errors	$\sum_{t=1}^n (y_{t+1} - y'_t)^2$	Ghobbar & Friend, 2004

For the future research, it would be of interest to explore this topic and to build a solid knowledge around accuracy indicators in order to have the possibility to exploit them for the best according to the specific case at stake

- Choice of cut-off values.** The determination of the cut of values still represents a challenge for demand categorization since their contextual nature. For instance, both Williams (Howard, A., & Eaves, C, (2002)) and Eaves (Syntetos, A. A., et al. 2005) works have been criticized because their categorization schemes provide arbitrary cut-off values that will be defined by the individual “*managerial decision*” (Syntetos, A. A., et al. 2005); Syntetos and Boylan in their work accomplish a first step towards the improvements of the determination of cut off values by computing them according to the performance of statistical models (Syntetos, A. A., et al. 2005). At the end of their article they address research to try to find a more systematic and meaningful approach to the demand categorization process since until now this topic has not gained enough attention from the literature. In addition, it has to be kept into mind that this categorization scheme has to be used by industrial managers and this is the reason why the decision tree developed during this research could be a powerful tool to be improved by future studies because it can be accessible by everyone in different contexts.
- Focus research on factors other than time history.** This study focus on the management of past demand data in order to make future previsions (e.g. time series analysis). It would be of interest for future research to try to develop and integrate the mathematical aspect of doing forecast with the “judgemental based approach” (i.e. the work done by Marmier, F., & Cheikhrouhou. N. (2010)) where the managers’ personal knowledge and external factors that cannot be retrieved by the scientific calculus, are taken into account. In this scenario, different experts and field of research could be involved in order to improve the forecasts accuracy: psychology, sociology, or the ability of linking customer habits / perceptions to the future forecasts
- Demand clustering.** As it has been explained in Chapter 3, the aggregation of demand into homogeneous groups highly facilitate the forecasting process and moreover it allows to improve the final forecast performance. The clustering of demand has recently gained attention by the current research: it is indeed important to develop the knowledge around this topic in order help managers to easily adopt this procedure in their routine; several examples of demand clustering are given by Kalchschmidt, M., et al. (2006) according to the market at stake:
 - Demand can be grouped according to the supply chain structure: direct or indirect (those who see an intermediary between them and the company) customer
 - For mass markets (i.e. food industry) demand variability is highly varies according to customers’ reactions to promotions, or special events; according to this, demand can be clustered into “huge customers”, those who strongly impact the final turnover, “small customers” those who do not contribute to the total number of sales and “correlated

customers” that overall have not an impact on the final sales but that present a similar behavior during promotional periods

Another suggestion could be to link demand to its daily sales-pattern (Huber et al., 2017). All of these propositions need to be developed and most of all implemented in the concrete industrial context in order to improve the current analysis thank to new applicative results.

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Annex A

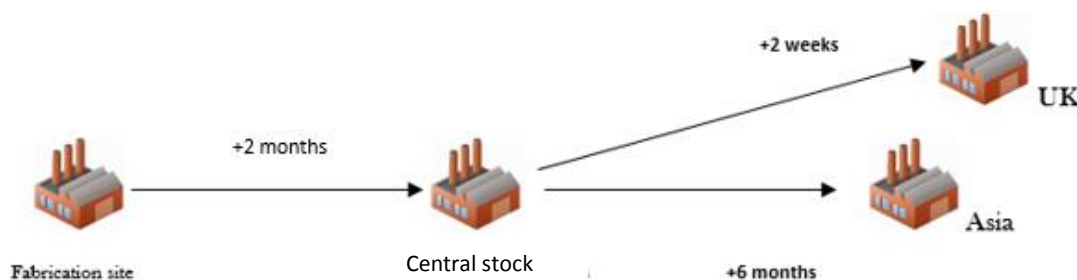
Company's details

A.1 Production and Lead Time Management

Each month the central stock gathers the total distribution orders sent by the individual local subsidiaries and send it to the fabrication sites. Once the orders have arrived in the plants the production plan for the next eighteen months can start. Products' actual production starts only for the next following two months. For instance, if demand orders are received at the beginning of January, the actual production will cover the month at stake and for February.

During the analysis, the demand planner has to consider another important element: the lead time needed for each transactions. According to the country at stake, delivery times will proportionally change. For instance, the time for finished goods to be shipped from the central stock to the UK is about two weeks but if the final destination is China, at least six months are needed to the shipped quantities to reach the subsidiary.

In addition to this span of time, the demand planner has to consider the 2 months lead time needed for the finished goods to be transferred from the fabrication sites to the central stock.



(Figure 69: example of the total lead time for different transactions)

Consequently, when sending the future previsions of demand for the next 18 months, the demand planner has to take into account the specific sum of the different types of lead times specific to the country. In the Chinese case, even if forecast for the next 18 months are constantly updated, when the previsions are sent to the central stock, the production immediately starts. Thus, by considering the Chinese total lead time of 8 months (2 months from the fabrications sites to the central stock plus 6 months needed for quantities to be shipped), the forecast of the month at stake will strongly influence the production of the next 8 months. Different is for European countries, where lead times are shorter and current forecast strongly affects the productions only for the next couple of months.

Lead time management is fundamental for the demand planning process in order to reduce waste and cost: a bad control of it could cause either a surplus or a lack of stock in the local warehouse that is equal to a loss of profit for the company.

A.2 The company inventory management

The inventory management for a multinational company represents one of the main sources of profit because it involves the final customer service, lead time management and cost performance. Therefore, a good inventory control decision gives origin to competitive advantage in the market.

The inventory decision management is strongly correlated top the future forecast. The stock replenishment process entirely relies on the demand forecasts strategy chosen by the demand planner.

It is important to solve the dilemma on the quantity of inventory to keep in the stock: too little inventory hinders a company's sales capacity in front of exceptional peaks in the demand or unforeseen customers orders caused by external factors; moreover, a small stocks dramatically increases the lead time of transactions along the supply chain. Contrary, having too much stock represents an excessive cost for a company; goods would risk to become outmoded before even reaching the mass market. In addition to this, considerable stock's quantity could damage the company's reputation among its investors, it would be the cause of the so called "down gradation" of the stock (APICS, 2009)

Kalis replenishment strategy

It is possible to classify four types of inventories: raw materials, work-in-process (WIP), finished goods and MRO (maintenance/repair/operations) inventory. In the case study held in Kalis, the finished goods inventory is analyzed, that is to say the ensemble of ready-to-use products waiting to be purchased by the final customer (APICS, 2009).

As stated above, the goal of inventory management is to be able to solve the trade-off between the level of stock and the final performance. In order to help the managerial process, multinationals with large markets and a broad variety of products lines need to put in place an inventory classification: different item cannot be treated in the same way because of their profitability and different life cycle path. As previously explained, the inventory classification adopted by the group is the ABC classification where products are classified according to their annual dollar usage (Chu et al., 2008).

Following, once the stock has been classified, the company inventory model is presented. An inventory model helps companies to solve the dilemma between cost reduction and customer satisfaction.

To manage the timing of its orders, Kalis uses a "fixed order point" procedure: orders are periodically submitted at the end of each month by each subsidiary. As regards the quantity, the orders amount is not fixed but can vary according to stock necessities; endorsing a fixed order quantity technique is surely less expensive and easier to manage (APICS, 2009) but at the same time it does not give companies enough flexibility of facing unexpected events.

Each stock of the group's subsidiaries is composed by a certain amount of safety stock, this latter varies according to the specific country's markets demand. As stated by APICS Association for Operation Management, the percentage of safety stock is generally determined by four different variables: the frequency of ordering, the variability of demand during lead time, the length of lead time and the accuracy of forecasting (APICS, 2009).

At the end of the month, the new replenishment order considered by the demand planner is computed by following this equation:

$$\text{New Order} = \text{Future demand forecast} - \text{Stock (M-1)} + \text{Safety stock}$$

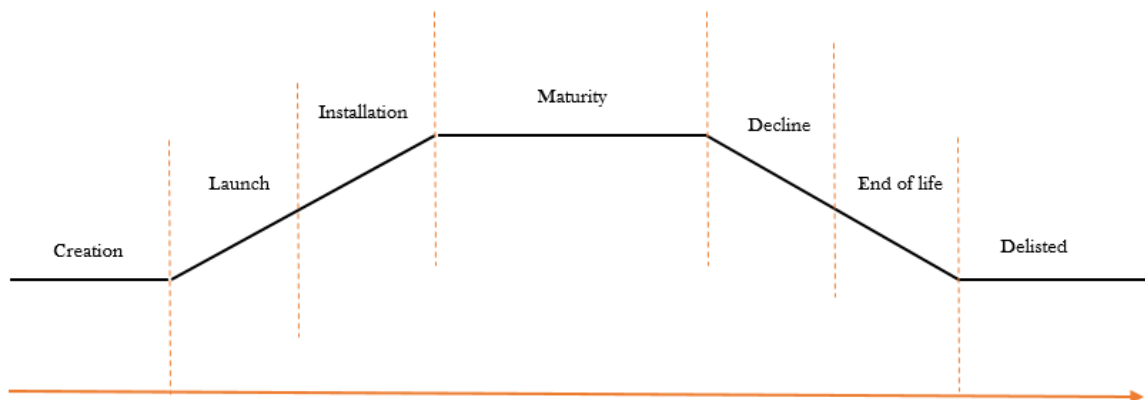
Thus, the supply planner has to consider not only the future demand but at the same time the quantity of safety stock which is proper to the country at stake. Neglecting this last factor could result in severe problems during unforeseen growth of demand or when exceptional events happen.

