The impact of product family aggregation on Sales and Operations Planning in a mass customisation context : An application in the automotive industry

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The impact of product family aggregation on Sales and Operations Planning in a mass customisation context: An application in the automotive industry

Soutenue par

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List of Abbreviations

3PL	Third-party logistics
ANRT	Association Nationale Recherche Technologie
ATO	Assemble To Order
CAFE	Corporate Average Fuel Economy
CCA	Capacity Criticalness Assessment
CCS	Capacity criticalness Score
CIFRE	Convention Industrielle de Formation par la REcherche
EU	Europe
FMEA	Failure Modes and Effects Analysis
MC	Mass Customisation
MENA	Middle East and North Africa
MP	Mass Personnalisation
MRP	Material Requirements Planning
MTS	Make To Stock
OPP	Order Penetration Point
OTD	Ordre To Delivery
R3	Right Car, Right Place, Right Time
RI	Research Intervention
RPN	Risk Priority Number
RRG	Renault Retail Group
S&OP	Sales & Operations Planning
SCOR	Supply Chain Operations Reference

Chapter 1. General introduction

1. Motivations

Depending on various up-stream industries (Chemical, textile, steel, mining, etc.) and linked to multiple down-stream services (Repair, insurance, mobility solutions, etc.), the automotive industry is one of the major drivers of the world's economy. With a very large network of suppliers and distributors, the automotive products represented more than 9% of the world's exports in 2017 (WTO), and are very distributed across the globe. In France, 80% of French manufacturers' cars are sold abroad with a total worth of 51 Billion euros (CCFA, 2019).

Such global distribution of automotive products requires effective supply chain management to handle complex network and diversified overseas operations. Indeed, effective supply chain management is considered an important lever for competitiveness (Li et al., 2006; Um et al., 2017). Today, mastering the supply chain is more than ever an essential issue for all companies in search of operational excellence. They must be able to take advantage of their strengths, challenge their way of working, and set up an agile organization to face the new challenges in terms of sustainability (Hong et al., 2018; Rajeev et al., 2017), resilience (Jain et al., 2017; Ruiz-Benítez et al., 2018) and risk management (Ho et al., 2015; Tang, 2006) imposed by the economic transformations of their sectors and their markets. This organization

necessarily involves cost reduction, more productivity, and an active optimization of the various links of the supply chain to enable viable business continuity in the face of economic uncertainty and intense competition.

On the other hand, the manufacturing paradigms have witnessed substantial evolvement during the last century (Esmaeilian et al., 2016; Hu, 2013). The shift in manufacturing strategies was necessary to accompany the growth and change of customers' needs enabled by the industrial revolution. In short, these paradigms have evolved from pre-industrial medium-variety handcrafted products made in small quantities to industrial standardized low-variety products made in high quantities, then back to high-variety mass customised products manufactured at high quantities to end up with mass personalised products, a limited derivative paradigm of mass customisation that proposes an unlimited range of variants at a high volume.

The following figure adapted from (Hu et al., 2011) retraces the chronological evolution of the production paradigms and their characteristics in terms of volume and variety.

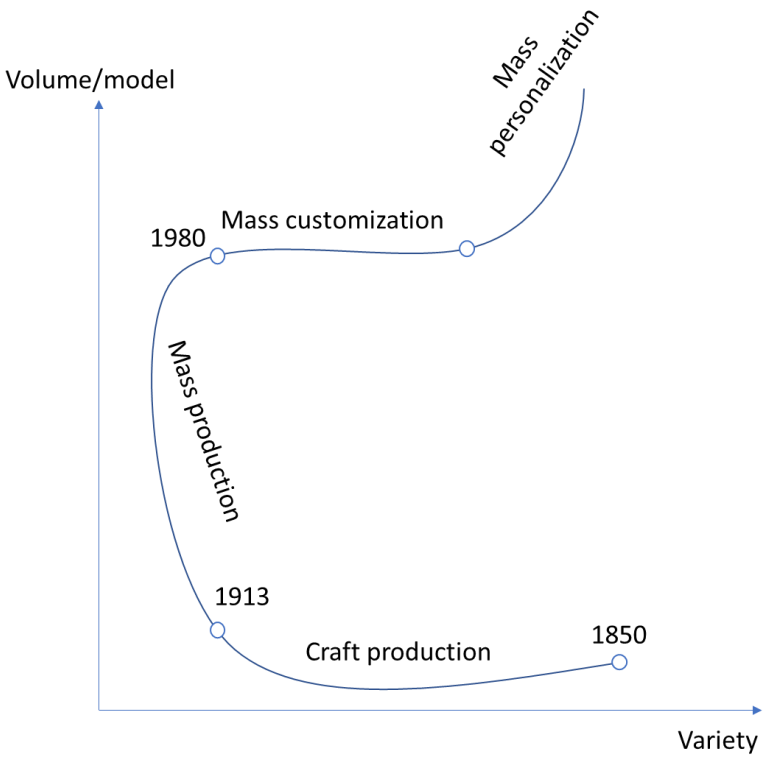

Figure 1.1: Production paradigms' timeline adapted from (Hu et al., 2011)

Thereby, in a nowadays global market characterized by a wide variety of customers' needs, manufacturers have adjusted their production facilities to produce more variety to increase their market share. Indeed, throughout the years, the customers' needs

have shifted from quality requirements to distinguishability and uniqueness requirements (Kumar, 2007). Mass customisation (MC) filled that need by combining the cost and quality advantages of mass production while offering a large panel of products to cover the maximum of customers' preferences similar to hand-crafted production. The deep differentiation proposed by the MC paradigm was a game-changer for many industries and pushed the customer experience to a new level (Merle et al., 2010). Consequently, the MC paradigm has gained success among manufacturers (Fogliatto et al., 2012).

Although MC succeeded to follow the ever-increasing customers' preferences for uniqueness and distinguishability, the growing need for new features enabled by the huge late developments in technologies came at a cost (Roy et al., 2011). The large product catalogues, typically exceeding the total number of orders, complexified the company's major operations (Lyons et al., 2020; Roy et al., 2011; Um et al., 2017; Wan and Sanders, 2017). Among others, the supply chain is one of the most affected functions alongside engineering and design (ElMaraghy et al., 2013). Indeed, dealing with an extremely large number of complex products distributed all over the globe, the supply chain management tools quickly reached their limits.

Thought the challenges of MC seem to be well known by the academic and practitioners and has been intensively discussed in the literature for almost 40 years (Fogliatto et al., 2012), most of the previous contributions focused on enhancing the product design and the production process in a context of high product variety (ElMaraghy et al., 2013; Roy et al., 2011). Our thesis, however, readdresses the customisation problem by targeting the poorly discussed planning process and investigating the impacts that high variety might incur on planning.

Our choice was motivated by the growing need for flexibility and responsiveness of the supply chain to remain competitive in an industrial context marked by the globalization of trade and unpredictable disruptions (Battistella et al., 2017; Shekarian et al., 2020). Consequently, effective anticipative planning seems key to mitigate the market volatility and the long delivery lead-times (Laurent Lim et al., 2014). In fact, despite the proximity to customers ensured by a global implementation, the globalization of the supply network negatively affects the responsiveness of far suppliers by increasing the delivery lead-time of parts which has undesirable consequences on the planning process (Laurent Lim et al., 2014) and on the customer willingness to wait or buy (Elias,

2002; Kalantari and Johnson, 2018). Besides, the high product variety reduces the probability of forecasting accurately the future demand since the pool of possible solutions is greater compared to a few variants' products (Randall and Ulrich, 2001; Wan and Sanders, 2017). As a result, inaccurate planning could incur huge costs to the company.

From an organizational point of view, sales and manufacturing have a long history of organizational conflicts (Malhotra and Sharma, 2002; Shapiro, 1977). Indeed, the high product variety enabled by MC creates opportunities for sales and marketing, while it introduces considerable challenges to the operations team. Consequently, sales managers prefer more variety to increase customer satisfaction regardless of the costs it might drive while supply chain managers push toward less variety to increase efficiency, which in return might impact sales levels. This organizational conflict remains unsolved and threatens the alignment among the firm's different business units (Oliva and Watson, 2011).

Accordingly, regarding the economic and the organizational challenges faced by the planning function, this thesis sets the Sales and Operations Planning (S&OP) process as a perimeter for the study. In practice, S&OP is a cross-functional tactical planning process. The process consists of a series of meetings that thrive to create a unique plan balancing an aggregated sales demand versus a set of major supply capabilities including procurement, production, and distribution capacities (Pereira et al., 2020; Antônio Márcio Tavares Thomé et al., 2012). The resulting plan constitutes a roadmap for both sales and supply chain downstream processes. At this level, alignment between the multiple involved actors is crucial for the success of the planning process (Goh and Eldridge, 2019; Oliva and Watson, 2011).

The current S&OP designs have proven to be unable to handle the ever-growing catalogues and to limit the negative impacts observed alongside the supply chain where poor performance is reported by academic and practitioner (Barrett and Steutemann, 2010; Matthew Spooner, 2017; Swaim et al., 2016; Antonio Márcio Tavares Thomé et al., 2012; Tuomikangas and Kaipia, 2014). The risks linked to bad planning include missed selling opportunities, high supply chain emergency costs, and a large inventory of unwanted products (Laurent Lim et al., 2014).

The choice of the S&OP process for our study was motivated by multiple reasons. First, the S&OP is a major tactical planning process which makes it subject to the challenges

a high variety could drive on planning when operating in the context of MC. Second, S&OP is particularly important because its data feeds the remaining supply chain processes, namely Source, Make and Deliver (Pereira et al., 2020). Finally, S&OP is a multi-actor process playing an important role of coordination between different business units, which might positively impact the up-mentioned organizational variety-driven conflicts between *Sales* and *Supply chain* departments.

Regarding the automotive industry, the product's modularity enabled by MC (ElMaraghy et al., 2013; Roy et al., 2011) offers different representations for the sales demand expression. At aggregate planning levels, the aggregated demand expression corresponds to a representation using a subset of features that characterize the product. We refer to each different grouping of product features as an aggregation level from which product families are derived. On the other hand, the supply capabilities depend usually on the expression of the major constrained capacities and are not subject to different representations like the sales demand.

The gap between these two representations is illustrated by the example provided in *Figure 1.2*. Assuming that only one car model is marketed, the top part of this figure illustrates an aggregated sales demand expressed using the engine and gearbox features for one time period. The down part illustrates the way capacities are expressed at production and procurement levels. There are five major capacities discussed in this example. First, a global assembly line capacity reflects the maximum number of cars that can be produced for the concerned period. Then, two procurement capacities represent engine and wheels procurement limitation and define the maximum procurement level for hybrid engines and two variants of wheels (15INCH and 16INCH). Finally, an assembly capacity related to specific engine/gearbox assembly workstations and reflects the maximum number of cars assembled for each valid combination of engine/gearbox per period.

One could observe that the demand vs. supply check is straightforward regarding the engine workstations and procurement capacities since both the sales demand and the assembly capacities are expressed using the engine feature. However, no direct judgment could be made regarding the wheels' procurement. Instead of ignoring this capacity, the sales demand is translated to match the expression of the wheels' capacity. This translation made necessary to verify the consistency of the plan and to adjust the capacity or demand if needed is ensured in practice via multiple data

aggregation-disaggregation operations using historical ratios. Such workaround solution is proven to be inefficient in a context marked by high volatility where history-based ratios are inaccurate (Sali, 2012).

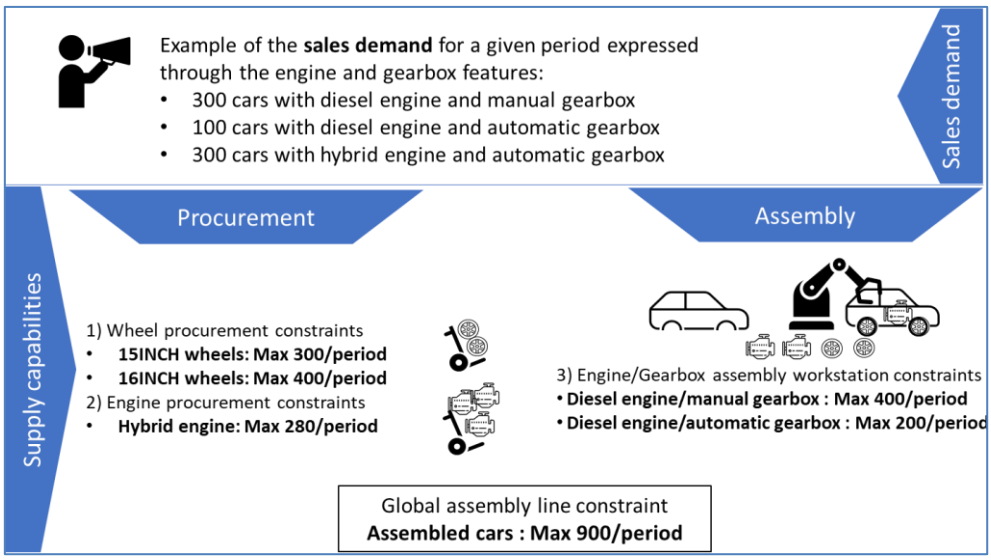

Figure 1.2: Demand vs. capacity expression

Assuming that the current planning data aggregation choices are not fit for industries operating under a MC production strategy where the product variety is high (e.g. the automotive industry), this thesis argues for a better design of S&OP that enables an improved organization and performance. It addresses the demand aggregation level problem and questions the viability of the current choices. It hypothesizes that better planning results could be obtained if a more convenient demand expression is provided. The new expression must be able to reduce all non-necessary data manipulation operations by selecting only appropriate features.

Therefore, the challenge is to design and propose a solution that guarantees quality planning data while maintaining a realistic and effective alignment between sales and operations teams in a context of MC and organizational conflicts.

To meet that challenge, we focus on understanding the impacts of the demand data aggregation level on the S&OP process in the context of MC and we propose a decision support model to identify alternative settings that mitigate the poor planning data quality. Thus, the central problem is as follow:

"*What is the best setting, in terms of the demand aggregation level, for a S&OP process in a mass customisation context that ensures better alignment and better performance?*"

To provide an answer to this problem, this dissertation is organized as a collection of four research papers that address chronologically the different development phases of the study. The first contribution reviews the existing literature to investigate the reasons behind the weak performance of the S&OP process in MC environments. The second contribution conducts an empirical diagnosis of the case process to identify the maturity level and the major pain-points of the process. The third contribution formulates the problem and proposes a decision support tool that provides more convenient solutions compared to the actual situation. Finally, the fourth contribution provides a capacity assessment framework to measure the criticalness of the supply capabilities and improve the results of the previous model. More details regarding each contribution are given at the end of this chapter.

Due to the complexity of the subject, some major theoretical and practical concepts relevant to the study will be discussed in the present introduction section because they have not been fully described in the provided papers whether for space considerations or for consistency with the main theme of the research paper. Accordingly, this first chapter will be organized as follow: the next section presents the context of the study as well as the industrial stakes and challenges. The third section situates the epistemological position of the author and details the methodology followed. The fourth section defines the problem background through a succinct description of basic concepts related to the problem. The fifth section formulates the problem and lists the research questions. Lastly, a conclusion is provided at the end of this chapter to describe the research objectives and to detail the general organization of the research.

2. Industrial context and challenges

This section is intended to present the context of the study as well as its challenges and stakes. The content of this part is organized as follows. First, we define the frame of our collaborative research partnership and its conditions. Second, we present some relevant characteristics of our research partner that we consider useful for the study. Third, we describe the initial problem definition as proposed by the partner and the changes that shaped the current problem definition. Finally, we try to situate our work compared to previous studies carried within the same partner. These studies contributed to broaden our knowledge on the research partner and provided valuable information on basic context-related concepts.

2.1. Thesis agreement

This thesis project is collaborative research conducted under a CIFRE[1] agreement and is the fruit of a partnership between Renault sas, Paris Dauphine University and the ANRT[2]. The project is funded by the ANRT and Renault sas under the convention N°: 2017/1507 for a period of three years starting from January 2018. The study was mainly conducted at Renault's offices with support from the Dauphine Research in Management lab [UMR-CNRS 7088] – M-LAB team. The project time repartition between the company offices and the university lab was around 80%-20% respectively and consisted of spending on average one day at the university and four days at the company offices per week.

2.2. Research partner

Groupe Renault sas is a French car manufacturer and a major player in the Renault-Nissan-Mitsubishi alliance. The worldwide presence of the alliance is based on a strong sales and supply network which positions it at the third position in terms of volumes with more than 10 million cars sold around the globe in 2019. In particular, Renault group sold 3,75 million cars the same year for the five different brands it possesses: Renault, Dacia; Lada, Alpine and Renault Samsung Motors (RSM) commercialized under different segments ranging from heavy to light, equipped with thermal or electric engine, personal or commercial cars, etc. (Renault sas, 2018). Such diversity of offers position the group as a generalized car manufacturer but also fuels multiple industrial challenges linked to the complexity of supply chain operations especially the planning function.

The thesis project is hosted by the supply chain production planning and control team which also explains the choice of the study perimeter. The operations team's responsibility starts with sourcing goods and ends when the car is delivered to the last distribution/storage point. Therefore, they don't manage the inventory of produced cars which is in return totally managed and owned by the sales team. Such an organization

[1] Convention Industrielle de Formation par la REcherche

[2] Association Nationale de la Recherche et de la Technologie

complexifies the management of production and gives less control to the operations team which has consequences on planning decisions.

Similarly, the dealers' network managed by the sales team shows a complex organization. Indeed, there exist two types of dealerships, those owned by Renault through the subsidiary Renault Retail Group (RRG) versus independent dealerships owned by independent entrepreneurs or managed by an importing country representative (that manages in return all the independent dealerships of that country). The dealers own the cars and pay for them upon order but could receive some incentives in case of selling difficulties, so the inventory is not totally managed by Renault which complexifies the operations and the planning.

The following figure defines the perimeter for each actor.

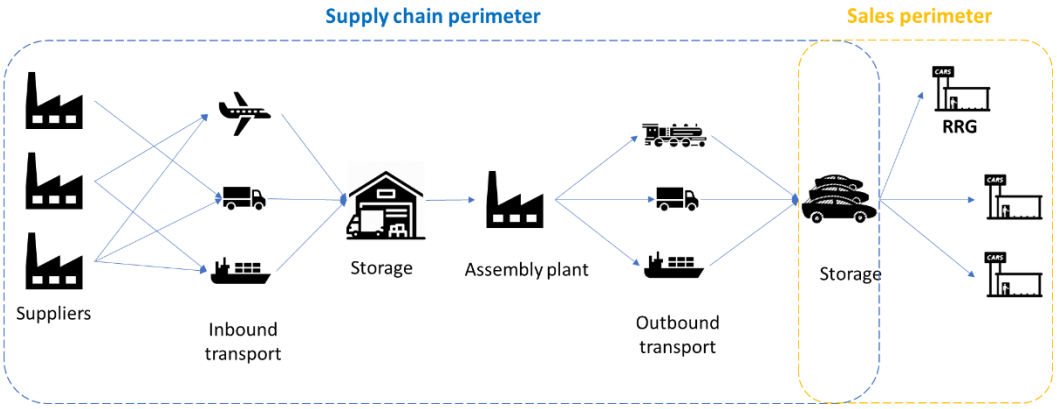

Figure 1.3: Car ownership perimeters

The operations team alongside the sales team has started a S&OP redesign and digitalization project which this thesis is part of. The project named R3 (standing for the Right car, the Right place and at the Right time) tries to integrate different S&OP actors using a unique IT tool to establish a cross-functional S&OP plan that respects the availability of supply capabilities and considers the demand risks and opportunities without exceeding the predefined budget.

During the development phase of the R3 project, questions linked to the choice of the demand data aggregation level were risen and remained unanswered. An empirical choice of aggregation was configured based on experts' suggestions. From an industrial point of view, this thesis is thus requested to first, confirm or reject the chosen configuration by identifying the properties of a good aggregation level and measuring its efficiency and second, provide more relevant alternatives if they exist.

2.3. Evolution of the project

The initial thesis title proposed by the industrial partner was: “Demand driven supply chain: product segmentation and differentiated operational management”. The initial problem consisted of studying the possible product segmentation that might enable better operational management of production and planning. A first study of the literature supported by an interview-based empirical investigation of the current process helped to define a more precise scope and objectives for the study. The process analysis and the conducted maturity interviews led to questions related to the structure of the demand data that seemed to be inconvenient for S&OP operations team. The practitioners claimed that a bad demand planning data structure could impact the quality of plans and thus introduce additional errors to an already poor forecast quality in the context of MC. The demand data structure in question consists of a group of car features. Consequently, the data aggregation at the tactical S&OP level was defined as a study perimeter for our thesis. We use *‘aggregation level’* to designate the group of car features expressing the sales demand and ‘*product family’* to designate a group of products sharing the attributes of the features constituting an aggregation level. The problem will be revisited and explicitly defined in section §4.5 of this chapter.

2.4. Industrial challenges and stakes

One major challenge for any industry making products subject to a high variety resides in accurately anticipating the exact needs long before the order date (Laurent Lim, 2014). This is typically the case in the automotive industry.

In the context of MC, the products are usually very customisable where each feature proposes multiple variants. The differentiation is obtained by proposing a wide range of parts and modules. Consequently, the probability of ordering exactly the needed parts that could match the specifications defined by the customer is very low.

For cars made purely to stock, it is very improbable to match the already produced car with the unique preferences of a random customer. In order to increase the probability of matching customers’ preferences, some commercial incentives are used to convince the buyer to choose an already produced car. Mutualized inventories are also used where all the pipeline and inventory products are proposed for all dealers (Brabazon et al., 2010). Unfortunately, this is not always possible when the car is for example owned

by an independent dealer or if the specifications are restricted to specific countries for some engineering or marketing constraints (c.f. §4.4*).* Therefore, since the dealers are dominated by the manufacturers (Jacobides et al., 2016), they buy 'pushed' cars even when they don't have a customer order. As a corrective measure, discounts are put in place to convince the buyers to buy cars that do not perfectly match their preferences. This category of costs related to marketing expenses is classified as Variable Marketing Expenses (VME) and is paid by the manufacturer to the dealers as compensation for 'pushing' them to buy unwanted cars (Jacobides et al., 2016). The reasons manufacturers push sometimes toward make-to-stock cars is linked to cost considerations (economy of scale) and to the relatively late ordering habits (compared to the production lead-time). Indeed, to fill the production lines, the manufacturers' central sales planning teams put some pressure on dealers to place orders.

These unnecessary costs can be avoided by improving the quality of planning data. There exist two ways to do that, by improving the quality of the planning inputs or by improving the planning process itself. In other words, either by improving the forecasting analytical computing techniques based on algorithms and strong sales channels or by improving the data management operations within the S&OP process.

The first method is largely discussed in the literature where multiple contributions try to improve the quality of forecasts using advanced analytical techniques (for example Gonçalves et al., 2020; Sagaert et al., 2018, etc.). However, the second track, less discussed in the literature, represents the main focus of our contribution where we try to identify the attributes that guarantee better planning. To do so, we consider the forecasting quantitative techniques as given and we focus on the data manipulation operations inside the S&OP process.

The challenge resides in defining an appropriate data form that will reduce internal data bias and error when manipulated by different business units, in our case, the data exchanged between sales and operations teams during the S&OP process. Indeed, a major issue related to the supply capabilities checking step was reported by the operations team which judged the original demand data form to be incompatible with the supply data structure. As a corrective measure, data manipulation at needed at the cost of distorting the original sales demand data and leading to poor planning quality.

The example mentioned in §1 suggests a set of supply capabilities linked to engines, gearboxes, and wheels features while the sales demand is expressed using only

engines and gearboxes features. In this case, the engine/gearbox capacities can be directly checked since we have compatible data form for both demand and capacity. However, the wheels constraint cannot be verified directly since there is no data regarding the requested volumes at the demand level. Therefore, a data pipeline needs to be built between the engine/gearbox combinations and the wheels' features using historical ratios to estimate the potential wheels' needs for each combination.

Now let's imagine another case where the sales demand is already expressed using wheels' feature on top of engines' and gearboxes' features. Consequently, direct verification of all supply capabilities could be obtained with no need for unreliable historical rates.

The use of history-based ratios distorting the demand planning data could lead to the following cases:

- In the first case, the underestimation of the demand using wrong ratios gives the false impression of non-blocking capabilities.
- In the second case, the overestimation of demand gives the false impression of blocking capacities that trigger unnecessary adjustments which could make other capabilities blocking.

The consequences of the incompatibility between the demand data and the capacity data could be either an excessive inventory or lost sales.

2.5. Previous studies

This contribution has profoundly benefitted from previous studies performed on the same research terrain and helped to shape the actual planning system. In particular, three thesis projects were very helpful in understanding the basic concepts, issues, and challenges linked to planning in a context of MC. More precisely, the thesis project prepared by Sali (2012) dealt with the impacts of poor demand forecasts on the upstream supply chain and tried to solve the observed problem of the bullwhip effect with an innovative MRP approach. The study was very helpful in explaining the different steps of the planning process for our case company. On the other hand, Lim (2014) developed an optimization-based S&OP model to deal with distant procurement challenges. His thesis dissertation provided valuable information regarding the challenges of S&OP in a context of high diversity and the cost impacts linked to the

globalization of supply. Finally, the work done by Chatras (2016) in his thesis dealing with the management of MC was very helpful to understand the product functional description and presentation system. He provided practical examples to explain the particular functional product representation and its link to planning. His dissertation was foundational to introduce the concept of aggregation level and to understand its impacts on the S&OP process.

All of these contributions, as well as many valuable scientific references, will be discussed in the *Background* section dedicated to reviewing the current literature toward the basic concepts mobilized for the study.

3. Epistemology

This section has three objectives. First, it describes the author's epistemological position that shaped the study and defined how to address the problem. Second, it presents the followed research methodology. Finally, it details the project macroplanning.

3.1. Research intervention

Epistemology is defined by the Cambridge dictionary as "the part of philosophy that is about the study of how we know things". The importance of epistemology lies in the influence of the adopted methodology on the relationships between the subject and the studied object, on the research design, and on the produced results.

Our research follows the guide lines provided by the research intervention (RI) methodology (Aggeri, 2016; David, 2000; Moisdon, 2015). The RI consists of conducting in-the-field research by working closely with the company practitioners to produce valuable knowledge. In this case, the company constitutes a field of scientific observation within which in-depth investigations are carried out and where researchers and practitioners exchange and build knowledge based on the obtained results (Krief and Zardet, 2013). The confrontation of the representations within the organization is a key element of RI. Indeed, each actor or group of actors has its own understanding of the organization and of its stakes. the role of the researcher is to identify and explain

these representations while proposing new alternatives that are of scientific and practical interest (Moisdon, 2015).

Accordingly, four properties distinguish the RI (Aggeri, 2016). First, the research assumes an immersion in the studied company and high proximity to the studied objects similar to anthropologists where the company is considered as a community with its own rituals, traditions, and interactions. Second, the RI drives a transformative action where observations and ideas are transformed to relevant conclusions and usable tools. Third, the research is assumed to be abductive creating logical links between the observations and the theories. Finally, the research is collaborative and assumes a strong collaboration between the researchers and the practitioners to produce valuable knowledge.

The RI approach has the major advantage of benefitting from the proximity with practitioners and the opportunity to deal with hot materials and analyse their interactions without being totally driven by the company directives and vision. Besides, access to data and unformal rich discussions are very helpful and could be difficultly obtained otherwise.

According to (David, 2000), five principles exist to accompany the RI methodology. Among these, *the principle of non-completion* indicates that “it is impossible to specify in advance the path and the results of an intervention research: It is the goal of the device to generate new knowledge that will help the organization evolve”. This approach fits very well with CIFRE thesis contracts and explains the natural evolution of the research project explained in §2.3.

However, special attention should be given to the risk of spending too much time with practitioners. Indeed, the researchers could be overwhelmed by the approach and techniques used by the practitioners and could be easily driven by the company policies and loose the objective neutral opinion required for research integrity. This effect of the transfer is dangerous for research authenticity but could be minimized by setting research instances to share findings with researchers and include them in the analysis which makes the RI different from classical consulting jobs (Aggeri, 2016).

For our thesis, multiple counter transfer instances were set-up regularly at different time paces:

- Weekly update meeting with the research supervisors,
- Quarterly steering meetings with the project members (researchers + practitioners),
- Bi-annual plenary sessions organized with peer Ph.D. students, multidisciplinary research teams, and multidisciplinary practitioners.
- Yearly seminar presentation in front of the Lab's senior researchers.
- Yearly contribution and participation in international conferences with peer-review committees.

3.2. Research phases

Following the RI methodology, the thesis was organized into three practical and logical phases.

The first phase is an exploratory phase performed in two steps and consists of exploring the existing academic resources as well as the implementation of the studied process. The first step consists of an academic literature review of the S&OP process and tries to formulate a relevant hypothesis regarding the reasons behind its bad performance. The second step represents an empirical investigation of the existing planning process intended to validate the hypothesis derived in the first step.

The second research phase tries to define a clear problem formulation that transforms the observations and hypothesis of the first phase into a formal problem definition.

Finally, the third phase represents a modelling phase and tries to provide a practical solution to the issues formulated in the second phase. In the RI paradigm, the proposed solution constitutes a new representation of the planning activity organization. Besides, the followed methodology brought a new perspective on the addressed management situation. The confrontation of different points of view enabled novel representations to emerge and produce valuable knowledge for both academics and practitioners. Figure 1.4 details the three phases established by four research papers.

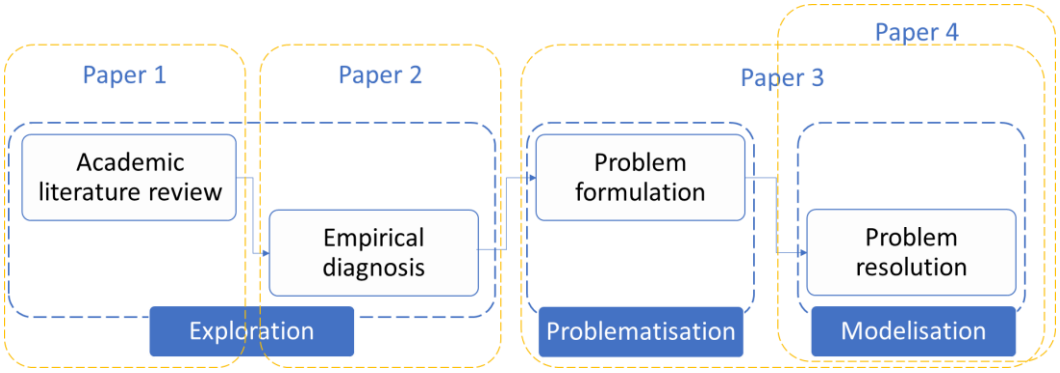

Figure 1.4: Research macro phases and contributions

4. Background

This thesis project investigates a planning problem under a context of MC through the case study of a major automotive manufacturer. The study focuses mainly on the tactical planning S&OP process. The choice of the study perimeter was motivated by two reasons. First, the project is funded by Renault which has already expressed many concerns regarding their planning process and was ready to collaborate and share data linked to the subject. Second, planning is the first supply chain process on which reposes all the following processes (source, make and deliver). Thus, any improvement within the S&OP scope would improve the downstream supply chain operations.