Stock surplus management

In Kalis there are three alternatives to manage a surplus of stock: first, products can be sent to other countries where the market is still stable, by the way this procedure does not frequently happen because of its transport costs. Another option is to try to sell the product line in secondary markets in order to gradually empty the stock. In the particular case where an old product line is substituted by its new version, the group follows a Product-In-Product-Out (PIPO) logic, that is to say that every time a product of the old line is sold, an item of the new line can enter the stock. However, having Kalis a premium position in the market, its image with its client has to be protected, this is why it is usually not advisable to manage the surplus through this alternative. Lastly, what it is happening for the most is the products' detriment which does not touch the company image and has a lower cost compared to shipping the products to other subsidiaries

A.3 The Product Life cycle

The life cycle of stable and successful products is characterized by specific steps through which they are passing through. According to each phase, the company has to put in place different strategies and marketing decisions. It is therefore crucial to be able to recognize in which stage of the cycle the product is currently placed. In Kalis group, the product's life cycle correspond in seven recognizable stages that are shown in the figure below:



(Figure 70: product's life cycle)

Where the different phases that can be recognized are:

- 1 = Creation phase

In this phase new products are studied and tested in laboratories and R&D departments in order to guarantee their quality and environmental sustainability. The length of this phase depends on the specific product's complexity and, since we are talking about skin care and perfumes items, its degree of danger. The company has to be ready to invest money, facing pitfalls and waiting before the project is ready to be launched. This phase is indeed one of the most delicate of the all cycle

- = Launch phase

The product can be brought to the market after it has been fully approved by the quality and research departments; at this stage, sales are low and gradually growing during time. In this phase the company has

to try to convince the consumer not to try the product but to choose the brand which is the reason why the choice of marketing strategies is particularly delicate in this phase (Levitt, T. 1965).

- = Installation phase

This first step is an evolution of the previous one: the product is growing its market share and demand is increasing faster. It is a market growth phase where the sales expands rapidly: here the number of available and potential distribution channels rapidly increases together with the rate of new consumers

- 4 = Maturity phase

If the product manages to arrive to this phase, its demand is stable and it could be represented by a constant. The first sign to recognize this phase is the market saturation given by the fully adoption of the product by the market. Now the main challenge is win competitors' proposed alternatives: it is essential for companies to directly communicate with the consumers (Levitt, T. 1965). By the way, this is the most stable phase of the market demand for the item that can rapidly be over passed in case of the fashion industry or last for many years by always keeping the same constant rate of sales

- 5 = Decline phase

At this stage, the product starts losing its consumers' interest even if its production it is still ongoing. The demand starts slowly decreasing. The industry during its phase has to start thinking how to manage the final stock remaining from the sales lost and as well as plan how to manage the overcapacity

- 6 = End of Life phase

The products starts quickly to approach the "end of its life" and it is here where its last production happens. At this stage become critical the management of the inventory control since the surplus of stock that was already present during last phases now becomes dangerous

- 7 = Delisted

The product automatically passes to this phase when no more stock is available in the warehouses. At this point, the product's life has definitely become to an end

As concerns forecast strategies, different techniques have to be considered during different stages. It is therefore essential for managers to foresee which exact phase the product is living and try to predict how long it will stay in it.

Following, the literature review will be presented in detail as the second source of information concerning the research topic.

Annex B

Theory on statistical models for future forecast

B.1 Naïve method

This statistical method is the simplest and oldest among all models. Indeed, it simply consists in considering the next future forecast equal to the most recent data available. For instance, in the given list

of statistical models presented at the beginning of this chapter, the models “As preceding years 1 Year” and “As preceding year 2 Years” are examples of naïve methods, where in the first case the forecast for the next 12 months is equal to the observed demand of the last year whereas in the second case the forecast for the next year is equal to the actual demand observed two years before the current one. To better understand how the method works, a table of example is given below:

(Table 21: Naïve method)

Period	Observed Demand	Forecast
1	12	
2	23	12
3	6	23
4	14	6
5	19	14
6	5	19

Even if easy to implement, this method is the worst performant because even in the most stable market there are still some forms of variability given by unpredictable factors.

B.2 Moving Average

The single moving average represents one of the most popular and used method by industrial companies. From a computational point of view, the model computes future period's forecasts through an arithmetic average of data gathered over a certain number of the most recent past time periods; normally, at least two or three periods are considered in the average (United States Government & US Army (2012); A first distinction can be done between “basic moving average” and the “moving average method”, the difference is simple: in the former one, the average considered to compute future forecast is fixed in time and never updates, whereas in the second one, the attribute “moving” comes from the fact that for each new forecast, the average is updated accordingly, it could be said that the average is “moving” with the new forecasts. Thus, when a new forecast needs to be computed, the earliest point in time considered in the average is canceled from this latter to leave space to the new most recent period.

If for instance, the number of last periods taken into account for computing the average is three, here it is an example of how the algorithm works:

(Table 22: Moving Average method)

Period	Observed Demand	Forecast	Algorithm
1	12		
2	23		
3	6		
4	14	14	$(6+23+12)/3$
5	19	14	$(23+6+14)/3$
6	5	13	$(6+14+19)/3$
7	20	13	$(14+19+5)/3$
8	10	15	$(19+5+20)/3$

As it is evident from the table above, the moving average smooth out all the peaks and variabilities of demand. When choosing the moving average method, it is indeed supposed that the market is stable and the demand does not represent significant variation in size and frequency therefore the last period of historical data are imagined to be the most representative for future forecasts.

A variation of this model is given when historical data are not considered all of the same importance, therefore it becomes important to give different weights to past periods of demand. For instance, if it is considered that the most recent periods of sales are more relevant compared to the earliest ones, more weight it could be decided to give more weights to them. In this case it is possible to talk about weighted moving average (apics).

To give an overall vision on the model, the list of its advantages and limitations is presented below;

Advantages:

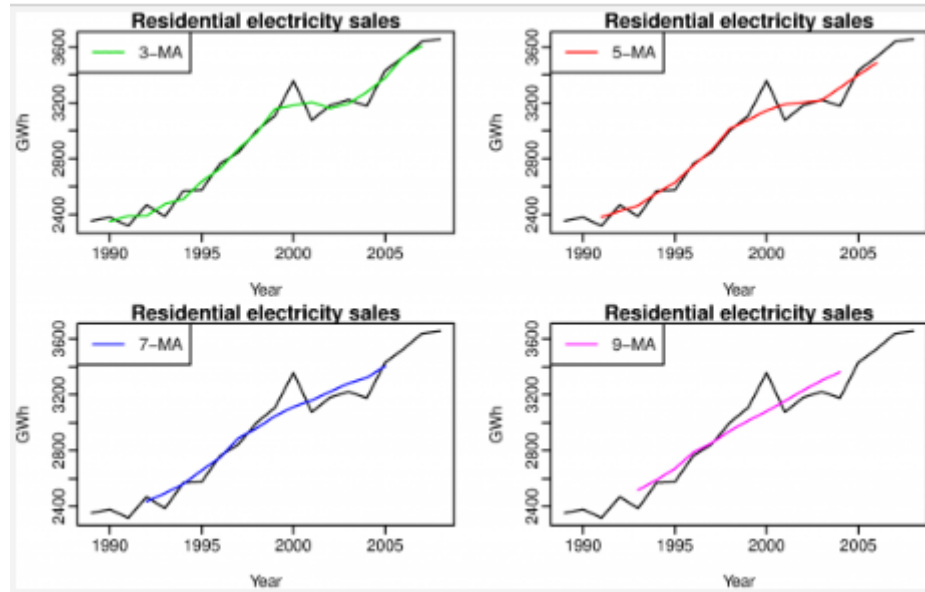
- Demand patterns are always characterized by misleading data given by abnormal factors that at some point can generate some exceptional fluctuation in the pattern. These kind of strange events are known as outliers. The moving average thanks to its smoothing nature, can decrease the importance given to unusual occurrences that are misleading the general trend (United States Government & US Army (2012))
- As previously said, moving average is useful when the market is supposed to be stable thus for stationary time series. When products arrive to their most mature phase in their life cycle, the moving average is one of the most convenient method that can be chosen to forecast their future demand

Limitations:

- If demand patterns present cyclical seasonality, a trend or cases of irregularity, the moving average method smooths out the real entity of the pattern. As a result, the final results are not realistically representing the real trend of data because it misses out all the random events that characterized it (Hyndman, R. J., & Athanasopoulos, G. 2013).
- When the market presents a stable upward trend; therefore sales are constantly growing, the choice of the moving average model could cause constant under forecast always because of its tendency in softening the general trend of the demand; viceversa, when actual demand is constantly decreasing the moving average tends to produce over forecast values. Once again, the method is not suitable for non stationary time-series (Chiang, T. C. n.d.)
- Since no weights are given to past time periods, e.g. all periods are considered of the same importance, it is not possible to give more relevance to those moments in the past that are considered critical for future demand (Chiang, T. C. n.d.)

It is now important to show one of the most crucial points of the moving average method: the choice of the number of past periods to take into account in the calculation of the average demand. In order to continue it is important to highlight that the order of the moving average model stands for the number of periods considered in the average. As it is shown in the past literature (APICS) (United States Government & US Army. (2012)), (Chiang, T. C. (n.d.) (Hyndman, R. J., & Athanasopoulos, G. 2013), the order of the moving average is the main determinant of the smoothness of the final results: it has been generally proved that the more periods are considered, the greater is the smoothing effect of the time series. A large order is generally considered for products without a significant trend / seasonal cycles.

Hyndman, R. J., & Athanasopoulos, G. (2013) show a nice representation about the impact of different orders for the model in four different cases representing the residential electricity sales data.



(Figure 71: Different moving averages applied to the residential electricity sales data. Source: Hyndman, R. J., & Athanasopoulos, G. 2013)

In the above representation it is evident to notice the changing of the smoothness of the model: the demand pattern considered presents an upward trend with seasonal cycles, therefore sales are not stable along the years. These tendency is better represented when an order of three periods is considered because the smaller order is chosen the more reactive the model is to unforeseen changings. Indeed, compared to the order nine moving average, in this case the model reacts much faster because one forecast point correspond to one third of the computation instead of one-ninth. While for an order of nine, the model is predicting almost a perfect linear representation of future sales and it completely smooths out irregular occurrences of the actual pattern.