This section is intended to discuss context elements and major concepts linked to the automotive industry and to planning in a context of MC. The discussed elements are important for a better understanding of the current situation. Together, these elements will serve to prepare for the problem formulation and to give a better understanding of the motivations and challenges of this work. The most relevant bibliographical findings, as well as practical examples of the studied concepts, will be provided. More detailed literature can be found in the corresponding contribution chapter.

A top-down approach is followed in this section. It starts from common issues description to reach problem-specific challenges in a funnel-like organization. First, we describe the supply chain paradigm challenges and its particular need for good planning to work effectively. Second, we discuss the different production and ordering strategies. Third, we introduce the S&OP process as the main brick of the study perimeter. Fourth, we detail the unique product definition system that defines the planning data, and the product constraints, key to understanding the data aggregation

level problem. Finally, the fifth subsection introduces the aggregation level concept and discusses its interaction with demand and capacity expressions.

4.1. The supply chain

Beamon (1998) defines the supply chain as: “an integrated process wherein a number of various business entities (i.e., suppliers, manufacturers, distributors, and retailers) work together to: (1) acquire raw materials, (2) convert these raw materials into specified final products, and (3) deliver these final products to retailers.”

The supply chain council identifies four basic supply chain processes under the Supply Chain Operations Reference model (SCOR) (Huan et al., 2004): “plan, source, make and deliver”. These processes are declined into multiple activities: “managing supply and demand, sourcing raw materials and parts, manufacturing and assembly, warehousing and inventory tracking, order entry and order management, distribution across all channels, and delivery to the customer”. While usually belonging to different business units, these activities are highly connected and share a high amount of data.

One should note the consistency of the use of the word ‘chain’ which hides two central concepts. First, a chain requires the existence of multiple rings. In our case, the rings are suppliers, manufacturers, distributors and customers. The different business units involved in the process will be denoted, from hereafter, as actors. Therefore, the supply chain is a process shared by different actors and requires their active involvement to work efficiently. Second, a chain refers to connectedness and strength. Connecting actors or functions requires mutual understanding and strong links. These two concepts require cross-functional alignment to work properly and effectively.

From a historical point of view, the supply chain is an old concept that existed with the roots of the first market. The silk road is one of the most ancient known supply chains. Started more than 2000 years ago (Vollmer, 2019), this road linked the East to the West and delivered goods for both sides.

In modern times, the supply chain managed to keep its place as an important lever for economic development. The automotive industry is one of the major industries that rely highly on the effective management of its supply chain (González-Benito et al., 2013). Indeed, this industry is known for its worldwide distribution network and the complexity of its products coupled with large volumes and long overseas procurement lead-times

(Laurent Lim, 2014). Complex products comprise multiple sub-parts provided by multiple suppliers globally dispersed which creates a complex network hard to manage.

Due to the extent of the supply chain network, its management has never been as complex as it is today, particularly in a context known for unstable markets and marked by the globalization of trade and the internationalization of activities where the borders of the supply chain have broadened and the network of suppliers and customers has expanded to cover all the globe (Aydin et al., 2014). Consequently, a remarkable increase in procurement and delivery lead-times have occurred which impacted the responsiveness of the supply chain and increased the inventory levels (Laurent Lim et al., 2014).

On the other hand, customers were showing less patience regarding delivery lead-time (Elias, 2002). Indeed, many studies show that fast delivery has become a major marketing and selling argument (Marino et al., 2018). The success of short lead-time strategies can be observed through the success of Amazon's one-day-delivery strategy and the boom of e-commerce (Premack, 2019).

To conclude, the main challenges of today's supply chain relate to adapting to complex and unstable environments. Companies are seeking to optimize their production, ensure effective coverage of their distribution agencies, reduce inventory stock-outs and reduce the return of unsold goods while controlling the costs and the environmental implication of their products. They must therefore manage multi-level, multi-product, multi-period and multi-criteria problems.

Given their complexity, these problems are tackled with decomposition approaches where decision levels are usually treated independently or sequentially (Gelders and Van Wassenhove, 1982). This decomposition, crucial for supply chain effective management, will be detailed later in this chapter.

To address these challenges, our thesis focuses on planning and targets the mid-term horizon in an attempt to improve the planning quality and enable better organizational coordination. The importance of planning resides in its position as a driver for all the following supply chain processes and in the role it plays within MC production systems. We discuss this production strategy in the following section where we also detail its challenges and perquisites.

4.2. Production and ordering system

As stated in §1, different production paradigms exist depending on variety and volume considerations: Artisanal production, mass production, mass customisation and mass personalization (Hu, 2013; Wang et al., 2017). This thesis deals with a production characterized by high volumes and high product variety. Therefore, we focus on the mass customisation paradigm.

Accordingly, many order fulfilment strategies exist: Traditional strategies including different X-to-order strategies versus Make-to-stock (MTS) strategy (MacCarthy, 2013; Olhager, 2003) (where X refers to Build, Make, Configure, Engineer or Assemble). Additionally, an automotive industry context-specific strategy coined as the Order-to-Delivery strategy was developed to meet the customers' wide range of choices and lead-time tolerance (Brabazon and MacCarthy, 2017). The choice of the appropriate type of order fulfilment strategy depends on many parameters linked to the production strategy which is in return influenced by the market and customer purchasing behaviour.

The following subsections will discuss in detail the definitions and the challenges of these paradigms.

4.2.1. *Mass customisation*

Mass customisation (MC) is a production strategy that aims to provide in high volumes a wide range of variants for a specific product. The concept was popularized in the 90ties and consists, according to Pine (1993), of "developing, producing, marketing and delivering affordable goods and services with enough variety that nearly everyone finds exactly what they want". The success of MC relies on the flexibility of production and supply processes and on strong organizational structures to ensure a high variety without affecting the price compared to mass produced products (Hart, 1996).

To meet the success factors of MC, mass customisation capability (Tu et al., 2004) has emerged as a performance measurement tool that measures the ability of the company to produce customized products at a large scale without a remarkable cost increase or quality degradation (Zhang et al., 2014).

Zhang et al., (2015) define mass customisation capability through four aspects: volume, cost, lead-time and quality. More precisely, the volume metric refers to the capability of aggregating various demands in a large batch common. The cost metric refers to the ability to provide cost-effective mass customised products with a price range similar to mass produced products. The lead-time metric stands for the ability to reduce the total delivery lead-time defined as customisation responsiveness. Finally, the quality metric refers to the customisation guaranteed quality for every customized product.

Alongside MC, mass personalization (MP) has emerged as a differentiation trend that consists of adding unique modifications (Wang et al., 2017). To the difference of MC which offers a limited but a very big range of choices where differentiation is done at a deep level, the MP provides an unlimited panel of modifications, however, these modifications, usually done at late differentiation stages, are superficial and consist mainly of esthetical personalization like graphics, painting, etc. (Kumar, 2007). Indeed, while MP was limited to superficial traits of the product, the MC consisted of bringing deeper customisation that even affects the choice of used parts (Baranauskas, 2019).

The literature linked to the two subjects shows that many authors do not consider the difference between the two concepts and tend to use the two concepts interchangeably while it is clear that the impacts on the product structure and the resulting challenges are not the same (Baranauskas, 2019; Hu, 2013; Wang et al., 2017). We deal in this thesis with MC since it represents a real challenge by involving deep differentiation linked to parts that affect planning and increase operational complexity. While this thesis doesn't take a position in the debate regarding the effectiveness of the product variety, it does however consider variety as input and tries to reduce its impacts on the supply chain as a whole and on planning in particular.

An established stream of research works to ease the pressure driven by the high variety of the different engineering and supply chain processes. Different techniques were developed to mitigate the negative impacts of customisation on the company's operational costs (ElMaraghy et al., 2013). One largely used technique focuses mainly on the modular design of products to offer large catalogues without exploding the number of needed parts by reducing the total diversity of parts (standardization) or proposing easy to perform differentiations (late differentiation) without reducing too much the final product variety (ElMaraghy et al., 2013; Zhang et al., 2014). More

innovative solutions of easy variations based on high technologies (e.g. update to better software version on-demand) were provided by new entrants like Tesla and Uber representing a new threat for classic manufacturers (Ferràs-Hernández et al., 2017).

Regarding the complexity it drives, many authors argue about the efficiency of MC. Some studies show no significant correlation between the size of variety and the volume of sold units (Pil and Holweg, 2004). On the other hand, it's clear that diversity increases substantially the complexity of multiple engineering and supply chain processes (Blecker and Abdelkafi, 2006), like for example the manufacturing process (Roy et al., 2011), or the planning process that failed to follow the explosion of product variety (ElMaraghy et al., 2013). Indeed, a notable result of extensive MC and its driven complexity is demonstrated by the exploding size of the product variety.

From a marketing point of view, there is a clear emphasis on the positive impact of product diversity on customer willingness to buy and on the competitive advantage it drives by reducing the chance of missing a selling opportunity (Franke et al., 2010). More precisely, the trend seems interesting since it offers a wide range of choices and satisfies the buyers' different needs. As a result, MC has invaded many industries and more particularly, the automotive industry.

From an industrial point of view, MC increases substantially the complexity of the supply chain operations. Indeed, several studies show how the complexity of the supply chain operations rises with the size of the proposed catalogue (Blecker and Abdelkafi, 2006; Roy et al., 2011). Besides, this trend showed some limitations related mainly to increasing production costs, flexibility issues, and additional costs to meet delivery engagement whether with inventory or fast delivery modes (Laurent Lim et al., 2014; Liu et al., 2012).

From a planning perspective, providing very large catalogues to impatient customers weighs heavily on planning accuracy. Indeed, it becomes very risky to produce based on inventory since the probability of producing the right car that matches the order of the customer is very low when the pool of possible solutions (the catalogue) is large. To mitigate the risks of planning under uncertainty, different order fulfilment strategies were developed and will be discussed in the next subsection.

4.2.2. *Order-to-Delivery strategy*

Depending on the market behaviour defined through the customers' willingness to wait and purchasing habits, there exist different order fulfilment strategies based on the position of the order penetration point (OPP), first introduced by (Sharman, 1984), defined as the manufacturing stage where a specific product is assigned to a customer order (Olhager, 2003). Two main categories are identified: strategies based mainly on constituting inventory of final products versus strategies based on building final products upon orders. To name just a few: build to stock, build to order, assemble to order, engineer to order, design to order and order to delivery. In extreme X-to-order strategies, an order can be placed before the design phase and thus the product will be developed, produced and delivered as requested by the buyer. While this mode of order fulfilment seems to satisfy the exact needs of customers without need for anticipation or extra inventory, it requires a larger amount of time to deliver the final product. Therefore, it is usually destined for mono-project industries (space rockets, houses, luxury products) where small quantities or unitary products are produced. This strategy guarantees a totally customized product but does not cope with mass production and is usually expensive for the buyer. Aware of the importance of delivery lead time, the beginning of 21st century has witnessed many projects initiated by major car manufacturers aiming to reduce their delivery lead times (Miemczyk and Holweg, 2004). Lately, the same issue was addressed by Renault which is currently working on a project to reduce the delivery lead-time by proposing a fast delivery option.

On the other hand, a fully build-to-stock strategy receives the order at the level of finished product inventory from which the customer can pick its preferred product. This strategy guarantees the fastest delivery lead-time but does limit the customer choice to the available production and does incur high inventory costs to the dealer.
Table 1.1 illustrates the different OPP as stated by (Olhager, 2003).

Table 1.1: OPP by ordering strategy

Ordering strategy	**Design**	**Fabrication**	**Assembly**	**Shipment**
Make to stock	----------	----------	----------	OPP
Assemble to order	----------	----------	OPP	

Make to order	---------- OPP
Engineer to order	OPP

In a MC context, the wide range of products makes a pure MTS production strategy very costly. Indeed, the high product variety decreases the likelihood of producing exactly what will be ordered by the customer which generates a huge cost of final product inventory or lost sales. Besides, an MTS strategy requires a considerable cost of marketing incentives to get rid of unwanted products.

On the other hand, the assemble-to-order (ATO) strategy, designed for automotive-like industries where the major process is assembly, seems more convenient to limit the impacts of MC on inventory and lead-times (ElMaraghy et al., 2013; Olhager, 2003). Indeed, thanks to the extensive modular part design, assembly requires fewer parts to be stored in inventory. Thus, the ATO strategy is more cost-effective reducing the final products inventory-related costs. Besides, the production is started by real orders that arrive at a later stage compared to other X-to-order strategies which reduces effectively the customer delivery lead-time. However, in a high variety context, despite the efforts made to reduce parts variety, the levels of parts inventory remain huge, which increases considerably their handling costs.

A hybrid ATO variant based on forecasts, coined as Order-To-Delivery production strategy OTD (or Virtual Build To Order (Brabazon and MacCarthy, 2004)) was developed for the automotive industry to cope with the effects of cost and time driven by the high variety resulting from customisation (Brabazon and MacCarthy, 2017). From one side, like the ATO, the OTD strategy relies strongly on planning to anticipate and meet the customers' requirements in terms of order fulfilment lead time (i.e. delivery lead-time). From the other side, the OTD is characterized by a floating OPP situated along the production pipeline to include earlier stages of production. The OPP floats on a range that starts at the final product inventory level and stops at the start of the production level.

Different from the ATO strategy that requires a real order to assemble a car, the OTD strategy start assembly upon fake orders. A fake backlog of orders is thus built, and part supply orders were launched based on these forecasts. Meanwhile, a matching algorithm runs to match the real orders with the forecasted fake orders from alongside

the range of the OPP. As a result, any customer order can be fulfilled from the final products' inventory or from the production pipelines which offers precious time compared to the classic ATO strategy while guaranteeing some flexibility due to the size of these two pipelines. However, it incurs the risk of constituting excessive final product inventory which is not the case in ATO. Besides, the reliability of the forecasts remains threatened by the vast product variety which puts high pressure on their quality (Wan and Sanders, 2017).

In practice, Renault, as well as PSA and other manufacturers use a matching algorithm that authorizes to assign a non-fully similar car to the customer and execute some minor changes on the cars already in the production pipeline for some specific horizon of flexibility (Laurent Lim, 2014). The system interrogates the production pipe and identifies with an algorithm the cars that resemble more to the order and allow the change in some minor functionalities for a scheduled fake car until a certain period of time to the production day known as the flexible horizon. The chosen car could be reconfigured and rerouted to the waiting customer and become no more selectable from the pipe. For example, let's assume that the order has specifications that match a car in the pipe regarding all features except for the colour. Knowing that the pipe car has not been already assigned to a real customer (i.e. based on a fake order), a change in the color to match the customer specifications can be authorized and the car will be assigned to that customer. Unfortunately, such a case is not very frequent.

While this solution appeared effective, it puts however a lot of pressure on the supply chain planning function. Indeed, the success of this production strategy relies highly on the quality of the demand forecasts and on the effective communication of the provided data alongside the supply chain actors. More precisely, the virtual production backlog is the result of the disaggregation of the forecasted plan established by a cross-functional tactical planning process commonly denoted as Sales and Operations Planning (S&OP). This multi-actor process serves to balance, at an aggregated data level, a sales demand and a set of critical supply capabilities while respecting the company budget. The resulting plan serves as a reference for elaborating the master plan. More details regarding the S&OP process will be given in the next subsection.

One should note that due to the large panel of markets, more convenient strategies can be applied for specific cases. Indeed, some markets, not subject to the pressure of customers' sensitivity to customisation, sell cars based on inventory (MENA,

Americas, and some EU countries for our partner). Therefore, the regional dealerships belonging to these markets place large orders with enough lead time to supply and produce the needed quantities.

4.3. Sales and Operations Planning

This section provides an overview of the S&OP process from theory to implementation and discusses the challenges it faces in a context of MC. First, we clarify the position of the process amongst the hierarchical planning system to emphasize the role it plays. Then, we define the process from an academic perspective, and we provide its properties. Finally, we present the practical implementation of the process where we explicit a data manipulation problem.

4.3.1. *Hierarchical planning*

Planning is a central activity for supply chain operations. It consists of establishing robust production plans to anticipate future orders. There are different levels for planning depending on the decision level. Typically, three planning levels exist: Strategic, tactical and operational (e.g. Gelders and Van Wassenhove, 1982; Pereira et al., 2020).

Similar to the decision levels, the planning levels are hierarchical and interconnected through different data aggregations (Gelders and Van Wassenhove, 1982; Liberatore and Miller, 1985; Özdamar et al., 1998). This section will clarify the hierarchical organization of the planning levels based on a three-level planning model.

The first level represents long-term planning and defines the strategic vision of the company (Pereira et al., 2020). The planning data is defined at the global product segment level where a strategic plan provides a set of long-term objectives. These objectives are developed using yearly time units and are validated at the top management level.

At the second level, a more detailed tactical planning is performed. This level serves to define more precise objectives for production on a medium-term range. The tactical planning data is defined at least at the product family level using a monthly time unit, which makes it more detailed than the strategic plan. The data is prepared by the operations team and is validated at a higher level. S&OP is one of the most popular

processes for tactical production planning. The process will be discussed in the next subsection.

The last level is the operational level. It consists of real ordering data combined with forecasted demand and defines the backlog of the production plan. At this level, data is disaggregated at the lowest level and uses at least daily time units.

The breakdown of the planning data on a different axis (i.e. temporal, geographical, or physical axis) whether by disaggregation or aggregation operations respects a certain set of rules (Hax and May, 1973; Özdamar et al., 1998). In general, when going up-stream the upper level parameters serve as constraints for the lower-level data. As a result, the aggregation of the lower-level data has to match the higher-level data. Thus, it is intuitive to reconstruct a higher-level plan from a lower level. However, when data is expressed at a high level, going down-stream is not trivial. Disaggregating data need to use extrapolation rates at each inferior (i.e. more detailed) level. For example, regarding the physical axis, if the tactical plan defines the volume of diesel cars for a specific model, rates will be thus needed for a more detailed plan to express the volumes for each type of diesel engine when many variants exist. On the other hand, aggregating the data is straightforward, a simple volume sum for each diesel engine gives the total volume of diesel cars.

4.3.2. *S&OP definition*

Being at the heart of the tactical planning, S&OP is an important decision process for medium and large-scale manufacturers largely discussed in the literature (Lalami et al., 2017; Olhager, 2013; Pereira et al., 2020; Staeblein and Aoki, 2015, etc.). The process serves to align an aggregated sales demand with available supply capabilities in economic conditions compatible with the strategic objectives of the company (Grimson and Pyke, 2007; Pereira et al., 2020; Antônio Márcio Tavares Thomé et al., 2012; Tuomikangas and Kaipia, 2014). S&OP is performed on a monthly cycle through a rolling horizon that goes from 3 to 18 months (Antônio Márcio Tavares Thomé et al., 2012).

Popularized in the late 80s (Ling and Goddard, 1988), the S&OP has rapidly become successful for connecting different decision levels and coordinating between the major supply chain actors by integrating mid-term decisions linked to various sales and supply chain activities in a single plan (Goh and Eldridge, 2019; Pereira et al., 2020;

Tuomikangas and Kaipia, 2014). As a result, S&OP was largely adopted by manufacturers and became a main brick in the planning process and a crossroad for different business plans with strong managerial and organizational implications.

In order to work effectively, the process relies on three types of inputs: demand data, capacity data and financial data (Antônio Márcio Tavares Thomé et al., 2012). Therefore, it relies on the alignment between the multiple actors to build a feasible plan that balances the different inputs (Goh and Eldridge, 2019; Oliva and Watson, 2011).

Positioned at the tactical decision level, the existing literature is full of numerous decision-making models that deal with different tactical planning decisions. Pereira et al. (2020) performed a literature review of the mathematical S&OP contributions and classified the provided decision-making models under four S&OP sub-planning processes: procurement, production, distribution and sales. Multiple modelling approaches were used across the literature to meet the requested sales demand. To name just a few, linear programming (e.g. Chen-Ritzo et al., 2010; Feng et al., 2013), non-linear programming (e.g. Thomas et al., 2008), uncertainty approaches (e.g. Fung et al., 2003; Nemati et al., 2017b) and simulation (e.g. Lim et al., 2017) represent interesting examples of developed mathematical models.

4.3.3. *The implemented process*

This subsection describes the different inputs and steps of the S&OP process implemented at the case company.

The described process relies on two major inputs. On one hand, the demand data prepared by the sales team represents a compilation of multiple market data regarding the future demand collected at the corporate level. At this level, the sales demand is built upon a mix between real orders and forecasts. The collected data serves to give an estimation regarding the market evolution. Typically, the demand for one product is usually represented as a smooth function as shown in Figure 1.5.

The sales team has an objective of not missing a selling opportunity or a market trend and thus satisfying their customers' needs in quantity and variety while achieving a predefined volume target. Consequently, sales plans are usually considered as "over-estimated" by the operations team.

On the other hand, the operations team prepares a supply plan based on the availability of major supply capabilities assessed at different supply chain levels (procurement, production and distribution). Different from sales, the supply chain objectives tend to maximize the utilization of the resources to fulfil an economy of scale and reduce inventory-related costs. From a sales perspective, the supply plan is considered "under-estimated" where higher volumes can be achieved with existing capacities.

The supply plan defines the physical limitations to the demand level and is adjusted when possible. Thus, it takes the form of a stairstep function as shown in Figure 1.5 (Olhager et al., 2001).

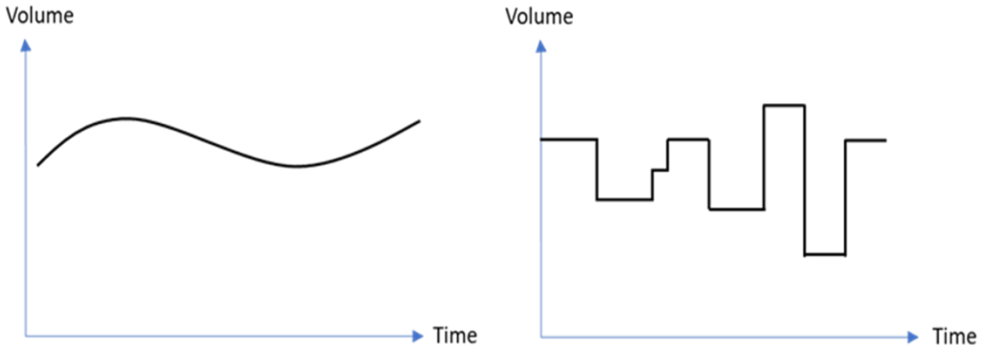

Figure 1.5: Demand (left) versus capacity (right) evolution for one product

This representation applies to a single product and a single resource capacity. However, in a context of MC, there could be multiple overlapping demand curves and capacity levels for each time period.

From a process organization point of view, our case study discusses a monthly four-step cyclic process described in the following Figure 1.6. The details of each step are given hereafter.

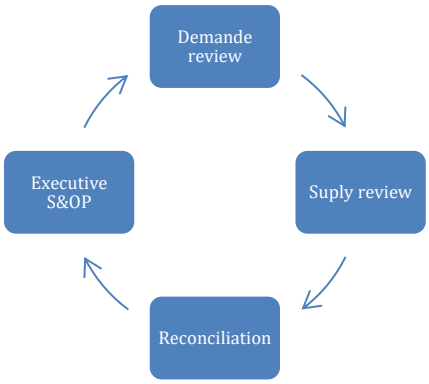

Figure 1.6: S&OP major process steps

A. Demand review:

The demand review represents a new cycle kick-off meeting. It constitutes the first step in a series of cross-functional meetings. Owned by the sales team, the meeting consists of presenting an unconstrained sales demand where overall market insights, risks and opportunities are detailed at the model level (i.e. demand volumes for each car model). Coordinated by the corporate sales team, the data is prepared on a monthly basis flowing a top-down orientation note then a bottom-up aggregation of the estimated demand forecast expressed at local and regional levels.

First, the central sales team provides an orientation note to the countries at the start of a new planning cycle. These orientations represent highlights of eventual major demand evolutions due to internal or external events.

Second, in the light of the orientation note, each country expresses its monthly unconstrained demand in volume and mix for each car model at a fine granular level. The mix is expressed using ratios for each important car attribute. The attributes detailed in the mix depend on the country and are linked to the commercial compatibility constraints which could indicate the existence or absence of an attribute. For example, some countries could specify in the mix the rate of 4x4 chassis while the same attribute could not be available for other countries. Additionally, the mix can change depending on the period since the attributes can be available only for a certain period of time (Chatras, 2016).

The third step consists of aggregating these forecasts at a regional level by expressing data at a higher (less detailed) granular level. The regions will then challenge the unconstrained demand expressed by their affiliated countries using the orientation note. Once the regions validate the forecasted demand of their affiliated countries, the corporate sales planning team collects this data and consolidate it to review its consistency before presenting it for the demand review meeting. This sales demand will be referred to as *the unconstrained demand*. It is worth mentioning here that this demand respects product compatibility constraints as will be explained in §4.4.2. Therefore, all the requested products are technically feasible and obey to marketing preferences and limitations.

B. Supply review:

The second step is owned by the operations team whose mission consists of verifying the ability of the supply capabilities to answer the requested sales demand. To do so, several meetings with the manufacturing teams, suppliers and distributors are held to present the sales demand and challenge the provided capacity plans. The supply capabilities are identified and updated, then they are confronted to the unconstrained sales demand to check the presence of constrained capacities.

This step requires multiple data extrapolation operations since the assessed capacities might be linked to features that are not visible in the original sales demand. Typically, the aggregated demand provides insights regarding major car features like for example engine, gearbox, etc. The supply capabilities, however, could concern uncommon components that do not figure in the original sales demand like a specific type of wheels or a type of radio. These capacities, invisible by the demand expression, could compromise the execution of the sales plan if not verified. Therefore, a disaggregation of the original demand data is performed using historical ratios to identify the requested volumes regarding the invisible capacities and check the feasibility of the sales plan.

One can note that at this level of decision, arbitration between demand and available capacities cannot be done at a very fine level of details (i.e. aggregation level) for both organizational and technical reasons which explain the use of an aggregated level. Indeed, in a context of MC, multiple levels can exist, which raises the question regarding the choice of the level to adopt. Therefore, the arbitrations are generally made after having grouped empirically the products into homogeneous families (ElMaraghy et al., 2013). The demand prepared by the sales team is defined by the dealers and refers to functionalities visible or chosen by the customer. On the other hand, the supply capabilities are expressed using functionalities linked to the supply chain resources. With the existence of different aggregation levels, a common ground that considers both supply and demand functionalities could reinforce alignment and improve planning data quality. Indeed, the supply review phase goes through many data disaggregation steps to verify the respect of the available capacities. These various data manipulation steps are described in section §4.5.

C. Reconciliation:

The third step of the process serves to study the possible scenarios and make decisions upon the confrontation of demand and capacity levels. These decisions concern mainly an update of the constrained blocking capacities and involve among other decision regarding negotiating with the social partners for extra shifts, an investment to buy more production capacity, or agreements to postpone production, etc. If none of these solutions is possible, the unconstrained demand will be cut down to the level of the constraint and repartition decisions of the new volumes have to be made for the concerned dealerships.

D. *Executive S&OP:*

The last step of the S&OP process is held at a top management level where the sales demand, the supply capabilities availability and major decisions regarding the constraints are presented. The aim of this meeting is first, to validate the consensus plan, and second, to resolve the conflicts that might have appeared if no consensus regarding some constrained capacities has been met at the previous step.

Once the plan is validated and officialised, more detailed calculations will be performed to create the master plan and launch the procurement orders.

This dissertation will focus on the problem of data disaggregation operations performed at S&OP supply review step level and impacting data quality and accuracy. The following *Figure 1.7* retraces the different data manipulation steps for the studied S&OP process where each level uses a different aggregation level.

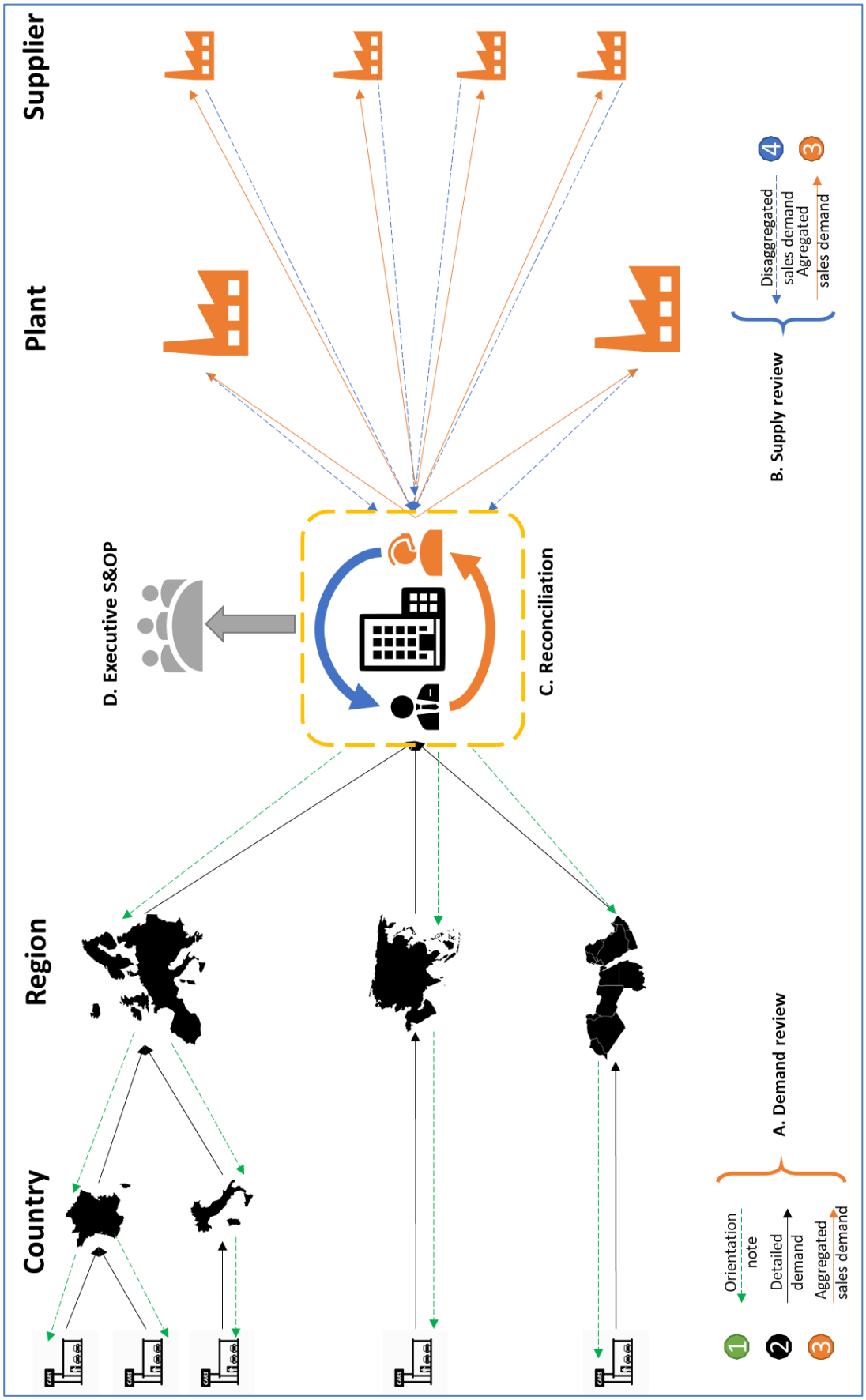

Figure 1.7: The S&OP data flow steps

4.4. Product definition system

A specific product definition system that defines the data structure is discussed in this section to give a clearer understanding of the planning data structure.