Finally, the technique to use in order to choose the averaging period that can give the most precise results is now discussed. The easiest and most adopted indicator for evaluating forecast accuracy is the mean absolute deviation (MAD) (Apics). It consists in a simple average that quantifies for each period in absolute terms the deviation between the forecast and the actual demand: to get a measure of the MAD, for every period of the forecast it is sufficient to compute the absolute difference between the prediction of demand and the forecast and afterwards divide it by the order of the model (i.e. the total number of period used to compute the average for future predictions). The best model's order is the one associated to the lowest value of MAD, indeed different averaging periods correspond to highly different MAD values and future forecasts.

$$\text{MAD}(n) = \frac{\sum |D|}{n}$$

Where $\text{MAD}(n)$ = mean absolute deviation of the model with period equal to n

n = order of the model

D = observed demand

F = predicted demand

In the past literature, it is also presented the double moving average (Hyndman, R. J., & Athanasopoulos, G. 2013), a variation to the classical model of single moving average. It is advisable to choose this variation when a trend in the demand patter is detected: thus, the double moving average extends the single moving average for cases when a steady upward or downward trend of the data is noticed (United States Government & US Army. (2012)). To compute a double moving average it is necessary to calculate a

moving average and then re calculate a moving average by using the averages from the first moving average as actual demand. This version of the model is still softening random variation but this time the pattern's trend is shown in the data.

B.3 Exponential Smoothing

The exponential smoothing technique is an updated extension of the weighted moving average: it is a parametric model where weights are exponentially decreasing as the observations get older (Hyndman, R. J., & Athanasopoulos, G. 2013)., that is to say that as the observation gets old, less importance is given to it. Recent observations are considered more important for future forecast thus they receive more weight in the computation (Kalekar, 2004). This method is particularly significant when only a few observations are available for predicting future forecast. Also for this case, different model's types can be found according to the trend and seasonality of the demand pattern.

Single exponential smoothing

In the single exponential smoothing (SES), demand patterns do not show a particular trend or seasonality. Future forecasts are computed as a weighted average of the current actual demand and the last smoothed forecast value, as showed below:

$$S_t = \alpha * X_t + (1-\alpha) * S_{t-1}$$

Where

X_t = current observation

S_{t-1} = forecast of the previous period

α = smoothing parameter and $0 < \alpha < 1$

As it is possible to notice from the above equation, the more the smoothing parameter alpha increases, the more importance is given to the current observation. Thus, the smoothing parameters controls the rate at which the weights exponentially decrease: at the extreme case, when $\alpha = 1$ the previous forecast is completely ignored whereas when $\alpha = 0$, the current demand is not taken into account.

Given the presence of the α parameter, the exponential smoothing is a parametric model therefore techniques to optimize the value of the smoothing parameter need to be explained. Either the mean absolute deviation indicator explained in the last section or the method of last squares might be useful for this case. The last mentioned method consists in the squared sum of the error did in the forecast where the error is simply defined as the difference between the observed demand and the forecast value. More explanations on accuracy measure will be given in the Annex B.7

Like in the moving average, the SES model is based on a recursive scheme that is to say that new forecast are re computed for each new observation.

It is interesting to compare the exponential smoothing with the moving average method.

Double Exponential Smoothing

A first evolution of the SES can be found in the double exponential smoothing where the trend component is taken into account and it is therefore used when data shows a particular trend (Chiang, T. C. n.d.). In order to consider the trend, a second smoothing parameter is introduced in order to control the weight given to the trend component. Thus, the equation is now composed by two main factors that are updated for every new observation: the level of the pattern which represents the predicted value of the forecast at the end of each

period and the trend component that gives an estimation of the average trend of the series at the end of each period in time (Kalekar, 2004).

When a new forecast needs to be computed, the method automatically updates the trend and level components, for the current period. This is done through a weighted average of the last components by using the two smoothing parameters as weights and the last estimated value of sales :

$$S_t = \alpha * X_t + (1-\alpha) * S_{t-1}$$

$$b_t = \gamma * (S_t - S_{t-1}) + (1 - \gamma) * b_{t-1}$$

Where

X_t = current observation

S_{t-1} = forecast of the previous period

b_t = the trend level

α = smoothing parameter $0 < \alpha < 1$

γ = smoothing parameter for the trend $0 < \gamma < 1$

Multiplicative and additive seasonality

As regards the seasonal components, two different variations of seasonality can be recognized: the additive and the multiplicative seasonality, as it has been previously introduced in the section.

(The additive method is preferred when the seasonal variations are roughly constant through the series, while the multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series. With the additive method, the seasonal component is expressed in absolute terms in the scale of the observed series, and in the level equation the series is seasonally adjusted by subtracting the seasonal component. With the multiplicative method, the seasonal component is expressed in relative terms (percentages), and the series is seasonally adjusted by dividing through by the seasonal component. Within each year, the seasonal component will sum up to approximately m)

A numerical expression of the two different cases is given by the following formulas (Kalekar, 2004):

Multiplicative seasonality

$$Y_t = (b_1 + b_2 t) S_t + \epsilon_t$$

Where

b_1 = the permanent component

b_2 = a linear trend component

S_t = multiplicative seasonal component

ϵ_t = the random error

As stated earlier in this section, the total sum of the length of the all seasonal factors has to be equal to the length of the season L :

$$\sum_{1 \leq t \leq T} S_t = L$$

Additive seasonality

$$Y_t = b_1 + b_2 t + S_t + \epsilon_t$$

Where

b_1 = the permanent component
 b_2 = a linear trend component
 S_t = additive seasonal component
 ϵ_t = the random error

The total sum of the length of the all seasonal factors has to be equal to the length of the season L :

$$\sum_{1 \leq t \leq T} S_t = 0$$

As stated in the theory (Kalekar, 2004), the multiplicative model generally gives better results compared to the additive case so in the next sections we will consider as an assumption the adoption of a multiplicative seasonality

B.4 Holt Winters method

The last and most developed version of the single exponential smoothing is the Holt Winters (HW) method. Compared to the previous models, the Holt Winters version can easily adapt to irregular occurrences such as changings in consumers' behavior (Goodwin, P. 2010). Moreover, it requires a low-data memory and it is simply to implement. Generally speaking, the method further enrich the exponential smoothing model by considering both the trend and the seasonality of the demand pattern (Chatfield, C. & Yar, M. 1988).

In order to handle the seasonality component, in the HW method one more smoothing parameter is added; accordingly, in the total there are three equations: one for the level, one for the trend and one for the seasonality (Hyndman, R. J., & Athanasopoulos, G. 2013) with the corresponding parameters α (level) γ (trend) and β (season). It is interesting to give a more precise explanation of the three different components (Goodwin, P. 2010):

- 3 The level of sales = the deseasonalized value of sales without the effect of random factors
- 4 The trend of sales = the variation that is expected between the current period at stake and the next one; for example, if the estimated level of sales is now up to 40 pieces but for the next period it is predicted to be 35, then the trend is expected to be -5
- 5 The seasonal monthly index (SI) = as explained during the analysis of the first research question, this index explains the monthly deviation of sales according to the annual average

When a new forecast needs to be computed, the method automatically updates the three components, the level the trend and the seasonality index, for that month. This is done through a weighted average of the last components by using the three smoothing parameters as weights and the last estimated value of sales demand (Goodwin, P. 2010). As said before, the more the smoothing constant increases in value, the more importance is given to the previous estimation of demand.

The procedure needed to update the new parameters estimates for each new iteration is as follows (Kalekar, 2004):

$$\begin{aligned} R_t &= \alpha * (y_t / S_{t-L}) + (1 - \alpha) * (R_{t-1} + G_{t-1}) && \text{Overall Smoothing} \\ G_t &= \gamma * (S_t - S_{t-1}) + (1 - \gamma) * G_{t-1} && \text{Trend Factor} \\ S_t &= \beta * (S_t / S_{t-L}) + (1 - \beta) * S_{t-L} && \text{Seasonal Index} \end{aligned}$$

Where

R_t = the estimates of the deseasonalized level

G_t = the estimate of the trend

S_t = the estimate of seasonal index

S_{t-L} = the seasonal factor for period T computed one season ago

α = smoothing parameter $0 < \alpha < 1$

γ = smoothing parameter for the trend $0 < \gamma < 1$

β = smoothing parameter for the seasonal index $0 < \beta < 1$

Note that in the updating equation of the overall smoothing, dividing y_t by S_{t-L} deseasonalizes the data that means that only the trend factor and the permanent factor contribute into the updating of the overall level

Finally, the value of the new forecast at the time t is:

$$Y_t = (R_{t-1} + G_{t-1}) * S_{t-L}$$

The formula to project the forecast T periods in the future:

$$Y_{t+T} = (R_{t-1} + T * G_{t-1}) * S_{t+T-L}$$

There are three main issues to take care of when implementing the HW's method (Chatfield, C., & Yar, M. 1988):

- 1) Normalization: seasonal factors should be normalized once a year to have a clear interpretation of them
- 2) The choice of starting values: three methods are available for the decision about starting values but this is not going to be explained here because it enters too much in technical detail
- 3) Choice of smoothing parameters: as it has been done for previous models, the sum of residual errors (the MAD or the SSE) can be minimized in order to choose the best performing combination of parameters

Generally speaking, the Holt-Winter's method is suitable for regular demand whose pattern is dominated by seasonality and trend properties; contrary, the choice of this model is not advisable when time series is showing exponential growth or several discontinuities during time periods.

Adaptive and non-adaptive technique

Two versions of the multiplicative and additive models exist: the non-adaptive and the adaptive technique which concern the management of the smoothing parameters (Kalekar, 2004). Indeed choosing the best technique to set the parameters is one of the main issues of the Holt Winter's method (Williams, T. M., 1987).