In general, a product can be defined in different manners. For example, a complex product like a car can be defined either as a combination of parts (a bill of materials) or as a combination of functionalities like the type of the roof, the type of the engine, etc. (Chatras et al., 2015; ElMaraghy et al., 2013; Roy et al., 2011).

For planning purposes, the second representation is used. Although it doesn't provide a direct link to the parts, it is more comprehensible for customers and is more suitable since it is lighter for databases (fewer parameters).

4.4.1. *Functional definition system*

The product functionalities, to which we refer as '*features*', represent groups of different alternative specifications to which we refer as '*attributes'*. Therefore, a car can be defined as the union of a set of attributes where each attribute belongs to one different feature (Chatras et al., 2016a).

For example, *engine* is a feature that has the following attributes: *Diesel 1.6L, Gasoline 1.3* and *Hybrid Gasoline*. Some attributes can also refer to an absence of the feature. For example, the feature *air conditioner* (AC) has an attribute: *Without AC* alongside with *Manual AC* and *Automatic AC.*

Note that a car can never have two attributes for the same feature. For example, we can't have two different attributes for the same feature engine in the same car. This means a car cannot have a *Diesel 1.6L* and *Gasoline 1.4L* engines at the same time as attributes for the feature *engine*. At the end a car is fully defined by a single attribute for each feature (for example, a car of model X, with engine E and color C and gearbox G, etc.)

Similarly, Renault uses the same functional definition system to express the supply capabilities. Consequently, a capacity is expressed using the attributes of the features concerned by the capacity. For example, a capacity *C1* linked to the volume provided by a workstation that assembles engines of type E1 is simply expressed as (E1) while

a capacity *C2* that defines the maximum assembly rate for engine E1 and gearbox G1 will be expressed using the combination of the concerned attributes (*E1* / *G1*).

The following table 1.2 provides a simple representation of the existing product definition system:

Table 1.2: Functional product definition system

Feature	**Engine**		**Gearbox**		**Wheel**		**…**	**Air conditioner**		
Attribute	E1	E2	G1	G2	W1	W2	…	NOAC	AC1	AC2
VAR 1	1	0	1	0	1	0	…	1	0	0
VAR 2	0	1	1	0	1	0	…	1	0	0
…	…	…	…	…	…	…	…	…	…	…
VAR n	0	1	0	1	0	1	…	0	0	1
Capacity C1	1	0	0	0	0	0	…	0	0	0
Capacity C2	1	0	1	0	0	0	…	0	0	0

Following this representation, the number of variants can easily explode with an increasing number of features. Indeed, modern cars propose a huge number of features. Our analysis of Renault's internal data shows an average number of features of around 150. If we assume that each feature has only 2 different attributes, the total unconstrained possible variety is equal to $2^{150} \sim 1.4 \times 10^{45}$ different variants. These numbers depend on the customisability of the car, they increase for highly customisable cars and decrease for simpler models.

Luckily, not all combinations are proposed. Multiple attributes are incompatible with others for different reasons which reduce the scope of what can be manufactured or sold. The next subsection will discuss the constraints on some combinations in detail.

4.4.2. *Compatibility constraints*

The compatibility constraints serve to avoid producing incompatible or unusable cars by prohibiting the combination of non-compatible attributes either for technical or

marketing constraints. Consequently, constraining the range of what can be manufactured and sold will eventually reduce the resulting product variety.

In order to understand how a combination of attributes could be constrained, let's take the example of an aggregation level built with three features: *Engine, gearbox* and *wheels*. We assume the existence of a technical constraint that unauthorizes the combination of engine E2 (hybrid engine) and gearbox G1 (manual gearbox).

The following table 1.3 shows how the compatibility constraints could decrease the total size of the variety.

Table 1.3: Compatibility table

Engine		**Gearbox**		**Wheels**		**Combination**	
E1	E2	G1	G2	15INCH	16INCH	Authorized	Unauthorized
1	0	1	0	1	0	1	0
1	0	1	0	0	1	1	0
1	0	0	1	1	0	1	0
1	0	0	1	0	1	1	0
0	1	1	0	1	0	0	1
0	1	1	0	0	1	0	1
0	1	0	1	1	0	1	0
0	1	0	1	0	1	1	0

The total number of combinations when all the attributes linked to all the features are considered is equal to eight (2 engines x 2 gearboxes x 2 wheels). When we consider the compatibility constraints on E2 and G1, only six (8 authorized – 2 unauthorized) combinations are feasible. In a complete example, the total unconstrained variety is drastically reduced thanks to the presence of many compatibility constraints. More detailed examples could be found at (Chatras et al., 2016a).

The compatibility constraints could be linked to two reasons:

A- Engineering constraints: what can be manufactured

Engineering constraints are technical constraints linked to engineering issues and have one role: *prohibit the combination of technically incompatible attributes*. As a general rule, the engineering constraints are global constraints and must be firmly applied, otherwise, the final product can present many defects. These constraints are defined at the product design phase by the engineering teams. They concern the proper functioning of the car regarding technical parameters. For example, the choice of the cooling system is constrained by the place where the car will be sold. Cars destined for hot countries are equipped with stronger cooling systems than cars destined for cold countries. Moreover, regulations in some countries impose a high level of security and thus attributes not respecting the regulations are automatically banned from the selection. For example, when ABS is optional, cars without ABS might not be proposed for many countries.

B- Marketing constraints: What can be sold

The marketing constraints are defined by central or regional marketing units and serve to define the specifications that apply to each market by regrouping some attributes in commercial packs or prohibiting others. For example, the marketing restrictions can be global where the corporate decides to sell-high value attributes as a pack together for all markets (e.g. sunroof is only available for highly equipped cars) or could be local where some niche markets do not include 'low cost' attributes in their proposed catalogs. Contrarily to the engineering constraints, relatively stable over time, the marketing constraints vary a lot with the product life cycle and are subject to multiple evolutions. Typically, some attributes start as *optional* and with time become *default*. For example, when first launched, the XENON lights were '*optional*' before becoming '*default'* for almost all new cars due to a decreasing technology cost.

One should note the hierarchy between marketing and engineering constraints. The marketing constraints define what can be sold only inside what can already be manufactured. They must operate under the engineering constraints defining manufacturable variants. For example, if engineering authorizes three choices of engines among four, then marketing can only propose variants for the three engines.

The following *Figure 1. 8* illustrates the hierarchy of the constraints where '*Marketing X'* refers to the marketing compatible diversity pool for the market or country '*X*'.

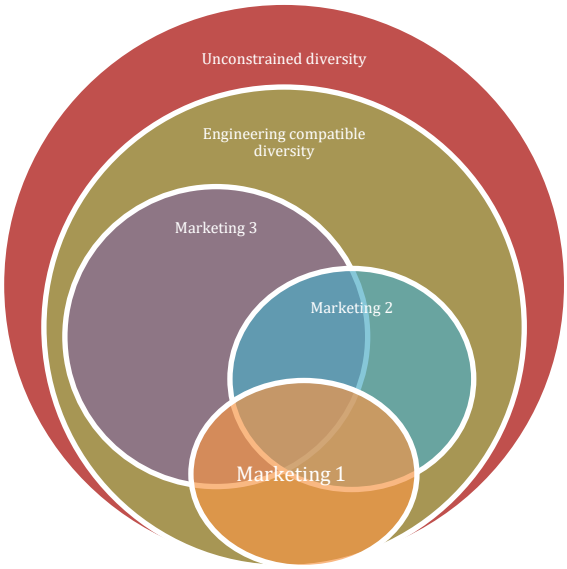

Figure 1.8: Hierarchy of the compatibility constraints

Despite the presence of multiple compatibility constraints, the size of the proposed variety remains enormous and many authorized combinations will never have the chance to be manufactured. Therefore, the question regarding the necessity of the size of the variety is often asked. An analysis made by Lim (2014) shows a perfect pareto where only 20% of final product varieties represent 80% of what is produced. From a marketing and sales perspective, the uncommon varieties that have never been sold are kept 'just in case' a customer place an uncommon order.

4.4.3. *Supply capabilities*

The supply capabilities are volume capacities linked to procurement, production or delivery limitations (Olhager et al., 2001; Pereira et al., 2020). These capacities are usually linked to economic considerations and require considerable investments to be levitated. We describe briefly the capacities used in the current S&OP process. A more detailed classification of these capacities and their assessment will be provided in chapter 5 of this dissertation.

There are different categories of capacities present alongside the different supply chain levels (Pereira et al., 2020). Two categories directly affecting the planning demand are discussed in this subsection:

- Production capacities: they refer to the assembly plants' capacity to produce cars and can be divided into three types:
    - *Production rate*: It refers to the volume that can be guaranteed for some features in a time period. There exist multiple rates for different combinations of features. For example, the daily volume of sunroof cars is limited by a specific rate. The production rate depends mainly on the availability of the production teams and is limited by the bottleneck capacity of the assembly line. The human labour resource capacity is relatively flexible and can be either increased or decreased by working in the weekend, closing for some days or adding/deleting some shifts. However, the machinery capacities are less flexible and could be expensive in case of an increase of production rate since they usually consist in upgrading machines or buying new ones.
    - *Engagement capacities*: They refer to a contracted minimum production level between the plant's production teams and the planning teams to guarantee a minimum level that covers the fixed costs of the plant.
    - *Ramp up capacities*: These capacities apply in the case of a new product launch and consist of increasing sequentially the production rate to respect the time needed by operators to master the new process.
- Procurement capacities: they refer to suppliers' production capacities and concern the contractual volumes a supplier can provide for a specific part. They might require some investment to be levitated which are usually paid by the client (i.e. the car manufacturer). They serve as a reference in the establishment of the procurement plan and are in general relatively flexible.

Each of these capacities is characterized by a degree of flexibility for an increase or a decrease of volumes. Therefore, we distinguish two categories:

- Soft capacities: They are relatively flexible and does not necessitate huge investments or long set-up time to be levitated. As a result, in case of a demand increase, the requested extra volumes can often be provided
- Hard capacities: They represent structural capacities that define the highest possible level of production for the current setting. Increasing these capacities usually requires huge amounts of investments and long set up time and is approved at the top level of management.

In general, the supply capabilities are managed by the operations team. More specifically, the hard capacities serving to define the acceptable levels of demand are verified during the S&OP process. To better understand the impact of capacities on planning, the next section will discuss the aggregation level concept and explain how to choose a level that enables better planning.

4.5. Aggregation level

This section introduces the concept of aggregation level for automotive planning. Data aggregation could be performed on a temporal, a geographical or a physical axis. The temporal axis could be expressed using yearly, monthly or daily time units. The geographical axis could be broken down to continent, region, country or city level. The physical axis, which will be discussed in this dissertation, could be expressed through car features and attributes. We provide examples to first, define and explain the concept of planning data aggregation level, and second, identify the optimal aggregation choices.

4.5.1. *Data aggregation level*

A data aggregation level could be defined as a partial expression of complete data. Therefore, it assumes hiding some information due to aggregation operations. In our case, an aggregation level on the physical product axis refers to regrouping based on a subset of features. Indeed, while complete data uses all the attributes of a car, the first operation of aggregation consists of using features instead of attributes for simplicity reasons. Then, a second operation consists of selecting only some features amongst all car features. Consequently, each different subset of features defines a unique aggregation level. Thus, multiple levels can exist where the most detailed levels use more features whereas the less detailed levels use fewer features.

For example, the S&OP is performed today on the "*car-model"* level which designates a highly aggregated planning level using the unique feature *car-model*. Namely, *Clio, Mégane and* ZOE are different attributes of the *car-model*. On the other hand, the combination of *car-model* and *energy* could provide a more detailed aggregation level which could be broke down as follow: *Diesel Clio, Gasoline Clio, Hybrid Clio; Diesel Mégane*, etc.

Therefore, we define a planning aggregation level as a subset of planning features.

Typically, the choice of features constituting the aggregation level is built empirically upon a compromise between different departments. The literature shows the absence of a clear definition of the appropriate data aggregation level and does not provide efficiency metrics for aggregation level quality. However, some contributions discussed production-linked parameters that can help to define an aggregation level (Gelders and Van Wassenhove, 1982; Herrmann et al., 1994; Kanyalkar and Adil, 2005; Kashkoush and ElMaraghy, 2016). Among these, we enumerate production constraints setup time, production means, job shop path, etc.

In practice, the observation of the planning process shows that when the supply capabilities are expressed with features not present in the original demand data, the operations team uses history-based ratios to disaggregate the original data and compare the extrapolated demand to the level of the supply capabilities. Such practice is very risky and negatively impacts the original demand data quality.

Recall the example developed in §1. The demand was expressed using the aggregation level composed of the features {engine, gearbox} (where *E1 & E2* are attributes designating *Diesel* and *Hybrid* engines, and *G1 & G2* are attributes designating *Manual* and *automatic* gearboxes, respectively*)*. We also reconsider the unauthorized combination of a manual gearbox G1 and a hybrid engine E2 designated here as Not Applicable (N/A). The following table details the sales demand for one time period.

The following table 1.4 reproduces the sales demand for one time period.

Table 1.4: Sales demand volumes

Engine	Gearbox	Volume
E1	G1	300
E1	G2	100
E2	G1	N/A
E2	G2	300

Now assume that we want to express this demand at a finer level by adding the feature *wheels* composed of *15INCH* and *16INCH* wheels. We suppose that no compatibility constraint exists between the feature wheels and the features {engine, gearbox}.

The following table 1.5 illustrates the possible variants:

Table 1.5: Disaggregated sales demand volumes

Engine	Gearbox	Wheels	Aggregate volume	Detailed volume
E1	G1	15INCH	300	?
E1	G1	16INCH		?
E1	G2	15INCH	100	?
E1	G2	16INCH		?
E2	G1	N/A	N/A	N/A
E2	G1	N/A		N/A
E2	G2	15INCH	300	?
E2	G2	16INCH		?

In order to accurately complete the detailed volume column, three different rates are needed to identify the wheels' needs for each combination of {engine, gearbox} (the sum of rates for each combination must be equal to 1 for because each car is equipped with wheels). However, since the sales team does not express the sales demand using the *wheels* feature, historical rates must be used instead.

One should note that the extrapolation operations are performed by the operations team which would apply the rates provided by an automated tool without much control on the output (a Blackbox). Besides, the operations team has no prior knowledge of the market evolution, unlike the sales team which masters the demand data. Consequently, these rates are not very reliable for planning with uncertainty.

To avoid the use of rates, one would go for the most detailed aggregation level and opt for a complete expression of the sales demand using all the available features. This option is not feasible for the following reasons:

- The generated variety (i.e. the number of possible combinations) will be tremendous. Recall that we could reach ~10^{45} varieties, therefore, almost half of this number is the size of rates that need to be prepared and calculated, which is impossible and useless.

- With a large number of features, the demand forecasts are far less accurate (Wan and Sanders, 2017).

Seemingly harmless, this problem of choice of aggregation level or grouping into product families has considerable consequences on the performance of the planning process. Besides, the data aggregation problem scope is general and goes beyond the strict framework of MC systems to encapsulate many supply chain problems with complex product structure and different decision levels.

An optimal data aggregation strategy will be discussed in the following subsection.

4.5.2. *Optimal aggregation strategy*

The sales demand is expressed at an aggregated level that uses features chosen by the sales team linked to major car components or cost dependent features. The aggregation level was defined empirically without considering among others, the structure of the supply capabilities. This is particularly important since the balance of demand and capacities will be performed based on these capabilities.

Indeed, a closer look at the planning process shows that during S&OP, the operations team checks the ability of the available capacities to correctly answer the demand. As explained in §4.4.1, demand and capacities expressions use the same functional definition system based on features and attributes. However, checking the sales demand against the supply capabilities is not always straightforward due to the use of different aggregation level (i.e. a different set of features). Therefore, special data manipulations are required to prepare the right data. The understanding of the aggregation problem is key to the thesis. Thus, the following example built on the pilot example presented in the motivations section is provided.

Recall that the demand expressed in table 1.4. On the other hand, let's reconsider a set of supply capabilities identified by the operations team as critical and linked to *engine, gearbox and wheels* assembly and procurement. We consider that in general, if no capacity is expressed on an attribute, then any level of this attribute could be fulfilled if the demand is not greater than the global line capacity. The following table provides an overview of the existing supply capabilities for one time period.

Table 1.6: Capacities' volume levels

Type of capacity	Capacity expression	Capacity limit
Production rate	Global assembly	900
Production rate	E1/G1	400
Production rate	E1/G2	200
Production rate	E2	280
Procurement	15INCH	300
Procurement	16INCH	400

During the supply review phase, a comparison between the table 1.4 and the table 1.6 is performed. Without data manipulation operations, the following straightforward conclusions could be derived:

- The global line capacity (900units/period) is enough to produce the requested demand (700units/period)
- We have enough line capacity to fulfil the sales demand for cars equipped with an engine E1 and a gearbox G1 (constraint = 400units vs demand = 300units).
- The global line capacity of E1 shows that we have at least 200units remaining for the demand of E1/G2. Thus, we can fulfil the demand of E1/G2 (constraint = 200 vs demand = 100units).
- We risk a shortage of 20 cars equipped with E2 and G2 if the forecast-based demand is accurate (constraint = 280units vs demand = 300units).
- No clear decision can be made regarding the capacity of the 15INCH wheels. The total number of cars that could be provided, considering the constraint on E2 (680units) is superior to the level of the constraint 15INCH (400units). Thus, if for example all the cars are equipped with a 15INCH wheel, there will be a procurement shortage of 280units.
- No decision can also be made regarding the respect of the 16INCH wheels capacity level. The capacity level is inferior to the total demand volume, thus risk of shortage can occur if all the cars will be equipped with 16INCH wheels.

Overall, a huge uncertainty can be observed on the risks of shortages when no clear information is provided by the sales demand since it does not include information

regarding the *wheels* feature. In such a case, additional data is provided using historical rates. Indeed, a mix rate for the attributes of the missing features can help define the appropriate repartition and consequently verify if the needed volumes can be achieved.

Now let's assume that the analysis of the historical demand for wheels shows a mix rate of 50% for each wheel type while real rates for that time period were 30% for 15INCH and 70% for 16INCH. Using this information, the operations team prepares the column '**Demand from history ratios'** to identify the needs for wheel attributes for the existing varieties. The column '**Demand from real ratios'** is given for comparison purposes between the extrapolated demand and the real demand. The next table 1.7 provides the results of the demand data extrapolation.

Table 1.7: Disaggregated sale demand based on history ratios vs real ratios

Engine	Gearbox	Wheel	Demand from history ratios	Demand from real ratios
E1	G1	15INCH	150	90
E1	G1	16INCH	150	210
E1	G2	15INCH	50	30
E1	G2	16INCH	50	70
E2	G1	N/A	N/A	N/A
E2	G1	N/A	N/A	N/A
E2	G2	15INCH	150	90
E2	G2	16INCH	150	210

Consequently, additional observations regarding the constraints can be derived:

A- Using historical ratios provided by the operations team:

- The demand for the 15INCH wheels (between 330 and 350units) will not be honoured by the suppliers (300units).
- All the demand lines with 16INCH wheels (330-350units) will be honoured by the suppliers (400).

B- Using real ratios:

- The demand for the 15INCH wheels (210units) will be honoured by the suppliers (300units).
- The demand for with 16INCH wheels (490units) will not be honoured by the suppliers (400).

Comparing the two cases, one can clearly see that we obtained opposite conclusions when using real rates. Therefore, we can derive that the use of non-accurate historical rates introduces a huge bias and lead to a combined effect of overestimation and underestimation of the detailed demand which might distort the resulting plan. Such case is very frequent when the ratios are prepared by the operations team that has no clear visibility on-demand evolution and no expertise with demand data manipulations.

On the other hand, the sales team has more chance of getting these ratios closer to reality. Therefore, adding the feature *Wheels* to the sales demand expression by the sales team from the beginning could enable more accurate capacity checking while avoiding useless extrapolations.

A legitimate question on the composition of the planning data aggregation level and on the ownership of the demand data can thus be addressed. Indeed, it is clear that performing transformation operations on the demand data is naturally a sales task, which raises the question on the effectiveness of using features that do not consider the supply capabilities and thus require data manipulations by the operations team.

Such an issue is central to this dissertation. Data quality and cross-functional alignment, crucial for the success of S&OP, are highly affected by the choice and the ownership of the data aggregation level. Therefore, defining a proper data aggregation level might improve the planning performance in a context of mass customisation and could enable more cross-functional alignment. This hypothesis will be verified and answered by the different contributions of this research.

5. Problem formulation & research questions

This dissertation deals with tactical planning in the context of MC. From the above concepts and challenges, one can observe the strong link between the MC of the automotive industry and the planning complexity. Without doubts, the specific context

of MC coupled with the volatility of demand, weighs heavily on the planning process by its multiple consequences that strongly impact the performance of the whole supply chain. At this level, we hypothesize that the data quality issues might result in a process failing to deliver robust and resilient plans capable of adapting with the high market volatility. More precisely, the feasibility of a production plan depends on the quality and interpretability of the information prepared by the sales team and discussed during the S&OP process.

To confirm these claims, this study focuses mainly on the supply review phase which represents a critical step of the S&OP process and serves to establish feasible supply, production and procurement plans. It consists of checking the sales demand against the available supply capabilities.

An in-depth study of the process shows that, at a tactical planning level, the planning demand data is expressed at an aggregated family level. Note that in the context of MC, where products are complex and hold multiple features, the notion of aggregated planning is ambiguous. Indeed, due to the extensive number of features, multiple aggregation levels exist where each level describes the data in a unique way. As a result, selecting the wrong demand aggregation level could hide a lot of valuable information. Thus, the proper choice of the aggregation level seems to be critical to guarantee good data quality for S&OP. Indeed, the demand data aggregation level can enable, if well defined, more alignment and better data quality, while on the other hand, a bad definition of demand aggregation level can introduce a lot of rework, substantially affect the data quality and result in very poor planning that impacts the cost of operations and the customer satisfaction.

As explained in section §4.5.1, the aggregation of the sales demand refers to a partial expression based on a subset of features. These features are selected empirically from functionalities chosen by the customer (for example *engine, gearbox, colour*). On the other hand, the critical supply capabilities linked to capacity limitations could be expressed using features that do not figure in the original sales demand. As a result, multiple demand data manipulation operations are needed to be able to check the demand against the capacities.

By its nature, the demand data expression is flexible since it is based on the aggregation of forecasted demand and real orders. Therefore, it could be expressed differently using various sets of features. On the other hand, the supply capabilities

represent structural capacities that depend on specific resources. Therefore, their data structure is fixed and cannot be expressed differently.

In order to reconcile the sales and operations teams, a common ground needs to be established. This common ground is traditionally obtained by reshaping the flexible demand expression to match the firm supply capabilities by extrapolating the demand expression to include new features linked to supply capabilities through multiple data disaggregation operations. Such practice is performed by the operations team and introduces a lot of rework that affects the quality of the resulting plans since it is done using history-based ratios. Therefore, it introduces a lot of bias due to the non-reliability of history-based ratios in volatile markets. In other words, the more the demand data structure (i.e. aggregation level features) is different from the supply capabilities data structure, the more data manipulation operations are needed and the more the risk on data quality is present.

Regarding such issues, we propose to express the unconstrained sales demand using features linked to critical supply capabilities and thus minimize the need for data manipulation operations at later supply review phase. Hence, the challenge of the thesis resides in identifying the best setting for an S&OP process (i.e. the set of features representing a good aggregation level) to ensure a good planning quality and better alignment. The choice must be done amongst different possible combinations of product families where the best combination has to satisfy the preferences of each actor while remaining acceptable for a tactical planning level.

To solve this problem, we had to go through three phases (section §3.2):

First, we needed to get familiar with the existing S&OP designs and with the challenges that might be driven by a MC context on tactical planning. To do so, we performed two studies: an academic review and an empirical investigation. The academic review constituted an explorative study and thrived to answer the following research question:

"Why do the existing S&OP models fail to deliver good performance in mass customisation environments?"

An answer to this question was provided through a literature review of the existing designs of S&OP where hypothesis regarding the observed weak performance of S&OP was derived. This study constituted our first scientific contribution.

The absence of relevant case studies or assessments related to our scope urged us to develop our own diagnosis of the case company planning process. The conducted empirical diagnosis consisted of developing and implementing a context-related maturity assessment. The assessment was designed to measure the performance of the current S&OP process in a context of MC and identify potential improvement axis. The diagnosis phase tried to answer the second research question:

"*What is the maturity of the currently implemented process and what are the major pain-points?*"

This question was answered by a series of semi-structured interviews and constituted the second contribution.

Thanks to the first explorative research phase, we were able to define the direction of the study, to understand how the process work and to identify its major pain-points. A clear problem formulation was then derived at the second research phase to answer the following research question:

"*How does the data aggregation affect planning and what are the metrics that serve to measure the quality of an aggregation level?*"

We chose to focus on the planning data aggregation level setting to guarantee better tactical planning in a MC context. Also, performance metrics were derived to measure the efficiency of a specific aggregation level.

Consequently, we were ready to tackle the third phase which consisted of designing a decision support tool based on the metrics of phase two as an answer to the third research question:

"*What is the best aggregation level that improves the performance of the S&OP process in a mass customisation context?"*

A decision support model was designed using a multi-objective programming formulation and constituted, alongside with the previous problem formulation phase, the third contribution.

Due to the importance of the supply capabilities, we provided a fourth contribution that identifies the different types of supply chain capabilities and provides a new capacity

assessment and classification framework. The framework serves to measure the criticalness of each capacity regarding multiple criteria. The accurate new scores will serve to improve the selection of features composing the planning aggregation level.

6. Conclusion

S&OP is an effective tool for supply chain planning. Positioned at the tactical decision level, the process provides valuable information for the downstream processes and decision horizons.

Motivated by the key position of the S&OP as a leading process for the supply chain operations, we tried to investigate the reasons for its weak performance. To do so, we integrated Renault's supply chain operations team to study the existing process and suggest improvements. Within the frame of a CIFRE thesis, we followed a research intervention methodology to conduct our study on the automotive industry in the particular context of MC, long procurement lead-time and expensive products.

The analysis of the scientific background combined with observations made on the research partner S&OP process revealed some issues. The aggregated demand data expression seemed to be incompatible with the supply capabilities structure. Therefore, we hypothesised that the current demand data aggregation choices negatively impact the effectiveness of the planning. The negative impacts are related the need for many data manipulation operations. The derived hypothesis is established following an analysis of the company process and the context parameters discussed in the background section.

Finally, based on the background elements and the specific context parameter, a central problem is formulated detailing the identified issues and presenting a roadmap to test and validate the derived hypothesis.

The remaining of this dissertation is organized as a collection of research papers. The central problem is answered following four complementary contributions. The first contribution reviews the theoretical frame of the study and defines a set of hypotheses on the possible reason for S&OP failure in a context of MC. The second contribution verifies the hypothesis of the first contribution by investigating the practical implementation of the existing process and assessing its maturity. The maturity

assessment reveals a number of major pain-points and organizational issues related to data quality problems. We try to enhance the data-related issues throughout the third contribution where a set of criteria and metrics are proposed to guarantee good data quality. Then, a multi-criteria decision support model is developed to identify the best data aggregation level setting and ensure better organizational alignment. Finally, a fourth contribution provides a new conceptual capacity classification and assessment framework to enhance the measurement of the supply capabilities criticalness, which represents an important input of the developed model.

Each paper represents a chapter and is self-contained and can be read in isolation. However, there can be some overlaps of concepts, examples, and texts between the introduction section and the different contributions' chapters as they are formulated in relatively similar kinds of settings and refer to the same concepts.

An executive summary of the provided scientific contributions is provided hereafter to give a brief idea regarding the objectives, methodology and results of each paper.

7. Contributions' summary

7.1. Contribution 1

Ghrab, Y., Sali, M., 2019. Sales and operations planning (S&OP) performance under highly diversified mass production systems. Published in: ACM International Conference Proceeding Series. ACM Press, Phuket, Thailand, pp. 42–47. https://doi.org/10.1145/3335550.3335580

Our first contribution provided a brief review of the existing S&OP models and their performances. In this first exploratory approach, we tried to reveal why the actual S&OP designs are not adapted to MC contexts and what are the possible causes behind their reported weak performance in general, and in MC systems in particular. The review was explorative and intended to increase our knowledge regarding the studied subject by exploring the existing contributions. In overall, we have observed a weak performance of the S&OP process despite a growing academic and practitioner interest toward the subject since the beginning of this century. Besides, we have noted a lack of context related S&OP frameworks considering specific context conditions that might affect planning as is the case for MC. The conclusions of this first exploration led us to consider the urgent need to update the S&OP process configuration and to focus on the definition of the planning data aggregation level in industries subject to high product variety driven by a MC production strategy.