In the non-adaptive case the parameters are initialized at the beginning of the process and then they remain the same forever, they are not modified never again. There are two advantages in this: parameters are initialized only once and past records can be forgotten since they are needed only in the first phase for the parameters' initialization.

In the adaptive version, parameters and contrary updated every two years according to the underlying process. The adaptive technique is useful for those time series that present steps, discontinuities and unforeseen occurrences (Williams, T. M. 1987) because it allows the model to adapt to its intermitted nature thanks to the periodical updating of its parameters. In his work, Williams T. M. (1987) introduces

the smoothed error and the absolute smoothed error to make parameters adaptive; in addition to this, he also brings some modifications to the HW's model's equations previously shown that allow to avoid the instability of the three components, the level the trend and the seasonality, that could occur when smoothing parameters are not stable anymore

Once again, the reason why the adaptive method should be chosen is given by the nature of the time series: if this latter one is changing its behavior over time then it is opportune that its relative parameters change accordingly; contrary, if the pattern presents a stable pattern, the non-adaptive technique is the most suitable since it could reduce computation time. Kalekar (2004) adds that the adaptive technique might be more useful when a large look back size is considered in the model so not when future forecasts are only based on the few recent periods.

The differentiation between the adaptive and the non-adaptive version represents a step forward to the overall amelioration of the HW model's performance. By the way, some recent new updates have been discovered and studied and this will be the topic of the next section.

The Robust Holt Winter's method

This section deals with the presence of outliers in the time series that could represent serious distortions in the future predictions of the Holt Winter's model; outliers are identified as abnormal occurrences such as promotions, strikes, economic conditions, etc. thus all those events that are exceptionally happening during the course of time (Goodwin, P. 2010). These unexpected events can cause severe problems when the three components, trend level and seasonality, are updated since they do not reflect the real demand pattern. For instance, low sales caused by strikes in the company during the current month could generate under estimation of next period's forecast that will be too high. Secondly; also the smoothing parameters could be distorted during their updating phase because in the equations both current and past data are taken into account, outliers included.

Recently this problem has been tackled by the development of the Holt Winter's model into a new robust version that can automatically identify the outliers and downgrades their impacts on the future forecasts. Thus, Gelper S. et al (2009) propose a new version of the model that allow both the smoothing and the parameters robust in front of these abnormal events.

In their model they simply substitute the observed y_t with a "clean" version obtained thanks to the standardization of the future forecast according to the forecast error which is given by the difference between the observed demand in t and its predicted forecast at $t-I$. More in detail, if the error is small, the observed y_t will be equal to its cleaned version, so no changes will be brought to the series. On the other hand, when the intensity of the error is big in value the last observation can be considered as an outlier and it is going to be replaced by a lower/higher value dependent on a given threshold. This latter automatically governs the outliers' management and consequently regulation in the model (Gelper S. et al 2009).

These modifications to the original model will permit to have more accurate future forecasts when exceptional events occur, moreover the new version is easy to implement for different types of data and it is stable in time.

B.5 Croston's method

The spare parts demand represents nowadays one of the main challenges for demand planners; intermitted demand can be defined as a random demand where customer orders happen sporadically and

lots of zero data exist in the pattern (Xu, Q. et al. 2012). A high frequency of zero demand occurrences has proven traditional statistical models such as Single Exponential Smoothing and Moving Average to be underperforming (Teunter, R. H. et al. 2012), this is because both the two methods do not focus on the demand size and demand interval and this is the reason why Croston's method is nowadays considered as the reference model for intermitted demand (Syntetos, A. A., & Boylan, J. E., 2005).

Croston's method is based on exponential smoothing and it tries to answer to the two main questions that managers are facing every day: when is the next demand occurring? What is going to be its volume (Xu, Q. et al. 2012)? Thus, Croston's method separately deals with the two main elements mentioned above: the demand is decomposed into the size of zero-demand and the probability so the time interval between the occurrences of consecutives demand. Globally, to each of these two parts is then applied the simple exponential smoothing method separately and then the forecast for the next period consists in the ratio of those two estimates (size/interval) (XU, Q. et al. 2012).

As it has just been said, the two main constituent elements of the model are the demand size, when this occurs, and the inter-demand interval. In order to go more in detail with the computational process, the former element is indicated with Z and the second one with P ; the probability distribution of positive demand is supposed to be a Bernoulli process (whereas the demand size is supposed to follow a Gaussian normal distribution (Syntetos, A. A., & Boylan, J. E., 2005). The estimate for the interval part, the probability of positive demand occurrence, is updated every each period while the estimation for the demand size is updated only when a positive demand occurs (Syntetos, A. A., & Boylan, J. E., 2005): that is to say that if in the current period t demand is equal to zero, this period won't be taken into account in the count of time periods since this latter is updated only when positive demand occurs; for this reason, since the demand interval is always updated, two different smoothing parameters are adopted.

The method is based on two strong assumptions:

- 1 The demand size is normally distributed with $E(z) = E(z') = \mu$
- 2 Demand occurs with a probability of $\frac{1}{p}$, therefore the inter-demand interval, p , follows a geometric distribution with $E(p) = E(p') = p$
- 3 Variables are independent between each other: consecutive intervals are independent, consecutive demand sizes are independent and demand sizes and interval are reciprocally independent (Xu, Q. et al. 2012).

By considering:

p'_t = forecast of the exponentially smoothed inter-demand interval updated only when positive demand occurs and $E(p) = E(p') = p$

z'_t = forecast of the exponentially smoothed size of demand whose estimate is updated only when positive demand occurs and $E(z) = E(z') = \mu$

z = observed demand at period t

p = time between two positive demands

q = period of time since last positive demand

α = smoothing constant, $0 < \alpha < 1$

Since the method updates the estimated demand size only when positive demand occurs, it is possible to write it down under formulas for the procedure of Croston's method:

If $z'_t = 0$, then

$$z'_t = z'_{t-1}$$

$$p'_t = p'_{t-1}$$

$$q = q+1$$

else

$$\begin{aligned} z'_t &= z'_{t-1} + \alpha(z'_t - z'_{t-1}) \\ p'_t &= p'_{t-1} + \alpha(q - p'_{t-1}) \\ q &= 1 \end{aligned}$$

And through the combination of these forecasts the forecast Y'_t for the next time period is given by:

$$Y'_t = \frac{z'_t}{p'_t}$$

With an average value, given the assumptions on probabilities distributions listed before, of

$$E(Y'_t) = E\left(\frac{z'_t}{p'_t}\right) = \frac{\mu}{p}$$

In the past literature, the theoretical superiority of this method has been proven not to be as well performing when applied in real simulations. Indeed, a mathematical error has been found in the estimation of the demand per period of time (Syntetos, A. A., & Boylan, J. E., 2001): by considering the assumption made by Croston regarding the independency between demand size and interval, it is possible to say that

$$E(Y'_t) = E\left(\frac{z'_t}{p'_t}\right) = E(z'_t) * E\left(\frac{1}{p'_t}\right)$$

$$\text{But } E\left(\frac{1}{p'_t}\right) \neq \left(\frac{1}{E(p'_t)}\right)$$

Syntetos and Boylan in their work, show the real value of $E(z'_t / p'_t)$ which is given by:

$$E\left(\frac{z'_t}{p'_t}\right) = E(z'_t) * E\left(\frac{1}{p'_t}\right) = \mu * \left[-\frac{1}{p-1} \log \frac{1}{p}\right] - \frac{1}{p}$$

Where μ is the average value of demand magnitude and $E(p'_t) = p$.

Thus, for instance, if α is considered equal to one, extreme case, the average of demand size $\mu = 6$ and the average of demand interval = 3 according to Croston's method the average estimated demand is $\mu/p = 2$ whereas according to the adjusted average that has just been showed above $E(Y'_t) = 6 * 0,549 = 3,295$ therefore the Croston's method is implicitly biased; for lower values of α , so for more realistic cases, the bias is decreasing accordingly so the major value of the bias is given when $\alpha = 1$. Thus, the magnitude of the error depends on the smoothing parameter being used (Syntetos, A. A., & Boylan, J. E., 2005).

Croston's method has by the way shown two main limitations:

- 4 The two separate forecast of demand size and inter-demand interval are correctly computed but their combination under the ratio form is not an accurate estimation of the demand per time period: this is the reason why the method has been shown to be positive biased by Syntetos study (Syntetos, A. A., & Boylan, J. E., 2001). More in detail, the bias' value increases when the value of α increases as well; it is therefore recommended to use the Croston's method only for low values of the smoothing parameters
- 5 When demand pattern shows many periods of zero demand, the method is underperforming compared to more traditional methods such as the exponential smoothing or the moving average (Xu, Q. et al. 2012) and this is because the method does not update after periods with zero demand so if the pattern presents several periods of zero demand, the forecast results not up to date and not useful for estimating the level of obsolescence. This latter is very important especially in slow moving and lumpy demand patters. Indeed, the risk of stock obsolescence is essential in

the inventory management where the main goal is to optimize the level of stock and therefore to understand when stock has to be removed because there is no demand at all (Teunter, R. H. et al. 2012).

Because of these two main limitations, model's variations have been developed and carried on during last years of research.

SBA: Syntetos-Boylan Approximation

The first innovating model that has been recently developed, is the one from Syntetos A. A. and Boylan J.E. (2001 & 2005) who focuses on the biased nature of Croston's method. Their ultimate goal is to find a new estimator for future demand that can equal the ratio given by Croston: $\frac{\mu}{p}$

$$E(Y'_t) = E\left(\frac{z'_t}{p'_t}\right) = E(z'_t) * E(f(p'_t)) = \frac{\mu}{p}$$

Where $f(p'_t)$ is a function of p'_t that needs to be found.