7.2. Contribution 2

Ghrab, Y., Sali, M., 2020. A New S&OP Maturity Assessment Model for Mass Customisation Production Systems: A Case Study of an Automotive OEM. Published in: Proceedings of The Eight International Conference on Information Systems, Logistics and Supply Chain. Austin, Texas, pp. 70-78.

Motivated by the absence of context related S&OP frameworks and by the observed weak performance of the planning process, our second contribution consists of investigating the case company implemented S&OP process to confirm the initial weak performance hypothesis. To do so, an assessment of the current situation was provided to identify the process weaknesses and the possible improvement areas. The first step consisted of reviewing the existing S&OP evaluation frameworks and revealed the absence of assessments that consider the impact of MC on the planning process. The second step consisted of developing a new assessment framework that evaluated, among others the impact of MC on the S&OP process. The new framework was tested and implemented in the third step through a series of interviews conducted with the company main S&OP actors. The compiled results showed a clear disparity in the perceptions of different actors on the current process maturity level. The given evaluation was very influenced by the position of the actor in the supply chain. Also, a clear impact of data quality on cross-functional alignment was revealed by the assessment. Finally, a notable process evaluation disparity was observed between managers and their subordinates.

The study helped to identify the major pain points of the current process as viewed by its major actors. It confirmed the poor data quality driven by a poor organizational alignment between the major actors. The conclusions of this contribution were helpful to define the major performance metrics used to design and test the solution provided in the third paper.

7.3. Contribution 3

Ghrab, Y., Sali, M., Chatras, C., 2021. Optimal product family aggregation for Sales and Operations Planning in a mass customisation context (InProgress)

The validation of the research questions viability from a theoretical and practical point of view provided by the first and second contributions led us to explore, in the third contribution, the properties allowing to reach a good data quality and a better cross-functional alignment for the S&OP through the choice of the appropriate sales demand aggregation level. With more focus on the data aggregation level discussed in the first contribution and measured in the second one, three efficiency properties are identified to qualify a good demand data expression: sales significance, supply significance and compacity. Each efficiency property is derived into a measurable variable and implemented in a multi-objective model solved using a lexicographic method. The model tries to identify the best subset of features that satisfies the three properties. The results of this contribution show the existence of alternative aggregation levels that guarantee better data quality and more alignment while reducing the planning variety. A simplified version of this contribution was submitted to the 14th international conference on industrial engineering, CIGI-Qualita 21[3]. The version provided in this manuscript is a more complete document destined for future international journal submission.

[3] CIGI-Qualita 21 : Conférence Internationale Génie Industriel QUALITA - Grenoble
5-7 mai 2021 Grenoble (France)
https://cigi-qualita21.sciencesconf.org/

7.4. Contribution 4

Ghrab, Y, 2021. Critical capacities' assessment: a conceptual classification framework. (Working paper)

The feature selection model developed in the third paper relies heavily on the property of supply significance, which depends on the criticalness scores of the supply capabilities. Being a major input for the model, any improvement on the measurement of the capacity criticalness score could yield a more accurate selection of features. Indeed, these scores were initiated in the developed model using a simple capacity volume formula. This contribution intends to develop a more sophisticated calculation method that takes into account the inherit characteristic of the different supply capabilities evaluated during an S&OP process. To do so, we first identify the different types and characteristics of the supply capabilities. Then, we develop a score calculation and classification tool inspired from an established risk assessment method widely used in the production maintenance literature. Finally, we propose to introduce a new meeting to the S&OP cycle to evaluate the critical capacities using the new scoring method. On the other hand, the tool could also be useful for capacity management investment decisions.

The provided document is at an early stage of development. A future improvement would consist of providing a real test of the efficiency of the tool using real supply capabilities and with experts. The new scoring method results will be compared to the old scoring method results and improvements will be done if needed.

An improved version of this document will be subject to a future submission in an international conference.

Chapter 2. Sales and operations planning (S&OP) performance under highly diversified mass production systems

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Abstract

Sales and operations planning (S&OP) is a midterm planning practice that is widely used in industries with relatively volatile demand and limited capacities to align demand and supply. Several research studies, as well as practical guides, have been developed to examine the design and implementation of S&OP processes. Most of these studies are general and have no reference to the industry behind them. However, regarding planning, each industry has its properties. Taking a “one size fits all” approach is not profitable for extreme cases, such as for an automotive industry known for the very large product portfolios. Our contribution intends to examine this issue in detail by performing a literature review on the effectiveness of S&OP and its impacts on supply chain performance. We try to reveal why actual S&OP practices are not fit for highly diversified mass production systems, and we deduce that there is a need to redefine the S&OP process for such industries.

Keywords: Sales and operations planning; Automotive industry; Diversity management; Supply chain performance; Planning.

1. Introduction

The supply chain is the value creation network that combines different production tools and actors (suppliers, producers, distributors, 3PL, and customers). The supply chain management aims to implement efficient organizations, integrated processes and collaborative tools to optimize procurement, production and distribution activities. As stated by (Dias and Ierapetritou, 2016) supply chain management is likely the most complex and challenging decision-making process in an enterprise, particularly in a context marked by the internationalization of activities, the demand volatility, the increased requirements for time and personalization (Ramdas, 2003) and the disruption caused by the new wave of start-ups colonizing every vacant function (Ferràs-Hernández et al., 2017). In this paper, we address a medium-term tactical planning process called "Sales and Operations Planning" with the objective of aligning demand and supply in a limited capacities context. We investigate the effectiveness of this process under highly diversified mass production systems while using the automotive industry as an example. We focus on two major challenges of today's supply chain: reinforcing intra-organizational collaboration and shortening delivery lead-time. As Childerhouse, Disney and Towill (2008) explain, coordination between supply chain and sales department is crucial in the automobile industry when the demand volatility is high. Conversely, customers are being more sensitive to delivery lead-time. Indeed, customers' habits have changed, as they used to be more patient regarding deliveries lead-time (Beckwith, 2017). Therefore, a large portion of the product value is shifted to lead-time (Daugherty et al., 2019; MH&L, 2016). Consequently, the waiting time until delivery has become a decisive selling argument (Marino et al., 2018).

Motivated by the previously noted challenges, sales dealers are seeking short delivery lead times with the opportunity to order any product as late as possible to satisfy the customers. Conversely, suppliers must be notified long before an order is placed because the assembly plants need to order many parts several weeks beforehand (which is strongly connected to the internationalization of production due to economic factors), based on unreliable forecasts due to the highly volatile demand (Laurent Lim et al., 2014). This finding makes supply chains more vulnerable to various disruptions such as uncertain demand (Tang, 2006).

To answer such issues, we decided to proceed by questioning the planning and coordination process in its early stages to ensure better collaboration between the supply chain stakeholders and to reduce lead-time. The first formulation for S&OP is unknown. Many authors argue that the concept emerges from another tactical planning process called the MRP (Material Requirements Planning). The S&OP garnered interest by researchers at the end of the last decade. To our knowledge, the concept's first recorded explicit contribution appeared in 1988 when Ling & Goddard wrote a book titled "Orchestrating Success: Improve Control of the Business with Sales and Operations Planning". A general and widely used definition of S&OP refers to a business process that links the corporate strategic plan to daily operation plans. This approach enables companies to match customer demand with production capacities (Grimson and Pyke, 2007; Tuomikangas and Kaipia, 2014). In practice, this approach consists of a monthly cycle of meetings between two core departments in the company: the sales teams and the operations teams. The meetings serve to compare the commercial demand (sales) with the industrial production and supply capacities (operations). Together, the meetings define the production volumes and the targeted stock levels corresponding to the overall corporate strategy reflected in the financial objectives. The meetings are scheduled on a periodic cycle with a rolling horizon that varies based on the company activity. Typically, this production planning forecast ranges from one year to three years.

An easy solution to address the planning problem and obtain short lead-times is to sustain huge inventories of parts. However, this is not an option for highly diversified production systems, especially when parts are relatively large and expensive (e.g., automotive industry). In reality, the requirements for components and the cost of certain parts are significant, which make it impossible to store all the needed parts.

Over thirty years, S&OP has proven to be a crucial tactical planning tool for industrial companies, especially those known for the high diversity proposed by the sales and marketing services to respond to client demand. Nevertheless, the definitions of S&OP have not shown substantial evolution, while most S&OP research questions and contributions were regarding the following: providing a new framework for implementation, debating about the requirements and steps for effective implementation, conducting standard cycle meeting, team composition and recommendations. Existing research maintains that S&OP has yet to fulfil its promise

(Jonsson and Holmström, 2016; Antônio Márcio Tavares Thomé et al., 2012; Tuomikangas and Kaipia, 2014). Practitioner studies indicate that most firms using S&OP either do not fully execute the process or achieve desired results (Muzumdar and Fontanella, 2006).

We are convinced that S&OP process needs to be improved for highly diversified mass production companies. In this paper, via a literature review, we attempt to collect the evidences of the weak performance of S&OP and to understand the root causes behind its malfunctioning for such production systems.

2. Research methodology

As stated by (Burgess et al., 2006), literature reviews are suitable for understanding the issues associated with a research topic and offer directions for future studies to address identified knowledge gaps. In this paper, we aim to provide insight into the S&OP existing models, their definitions and the barriers to efficient S&OP operating in a highly diversified mass production system.

In our study, we have performed a two-round literature review. The first round is a general literature review and consisted of exploring main context elements. The second round had narrower scope and focused on the topic of S&OP.

The first literature review provided us a general understanding of supply chain management in a mass customization context, while the second literature represented the main purpose of this paper. The objective of this section is to depict the steps followed to attain our findings with a small bibliometric mapping of the results.

The retrieving process of the articles have been nearly the same for the two sets of literature. In sub-section *2.1,* we describe the general process applied for both rounds. In sub-sections *2.2* and *2.3,* we describe the slight changes related to the literature review processes of each round. Bibliometric results of the second-round literature review are presented in sub-section *2.4*.

2.1. General process

Seeking consistency of the results, we have adopted a logical retrieving methodology detailed as follows. We first defined key words for each set. Then, we identified three databases that contained scientific literature relevant to the field of our study. To avoid highly dispersed results, we applied the search filter “In Title” or “In abstract” for each keyword.

The databases selected for the search are EBSCO Business Source Complete, Emerald, and Science Direct Elsevier. These databases cover the majority of scientific journals contributing in the spheres of operations management, organizational management, and social sciences (Antônio Márcio Tavares Thomé et al., 2012). In the database research results, we applied two types of filters. The first filter is “year filter” to collect articles beginning with 2010. The second filter is “no filters”. The sorting is always by relevance. We retrieved the first 100 papers for each filter. We then eliminated the duplicates. The idea behind this process is to obtain the recent relevant article first; then, we wanted to obtain the older but relevant articles if they surface during the second round. The final selection has been fully treated as going to be detailed hereafter.

For the first review round, we adopted a three-step approach. We first read the titles and scanned the abstracts. Then, we eliminated the papers that have no direct link to our scope although they contained one of the selected keywords. Thereafter, we eliminated some papers after fully reading their abstract. We read and analyzed the full text of the remaining papers. While reading, we added many interesting papers that were cited in the originally selected articles.

An illustration of this simple process is presented in Figure 2.1.

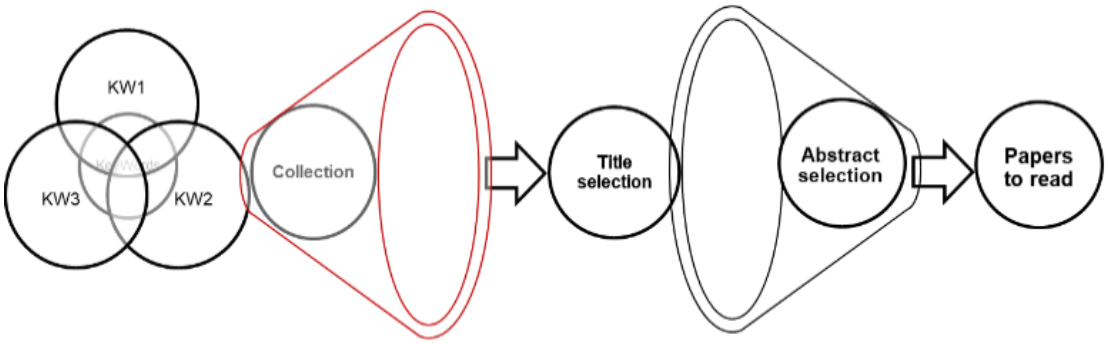

Figure 2.1: Papers’ retrieving and selection process

2.2. First round: general literature review

The general literature review was an initiation for our research addressing a mass customization context and an automotive industry. The aim of this first round was to obtain a general idea and an update of the state of the art, the main trends and the main challenges confronting the academic community. This objective covers the evolving paradigms of the automotive supply chain under a mass customization production system. The main keywords related to that problem are "*Automotive industry* OR *Automobile industry*", "*Supply chain management*" and "*Mass customization*". To enlarge that scope and obtain a broader understanding of the actual issues related to our context, paper collection was performed for each keyword separately (i.e., we collected papers for *Automotive industry* OR *automobile industry*. Then, we collected papers for supply chain management. Finally, we performed a research using only "*Mass customization*" as a keyword).

The results of this literature review have helped us define the main elements of the introduction and problem definition. Other findings from this round will be embedded in the results related to sales and operations planning review (section 3).

2.3. Second round: S&OP review

For the second review round, we focus on our main problem related to "Sales and Operations Planning". The keywords used were "*Sales and operations planning*" OR "*S&OP*". The steps of methodology followed have been slightly modified compared to the general process. Since we were attempting to focus more on the scope of research, we added a rule that requires the keywords to be exclusively in the title and/or the abstract. Thus, we obtained a smaller number of papers than the general literature that focus only on S&OP matters. Since the number of retrieved papers is relatively smaller than the first round, we had no need for the first step of paper selection, which consisted of performing a preliminary read of titles to exclude non-relevant papers.

2.4. Bibliometric results

In this sub-section, we present the bibliometric results of the sample of contributions we have analyzed in the second round of the literature review. We note here that the

papers analyzed are only those found to be relevant to our study. We note also that they do not represent an extensive representation of the body of research covering S&OP problems.

Figure 2.2 represents the timely distribution of reviewed publications with the ratio of Academic (blue) vs Practitioner (red). The total number of reviewed articles is 58; 46 papers are academic papers, while only 12 are practitioner papers. We observe that our selected sample contains more academic papers than practitioners. We also observe that the issue has garnered the interest of both researchers and practitioners in the recent decade, especially since 2005.