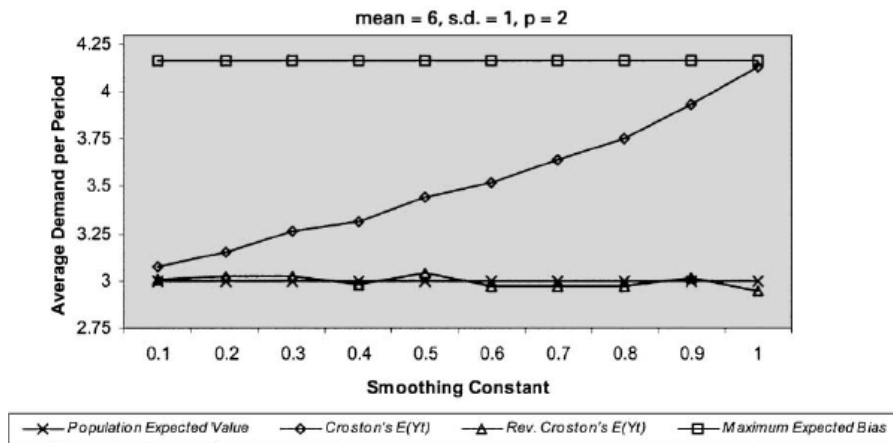
Later in their studies, Syntetos and Boylan contributed to the development of the model thanks to their estimation of the bias' value that they found out to be equal to $\frac{\alpha}{2-\alpha} \mu \frac{p-1}{p^2}$.

By always considering the assumptions made by Croston, the identical and independently distributed (i.i.d.) demand size and demand interval, normally distributed demand size and geometrically distributed demand intervals, the new estimator of the average future demand at period t is:

$$Y'_t = \left(1 - \frac{\alpha}{2}\right) \frac{z'_t}{p'_t}$$

Where α is the smoothing parameter used to update both the demand size and the inter-demand interval. Both demand size and interval are updated with exponential smoothing only when positive demand occurs and if demand does not occurs, the estimation remain the same as in the original model.

By using the new estimator of future demand, the two authors show that their new model outperforms the original Croston's method by being unbiased; they proved for a range of different α 's values the relationship between the forecasts made by the original model, the forecasts of their innovative model, the maximum value of possible biased estimation and the theoretically expected demand per time period:



(Figure 72: Croston and SBA models, Source: Syntetos, A. A., & Boylan, J. E., 2001)

As it is evident from the picture, as the value of the smoothing parameter α increases, the Croston's method over forecast the real observed average demand that is to say, it become more biased until the extreme level when $\alpha=1$ and the Croston's estimation equals the maximum value of biased forecast. In addition to this, the new version of the model proposed is almost totally unbiased and equivalent to the estimated theoretical average.

Moreover, to show the improvements of their new estimator for future demand, Syntetos and Boylan compared its performance with the original Croston's method the simple exponential smoothing (SES) and the simple moving average on 13 periods (SMA(13)); they ranked their results according to the Percentage Best accuracy measure that determines the best estimator that has to be used for different values of α by differentiating when all points in time are considered from when only period of positive demand are taken into account in the calculations:

Ordering of methods by percentage best (RGRMSE)			
Percentage best (RGRMSE)			
All points in time		Issue points only	
$\alpha=0.05$	$\alpha=0.1, 0.15, 0.2$	$\alpha=0.05$	$\alpha=0.1, 0.15, 0.2$
1. SMA(13)	S-B	SMA(13)	S-B
2. S-B	SMA(13)	S-B	SMA(13)
3. SES	SES	SES	SES
4. Croston	Croston	Croston	Croston

(Fig 73: Croston and SBA models, Source: Syntetos, A. A., & Boylan, J. E., 2005)

From the above figure, it is proved that the Croston's method is the worst among all for every value of α , the new version of the model (SB) is always the best one to choose except for low level of α where the SMA(13) is the most suitable.

However, this advanced model's adaptation still presents some issues: the method empirically presents several biased estimation and most of all, it is not updating demand's size and interval separately and, like in the original case, it does not take into account all points in time because forecasts are updated only when periods of positive demand occur. Thus, also this new version of the model fails to recognize the risk of obsolescence mentioned before in this section.

To tackle these problems revealed by researchers, a different reformulation of Croston's method has been recently proposed by Teunter, R. H. et al. (2012) and this is what the next section of the paper is about.

TSB : Teunter, Syntetos, Babay Approximation

In this new version of Croston's method, the demand size and demand interval are studied separately always by using the exponential smoothing estimation and this is the reason why two different smoothing parameters are used: α and β with $0 < \alpha, \beta < 1$. The choice of a second parameter is given also by the fact that now the demand probability is more frequently updated compared to the demand size, indeed the estimation of inter-demand interval is updated at each point in time whereas the estimation for the demand size is updated only when positive demand occurs.

That is to say:

If $z'_t = 0$, then

$$\begin{aligned} z'_t &= z'_{t-1} \\ p'_t &= p'_{t-1} - \beta p'_{t-1} \\ Y'_t &= z'_t p'_t \\ q &= q+1 \end{aligned}$$

else

$$\begin{aligned} z'_t &= z'_{t-1} + \alpha(z'_t - z'_{t-1}) \\ p'_t &= p'_{t-1} + \beta(q - p'_{t-1}) \\ Y'_t &= z'_t p'_t \end{aligned}$$

$$q = 1$$

One of the main issues of statistical model is the definition of smoothing parameters' value and both Syntetos and Teunter suggest to use fixed values between 0.05 and 0.2; it is important to remark that in particular for the TSB method, the choice of the smoothing constants depends on the length of periods of time: if monthly periods are considered, then the range of values suggested above is correct whereas for shorter periods such as weekly or daily periods, smaller values of the parameters are suggested. In addition to this, the authors of the study show that the demand's variation is positively correlated to the value of the smoothing parameters thus when the value of these latter increase the value of the variance accordingly does so. This means that for stable patterns of demand, it is advisable to use not "too large" values of the smoothing constants in order to better represent the nature of the demand. On the other hand, values cannot be too small either otherwise in case of intermitted demand, the model won't be reactive and adaptive to sudden changes in time.

In order to deal with obsolescence, so to improve the reactivity of the model when demand pattern is slow and intermitted, the demand probability, contrary to the Croston and SBA methods, is updated at every point in time. When positive demands occurs, probability is adjusted upward, on the contrary when demand is null, probability is downward adjusted. Thus, after periods with several zero demand occurrences, demand's probability approaches the zero value and so the estimate of demand per period of time. Both the Croston's and SBA versions are slower to react to obsolescent situations since demand interval is updated only when positive demand takes place. Therefore the TSB method is considered to produce better demand estimation because of its capability to rapidly react to obsolescence where demand no longer occurs thank to its constantly up to date estimations.

In their work, Teunter et al. to prove the improved performance of their findings, compared different statistical methods (the SES, Croston's, SBA and TBA) applied in three specific situations: when demand is stable, constantly decreasing and when sudden obsolescence occurs.

For the first case, when demand is stable, cases with slow moving demand of constant size are considered; here both the SES and the TBA models outperforms the others two because when all points in time are considered, the first two have lower biased results. By narrowing the problem to numerical accuracy, the TBA method is finally proved to outperform the SES technique because the former one presents a better MSE (Mean Squared Error) performance, only for low values of β , given the stationary nature of the demand.

When demand is linearly decreasing, all the methods considered present biased results because they do not study the demand's trend separately from the other elements. By the way, the Croston and the SBA method have still the most positively biased results since by not updating demand probability every point in time, they adapt slower to changes in demand, as it has already been previously explained.

Finally, the most significant case is when obsolescent events occur: since the Croston's and SBA methods are totally unable to adapt to spare parts demand, the TBA is strongly improving the final results thanks to its flexibility nature given by the techniques studied before to reduce the bias intensity. The table below shows the MSE and ME values for different values of the parameters for this last situation of demand where it is clear to see that the better performance of the TBA and SES techniques:

Estimator	ME			β	MSE			β
	α Smoothing constant				α Smoothing constant			
	0.10	0.20	0.30		0.10	0.20	0.30	
SBA	0.2360	0.2174	0.2000		0.2460	0.2390	0.2339	
Croston	0.2617	0.2695	0.2798		0.2592	0.2658	0.2757	
SES	0.0420	0.0210	0.0140		0.1421	0.1440	0.1502	
TSB	0.1888	0.1888	0.1888	0.01	0.1995	0.1995	0.1995	0.01
	0.1471	0.1471	0.1471	0.02	0.1746	0.1746	0.1746	0.02
	0.1174	0.1174	0.1174	0.03	0.1614	0.1614	0.1614	0.03
	0.0959	0.0959	0.0959	0.04	0.1539	0.1539	0.1539	0.04
	0.0801	0.0801	0.0801	0.05	0.1493	0.1493	0.1493	0.05
	0.0419	0.0419	0.0419	0.10	0.1421	0.1421	0.1421	0.10
	0.0210	0.0210	0.0210	0.20	0.1440	0.1440	0.1440	0.20
	0.0140	0.0140	0.0140	0.30	0.1502	0.1502	0.1502	0.30

(Figure 74: MSE and ME results for sudden obsolescence, source: Teunter, R. H. et al. 2012)

In conclusion, thanks to the separate study of demand size and demand probability, the new TBA has finally managed to further improve to Croston's method by giving unbiased results of future demand forecast and most of all by formulating a model that is highly adaptive especially when demand is slow moving, thanks to the periodical update of the demand probability. By the way, attention has to be paid to the determination of the smoothing parameters values for the model because they are the main drive for the final estimations and future research should provide more in detail guidelines to follow in this topic.

B.6 Forecast accuracy measuring techniques

As it has been underlined throughout the all analysis, a bad management of future forecasts means for companies an increase of safety stock that represents a cost for the whole organization. Thus, the common scope of forecasting techniques is to reduce at minimum the level of errors in the predictions of future demand; this error is generally identified as the difference between the estimated value of demand and the actual observed demand (Ghobbar, A.A. & Friend, C.H. 2004). So if D_t is the observed demand and F_t is the estimated forecast for period t , the error of forecast for that period is estimated as:

$$E_t = D_t - F_t$$

In order to keep under controlled and monitored the forecast techniques adopted, a number of measures of forecast error is nowadays used the performance of the strategy adopted. These measures of error can be divided into two main groups: the relative and the absolute measures of error.

Before starting to show the main measures, it is important to remark that to each observation is associated a forecasting error so in the case of multiple observations, for instance n , there will be n residual errors.

The first group presented is the absolute forecast error measures (Ghobbar, A.A. & Friend, C.H. 2004):

- Mean error (ME):

$$ME = \sum_{t=1}^n \frac{E_t}{n}$$

- Mean absolute deviation (MAD):

$$MAD = \sum_{t=1}^n \frac{|E_t|}{n}$$

- Mean square error (MSE):

$$MSE = \sum_{t=1}^n \frac{(E_t)^2}{n}$$

- Root mean square error (RMSE):

$$RMSE = \left[\sum_{t=1}^n \frac{(E_t)^2}{n} \right]^{\frac{1}{2}}$$

- Sum of squared error (SSE):

$$SSE = \sum_{t=1}^n E_t^2$$

Secondly, the relative forecast-error measures are listed:

- Mean percentage error (MPE):

$$MPE = \sum_{t=1}^n \frac{PE_t}{n}$$

Where PE is given by

$$PE_t = \left[\frac{D_t - F_t}{D_t} \right] * 100 \quad \text{when } D_t > 0$$

$$PE_t = \left[\frac{F_t - D_t}{F_t} \right] * 100 \quad \text{when } D_t = 0$$

- Mean absolute percentage error (MAPE):

$$MAPE = \sum_{t=1}^n \frac{|PE_t|}{n}$$

As regards this last indicator, the MAPE, it has been proved that it presents biased results when the forecast is smaller than the actual demand. In order to solve this problem, a new version of the measurement has been realized:

$$MAPE_t = \left| \frac{(D_t - F_t)}{(D_t + F_t)/2} \right| * 100$$

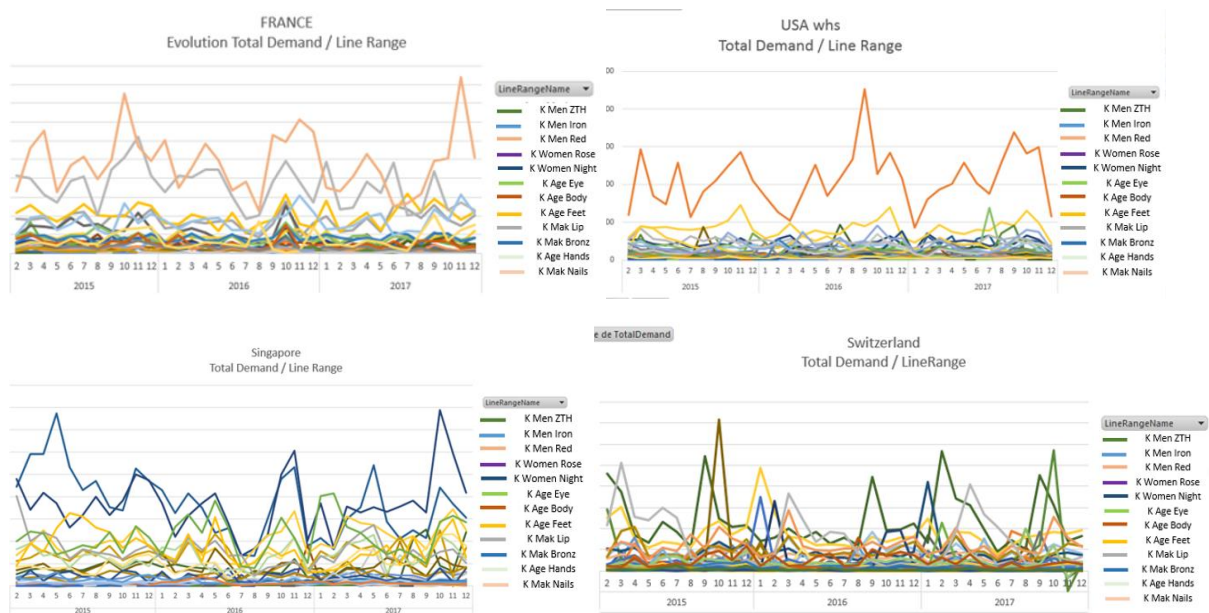
It is important to remind that this long list of indicators is given because in order to have the most precise measure of performance possible, a combination of these latter has to be used. A final convergence of several indicators on the attempted result can give a precise quantification of the forecasting error. In addition to this, managers have to keep in mind that forecasting performances cannot be judged only on the base of these measures of error but in combination with other kind of measures that have more practical implications. For instance, the service level accuracy or the average inventory level can be considered as future target for the company's goals (Teunter, R.H. & Duncan, L. (2009). Indeed, every company adopts its own performance criteria in order to control the stock level and the net sales. As an example, Kalis managerial measurements are presented in the next paragraph of this section.

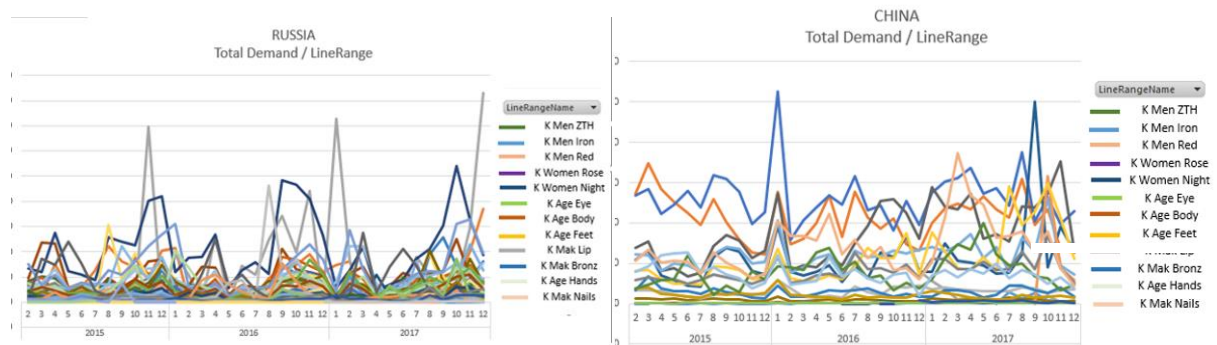
Annex C

Aggregation of demand

C.1 Analysis of the filters for demand's aggregation

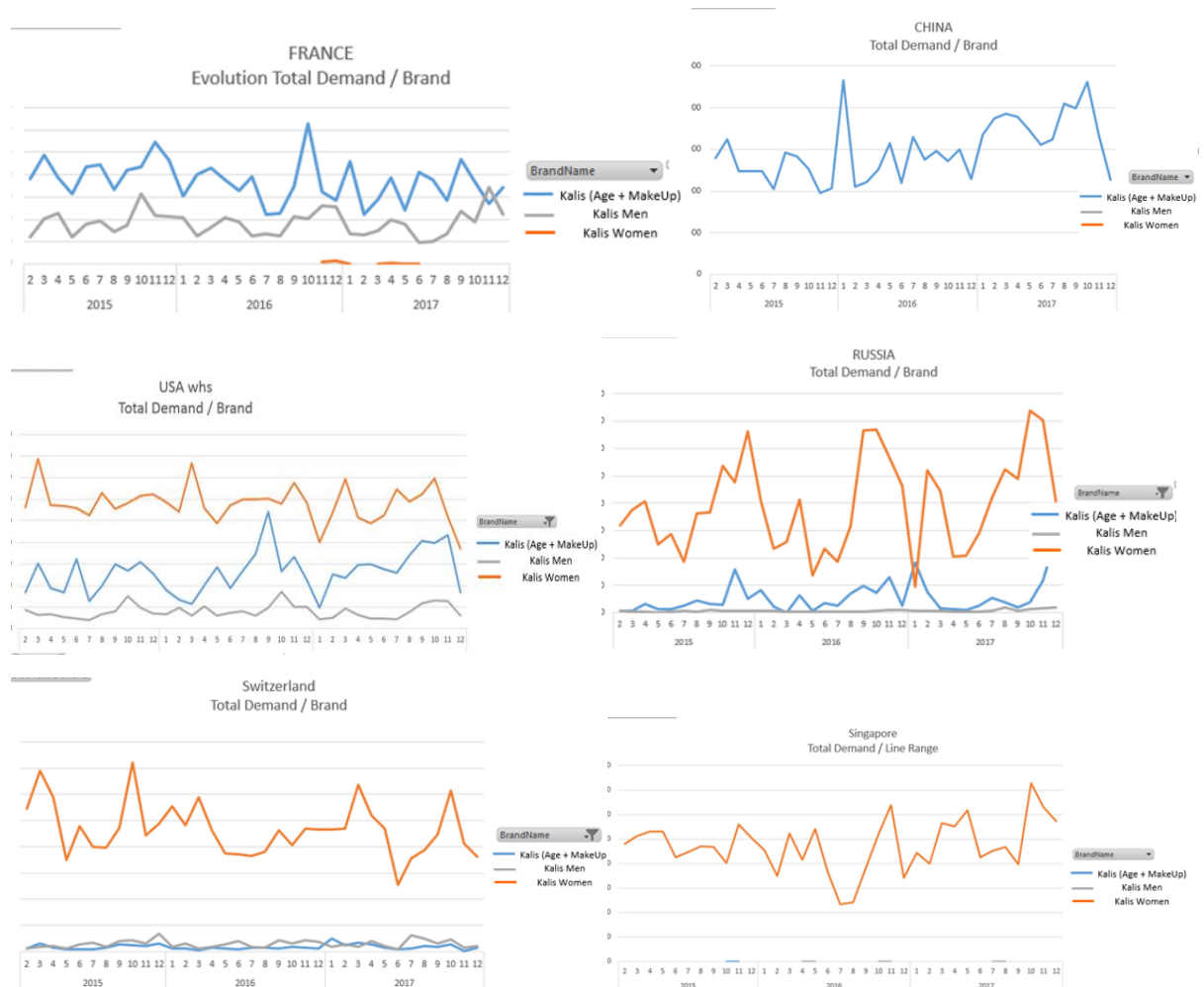
First filter: product Line Range





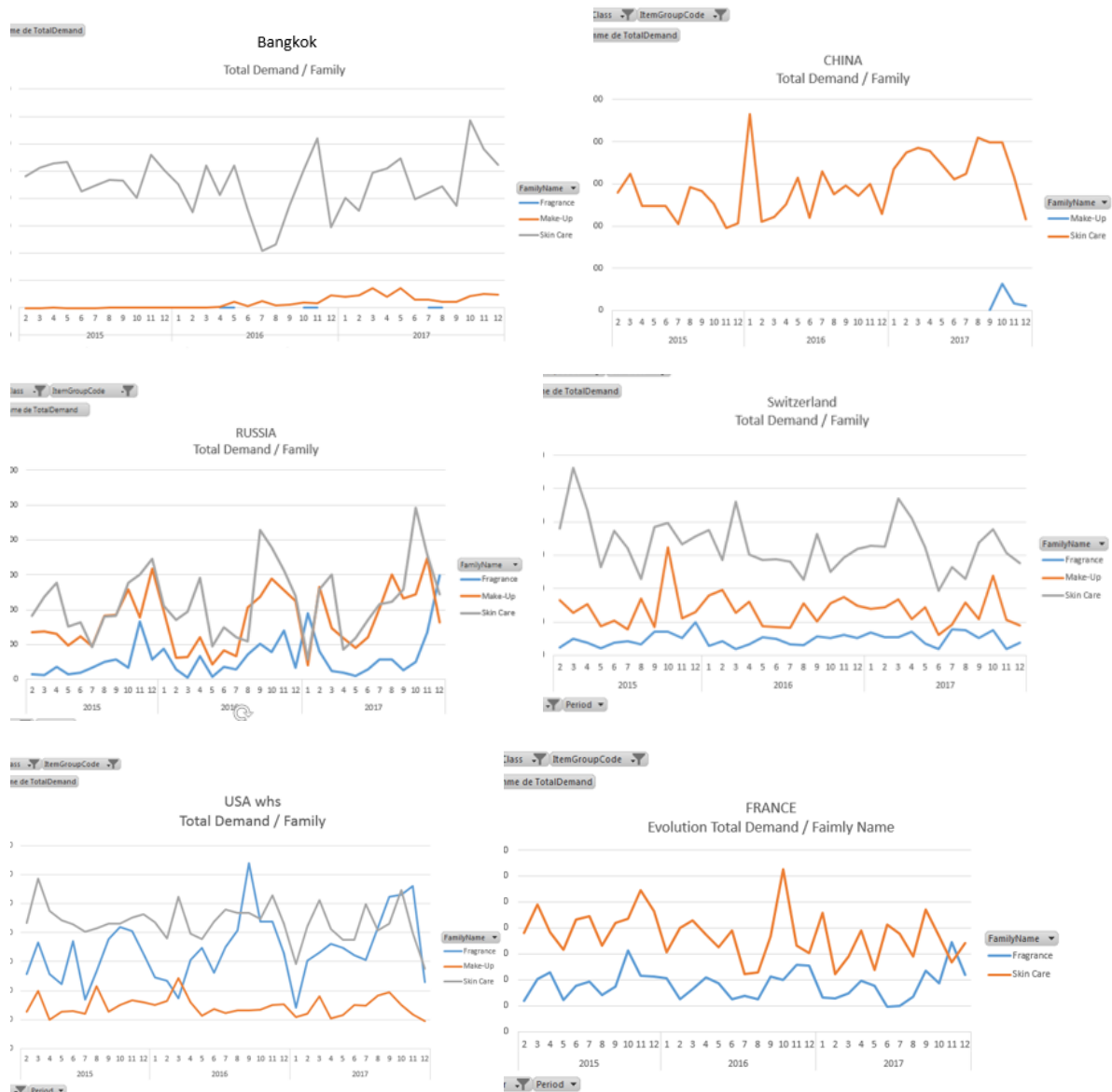
(Figure 75: application of the Line Range filter to cluster demand)

Second filter: product Brand



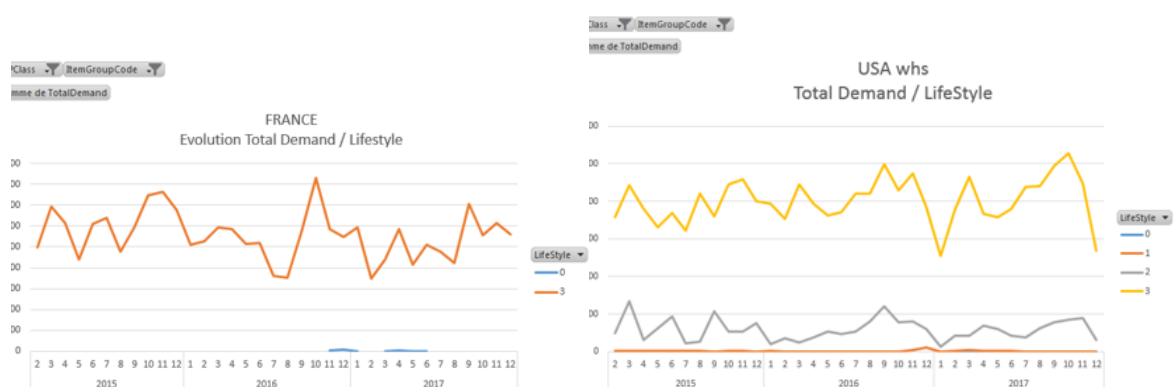
(Figure 76: application of the Brand filter to cluster demand)

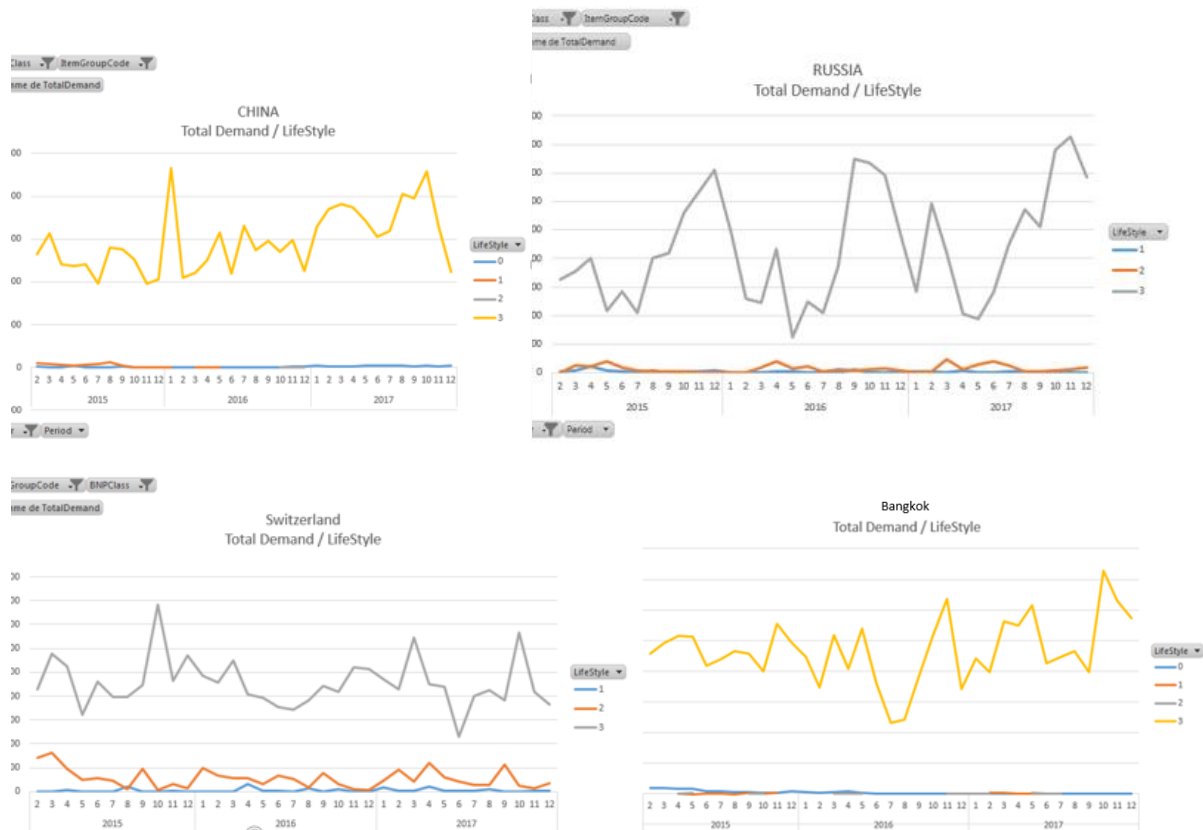
Third filter: product Family



(Figure 77: application of the product's family filter to cluster demand)

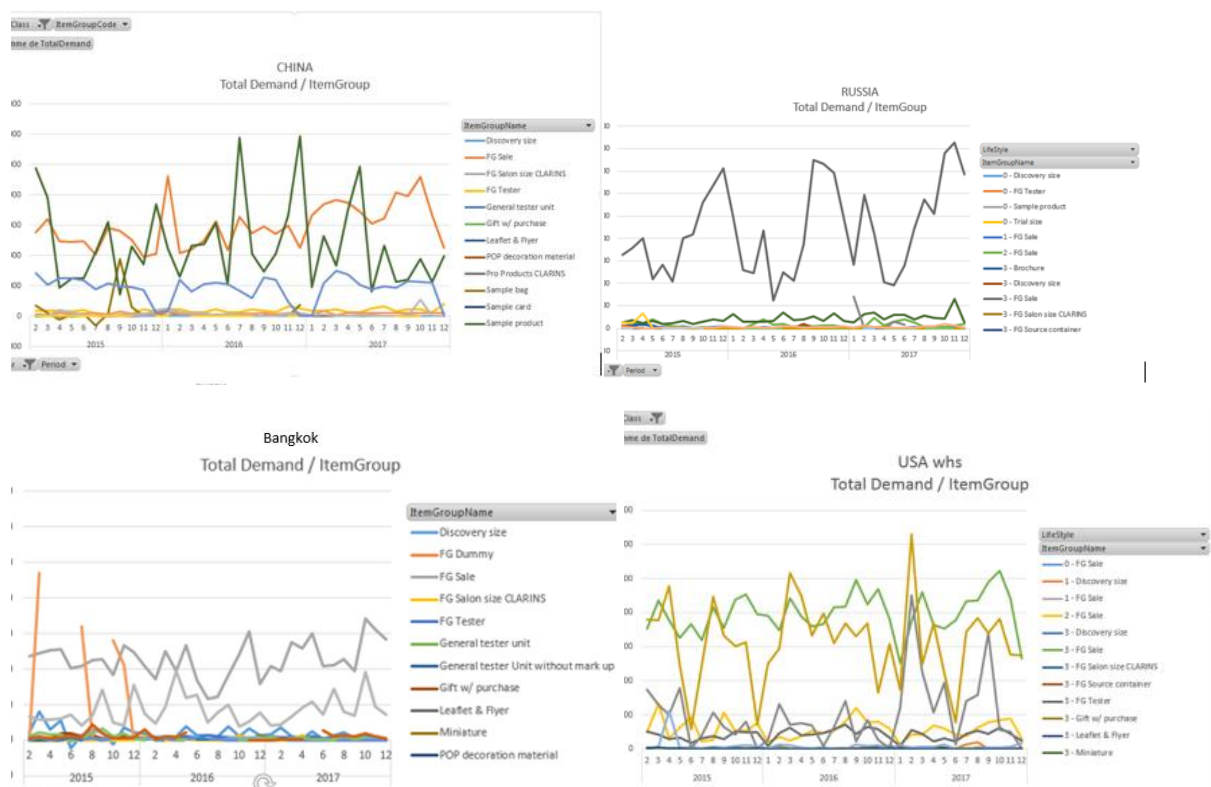
Fourth filter: product Life Style

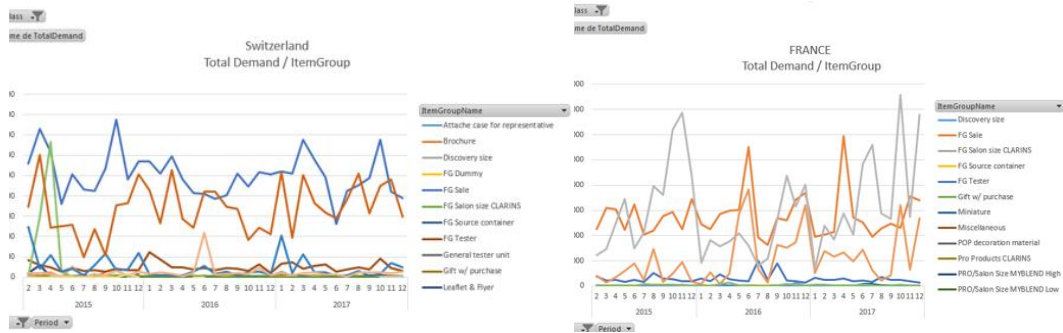




(Figure 78: application of the product's life style filter to cluster demand)

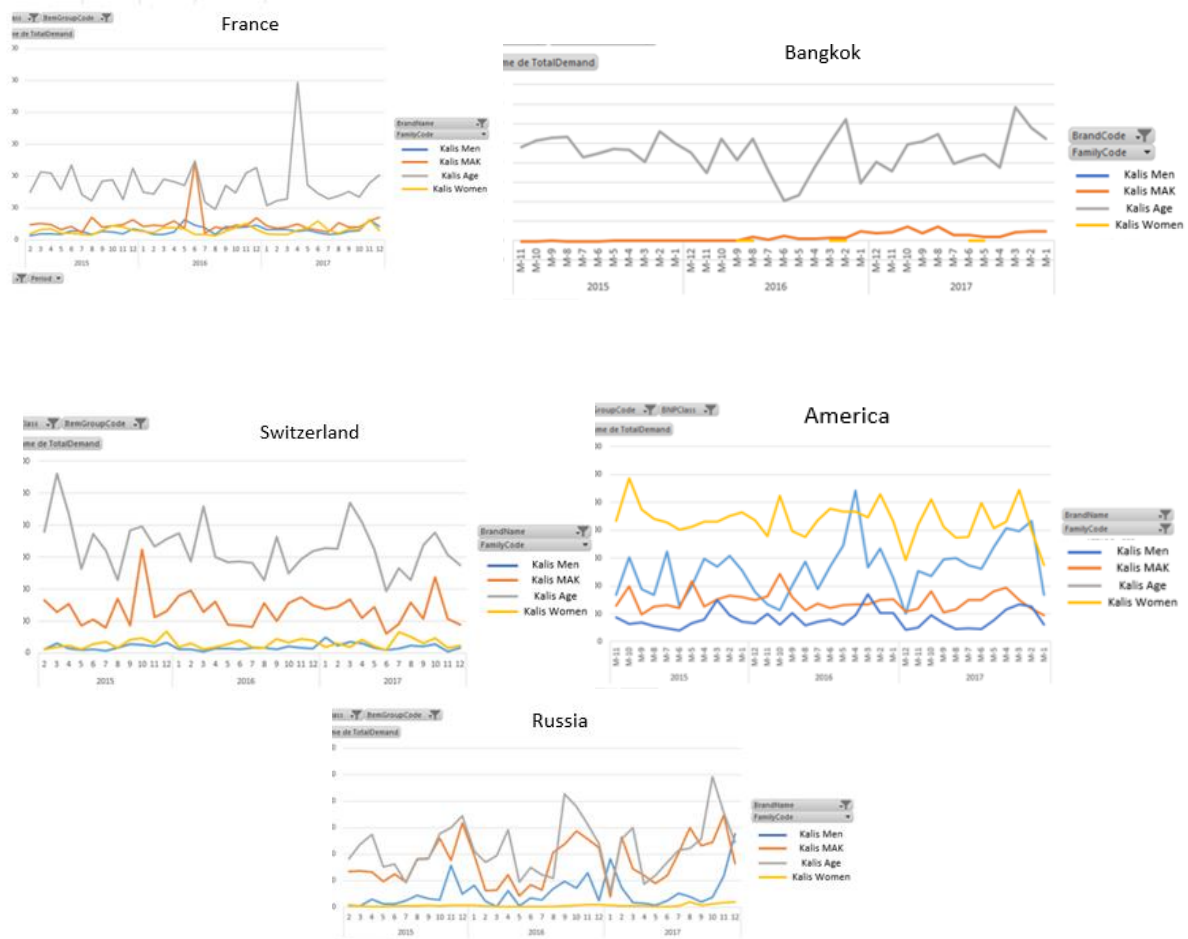
Fifth filter: Item group





(Figure 79: application of the Item Group filter to cluster demand)

C.2 Application of the found filter



(Figure 80: application of the filter found to cluster demand)

From the above graphs it is easy to notice that in some cases it will be essential to distinguish between the product's family segment since the two categories (make-up and skin care) have totally different evolution during time. For instance in the case of Bangkok hub, Kalis make-up has a quite stable evolution of

demand rather than the skin care category whose orders are highly erratic. In some others, like for the Russian case, the trend of data both for Kalis MAK and Kalis SKN does not show particular deviations, therefore there is not the need of sub divide the analysis into sub clusters. It is also interesting to add that in some cases, such as the Swiss one, two different Brands, Kalis Women and Kalis Men, can be grouped together since they present the same exact pattern during the years

C.3 The seasonality index (SI)

By following the guide of the APICS literature (APICS, 2009), the simple passages to follow to compute the SI are now described by using, for example, three years of monthly demand data. Three factors are needed to be computed:

1. The seasonal average of monthly sales for each of the 12 months in the past three years: for each month, the number of total sales has to be divided by 3
2. The deseasonalized average monthly sale during the past three years: the average of the 12 monthly seasonal averages calculated at the step before
3. The seasonal monthly index; for each month, this is the ratio between the average of the particular month divided by the deseasonalized monthly average

Seasonality Index				Seasonal Avg. Demand	Deseasonalized Avg. Monthly Demand	SI
Month	2015	2016	2017	2015-2017		
January	16	18	20	18	17,22222222	1,04516129
February	20	25	30	25	17,22222222	1,4516129
March	13	12	11	12	17,22222222	0,69677419
April	8	7	6	7	17,22222222	0,40645161
May	5	4	3	4	17,22222222	0,23225806
June	4	3	2	3	17,22222222	0,17419355
July	8	8	10	8,66666667	17,22222222	0,50322581
August	25	30	34	29,66666667	17,22222222	1,72258065
September	16	17	18	17	17,22222222	0,98709677
October	25	29	32	28,66666667	17,22222222	1,66451613
November	32	30	34	32	17,22222222	1,85806452
December	20	22	23	21,66666667	17,22222222	1,25806452
Total Average Annual Demand = 206,67						
Average Monthly Demand = 17,22						

Annotations:

- $(16+18+20) / 3 = 18$ (points to the 2015-2017 column for January)
- $18 / 17,22 = SI$ (points to the SI column for January)
- $(Tot Avg Demand) / 12$ (points to the Average Monthly Demand row)

(Figure 81: SI computation)

Therefore, the seasonal index indicates occurrences that happen periodically every month such as Christmas, summer time, St Valentine's Day, etc. At the end of the total seasonal cycle, i.e. the year, a new cycle begins with the same seasonality occurrences.