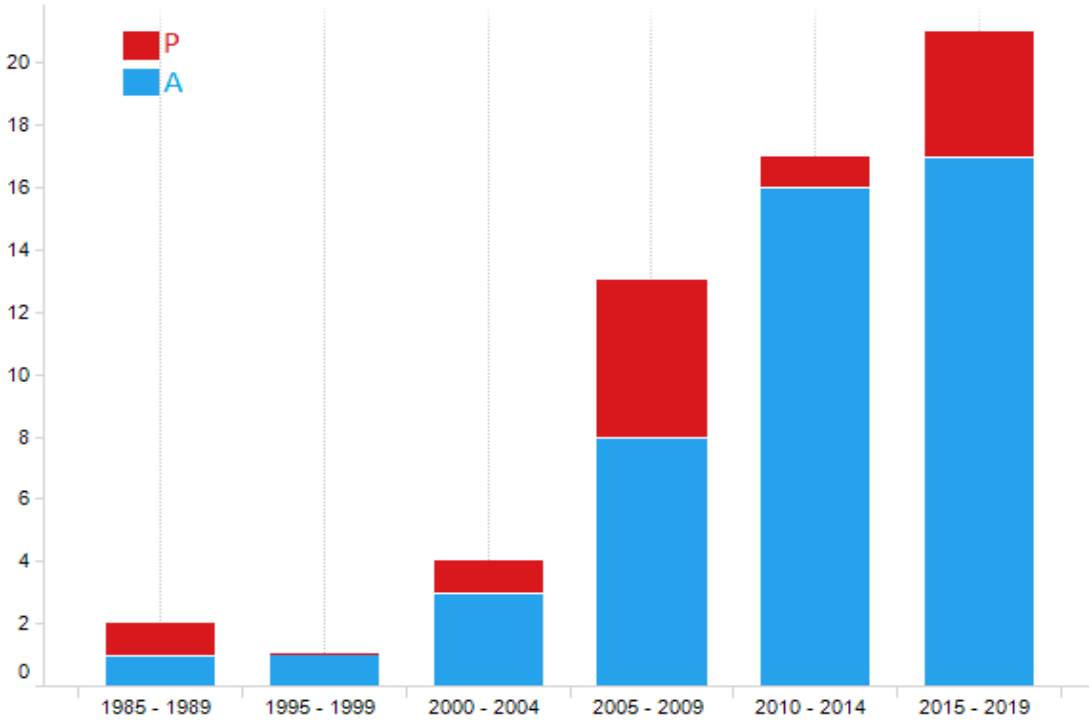

Figure 2.2: Time distribution of publications

3. Literature review findings

In this section, we analyze the retrieved articles to identify the causes and evidence related to the weak performance of S&OP under highly diversified mass production systems. The objective is to provide a quick scan of the identified contributions related to our problem. Therefore, we provide the reader with the main ideas for each paper.

3.1. Stable definition of S&OP over thirty years

As previously stated, S&OP was first defined in the late 1980s (Ling and Goddard, 1988). The authors described it as “a regular management process orchestrating the activities of different departments within the organization that are working towards a consistent plan answering company objective”. The planning is done on an aggregate family level and covers a sufficiently long timespan to ensure required resources are available. (Wallace and Stahl, 2008) focused on the dynamism of a monthly rolling S&OP process to make companies more agile in response to market changes and address risks that arise in the future. (Feng et al., 2008) have provided a classification of S&OP in three different concepts that have evolved over the years. The classification is based on the integration degree of a supply chain; however, they used the same definition as (Ling and Goddard, 1988). The most recent definition was provided by (Tuomikangas and Kaipia, 2014) in their systematic literature review. The researchers define the S&OP as a key business process striving to match customer demand with supply capabilities in the medium term. The researchers qualify S&OP as “a dynamic collaborative planning and decision-making process”. Interestingly, (Plank and Hooker, 2014) affirm that practitioners’ S&OP definitions have been consistent with academic ones. The association of supply chain management APICS definition has been one of the most cited. We quote here the full text from the association’s dictionary: “A process to develop tactical plans that provide management the ability to strategically direct its businesses to achieve competitive advantage on a continuous basis by integrating customer-focused marketing plans for new and existing products with the management of the supply chain. The process brings together all the plans for the business (sales, marketing, development, manufacturing, sourcing, and financial) into one integrated set of plans. It is performed at least once a month and is reviewed by management at an aggregate (product family) level. The process must reconcile all supply, demand, and new-product plans at both the detail and aggregate levels and tie to the business plan. It is the definitive statement of the company's plans for the near to intermediate term, covering a horizon sufficient to plan for resources and to support the annual business planning process. Executed properly, the sales and operation planning process links the strategic plans for the business with its execution and reviews performance measurements for continuous improvement.” (Blackstone and Cox, 2005). All these definitions were faithful to the initial design presented by (Ling and Goddard, 1988); this raises the question regarding their validity in an ever changing

environment, while real world applications report an overall weak performance of S&OP (refer to section *3.2*).

Figure 2.3 represents a word cloud for the most used words in the definitions found in literature.

Figure 2.3: Word cloud of definitions reviewed in the literature

3.2. Weak performance of S&OP

As previously noted in the introduction, S&OP occupies an important place in the planning process of companies. Despite such importance, the literature shows that companies are struggling with the S&OP and cannot obtain positive results (Swaim et al., 2016; Antônio Márcio Tavares Thomé et al., 2012; Tuomikangas and Kaipia, 2014). For example, (Thomé et al., 2014) have analysed data from 725 companies in 34 countries, gathered in 2009–2010, and concluded that there are few empirical, survey-based, mathematical modelling and case study research studies that demonstrate a positive impact of S&OP practices on firm performance. In particular, in his Gartner report, (Matthew Spooner, 2017) claims that over 70% of the more than 100 companies assessed have a low maturity S&OP process. Furthermore, S&OP has no significant value in the business for a large proportion of these companies. Consequently, he concluded that half of the surveyed companies S&OP's are "poorly aligned with either demand or supply, resulting in multiple sets of disjointed plans".

(Barrett and Steutemann, 2010) found poor overall S&OP performance capabilities, upholding that “Although S&OP is nearing its second decade, only 18% of companies rate themselves as proficient”. Worse, year-over-year data shows that industries are going backward, not forward. This finding indicates that companies lack guidelines and advice about how to implement S&OP in order to facilitate coordination across functions and organizations.

Consequently, we agree with (Danese et al., 2018), who believe that evolving between maturity levels requires changing S&OP design.

3.3. Models and frameworks for implementation

An interesting roadmap was developed by (Boyer Jr, 2009) who established a 10-step methodology to implement S&OP. The roadmap covers the team constitution, the meetings standard to be followed, the calendar and the best practices. The described process is a five-day monthly cycle with ten steps joining three key pillars: performance, demand and supply. (Lapide, 2004) has provided 12 success factors for S&OP related to the process to be followed during a S&OP cycle. The researchers model helps choose the optimal procurement policy that reduces logistic costs while guaranteeing an acceptable level of customer satisfaction. (Wang et al., 2012) have been interested in the benefits of integrating different supply chain layers on S&OP performance. The researchers proposed a global S&OP framework that integrates four supply chain stages of demand, purchasing, production and transportation with different planning strategies, while (Swaim et al., 2016) have been interested in defining five antecedents to effective S&OP implementation. A model deriving the relationship that exists between these antecedents was then developed and tested. The model has shown that organizational integration would enhance standardized S&OP process with which S&OP prioritization will reinforce the organizational engagement to get at the end an effective S&OP. Finally, certain authors have proposed frameworks for maturity assessment that extend from three to a maximum of six stages and cover essential dimensions for S&OP performance (Grimson and Pyke, 2007; Hulthén et al., 2016a; Lapide, 2005; Wagner et al., 2014). Some of these papers have included a case study that performed as an application of the framework, and the results confirm that S&OP is yielding an overall weak performance.

The next subsections will address elements that were not covered in the existent literature and that highly relate to our context of highly diversified mass production systems.

3.4. Dynamism and granularity of S&OP

All the definitions provided in the first sub-section show that S&OP is a dynamic process. However, we observed that the discussions regarding dynamism in the literature refer mainly to the temporal dynamism of meetings, periodicity, hierarchy planning levels, being either at a strategic level or at a tactical level and argues about the length of the planning horizon (Antônio Márcio Tavares Thomé et al., 2012). While these perspectives are important, we believe that there is a significant dynamic aspect related to the planning granularity in a context of highly diversified mass production systems.

The planning granularity refers to the aggregation degree of products chosen as the arbitration level between supply and demand. This aggregation level should be a common language that allows for sellers to express the demand and for manufacturers to cover their main industrial and logistics constraints. According to the existing definitions and proposed models in the literature, when S&OP meetings occur, discussion regards aggregated product-families. The planning granularity is generally admitted as fixed. However, in a context of mass customization, the industrial constraints may evolve over time, questioning the aggregation level.

To illustrate this phenomenon, let us use an example from the automotive industry where the aggregation level corresponds to the so-called “major-items” since diversity makes it impossible to plan at the finished product-level. Major items are the important parts shared by many final products and are relatively expensive (e.g., engine, gearbox, and equipment level). Stakeholders define demand and review the supply capacities only at the major items level. Thus, no estimation is made for the remaining options or the minor parts that hide behind these major items. If one of these hidden parts suffers from a lack of capacity due to a special event, the S&OP process will not be able to detect it, and the agreed plan at a high aggregation level will not be feasible.

Therefore, defining a dynamic list of planning items that changes considering the dynamic disruptions affecting the company environment in S&OP meetings could help

in avoiding unfeasible plans in the future. To our knowledge, deciding the granularity of planning items during an S&OP meeting and defining a dynamic list of critical items updated periodically according to the present and future context is an aspect of dynamism that was not discussed in the literature and can solve huge shortage issues.

3.5. Ignored family aggregation level

In this sub-section, we raise the question regarding the importance of the S&OP product family definition and its aggregation level in a highly diversified mass production system. The question stems from our analysis of the reviewed papers that, to our knowledge, has not been treated in existing literature. Indeed, we observed that all the reviewed papers, except for (De Kok et al., 2005), has defined the planning items as aggregated product families (Ling and Goddard, 1988; Swaim et al., 2016; Antônio Márcio Tavares Thomé et al., 2012; Wallace and Stahl, 2008).There were no questions raised nor details provided regarding how to constitute a product family and which level of granularity is the most appropriate. However, the issue is very important in a context of mass customization in general and for the automotive industry in particular. In fact, car assembly is a complex process that joins thousands of parts together. There are different means to define a car in planning items; these range from the highest level that define a car as a model to the lowest level that define a unique car by the combination of all the proposed options. Logically, the more details are provided in the planning item, the fewer shortages and overloads will occur. To clarify the issue, we cite two extreme examples from car industry: the extreme case where the planning items are at the finest aggregation level (case 1) and the opposite extreme case where the planning items are at the most aggregated level (case 2).

- Case 1: In general, families constituting the planning item can be defined by model, engine power and energy (i.e., Diesel, Gasoline, or Electric), or the combination of both; even further, it can be defined by the level of equipment, and finally, the combination of all options and standard parts that define a unique car, which we will call CDV (Completely Defined Vehicle). The first extreme case would consider the CDV as the planning item, in other words, deciding the volume for each CDV during the S&OP process. In fact, there are millions of CDVs for a single model in highly diversified production systems. Since the S&OP is a human judgemental process (Syntetos et al., 2016), it is nearly impossible to push S&OP planification items to CDV when operating in this context. Consequently, when confronting such volumes and diversity, aggregation is needed.

- Case 2: The second extreme case supposes that the planning items correspond to the car model, which means that decision makers will need to decide only the volume for the car models. This macro-information provides no reference to the mix of lower level items such as the engine and other important parts for which no decision will be made. Therefore, a large portion of the supply constraints will be evaded by the agreed plan, which will be finally unfeasible.

Therefore, a trade-off should be set to define the best level of granularity for the planning items that discusses the important contextual items while not containing excessive information for decision makers to take actions.

Consequently, due to the importance of planning systems in S&OP under highly diversified production, we believe that establishing the rules to constitute a product family then defining the appropriate aggregation level and the dynamic planning items in a robust scientific approach would be of great importance.

4. Conclusion

In this paper, we have attempted to highlight some pain points of S&OP practices in the context of highly diversified mass production systems such as automotive industry. Our initial hypothesis towards the need to review and redefine the S&OP process was confirmed by a short literature review. We first tried to show that the automotive industry is experiencing a phase of major changes related to customer sensitivity towards delivery lead-time, and this is urged due to the disturbance caused by the new techy entrants. Then, we elucidated the complexity of planning under a highly diversified production system, and the absence of models that cover the identified issues, which led us to consider reviewing the S&OP actual practices for such industries. The results of the review were described. We observed that while the industry is on perpetual change, the S&OP definitions have remained stable for over thirty years with a “standard-size” for all types of industry. Our second finding shows the observed weak performance of S&OP reported in the reviewed articles and strives to support our first assumption for the need to revisit actual S&OP definitions for the highly diversified production systems considered as “non-standard” in terms of planning. Many researchers and academics have attempted to develop numerous models, frameworks and practical guidelines for implementation and optimization. However, these models

have not shown substantial improvements. Therefore, we suggest that future research should focus on two major issues that we identified as gaps linked to the highly diversified mass production systems. First, the S&OP is a dynamic planning tool and thus should be its planning items. Second, the aggregation level is a deterministic parameter for S&OP in highly diversified production systems, and rules should be set to properly define the most appropriate level that could be deep enough to detect issues, and high enough to remain as a tactical planning tool. We believe that these subjects directly impact the S&OP performance. Indeed, the temporal dynamism of S&OP reveal how certain planning items are ignored and may impact the planning results in the future. This observation introduces us to the second issue of the absence of rules to define a product family and to choose the appropriate level of granularity that constitute the planning item. We clarify why it is important to set rules that defines the level of aggregation for a product family.

The role of this paper was basically to explain the weak performance of S&OP by revealing the previously noted two issues in a context of mass customization. Further work is needed to develop appropriate theories, models and applications that will validate our assumptions and contribute to a better understanding of S&OP.

Chapter 3. A new S&OP maturity assessment model for mass customization production systems: a case study of an automotive OEM

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Abstract

Sales and Operations Planning (S&OP) is a critical business alignment process for industries with large product portfolio. Indeed, high variety is a driver of complexity and results in a poor planning efficiency. Diagnosing the root causes of the process failure starts by assessing the maturity of its actual technical and organizational performance. The existing body of research lacks context-related maturity assessment frameworks that measure the maturity regarding activity-related dimensions. In this paper, we intend to propose a new S&OP maturity assessment model that considers the critical attributes linked to the context of mass customization production systems. Our review of existing contributions on maturity assessment combined with the results of workshops organized in a major automotive company ended-up on a suitable context-related design. The new framework has been tested within the automotive company by interviewing major decision makers and operational teams involved in the S&OP process.

Keywords: Sales and operations planning, Context-related maturity assessment, Performance, Automotive industry, Product variety, Mass customization production systems

1. Introduction

New consumption paradigms are shaping today's markets. Customers nowadays seek unique on-size products and are more sensitive to delivery speed(ElMaraghy et al., 2013; Xia and Wang, 2008). Consequently, manufacturers are pushed to offer a large panel of choices in their catalogues to avoid the chance of missing a selling opportunity and to stand out among competitors. This trend has exploded product variety (Danese et al., 2018; Pil and Holweg, 2004). As a result, manufacturers deal with a lot of data which weighs heavily on their planning processes. In a previous paper (Ghrab and Sali, 2019), we outlined the importance of S&OP as a business process, the critical alignment role it plays in mass customization production systems and the challenges it faces. Our findings show that S&OP struggles to deliver the intended outcomes despite the relevant number of academic and practitioner contributions on the subject. We hypothesized that the observed weak performance is linked to the poor management of product variety and to the absence of clear aggregation rules. Undeniably, choosing which product to produce among billions of alternatives is challenging, especially if such decision must be taken long before the order date to anticipate the long delivery lead time for some parts. Regarding these challenges, considering the product high variety impact on S&OP performance seems promising.

To test our hypothesis, we needed a tool that diagnose the current situation and measure performance. Maturity models fill exactly that requirement. Indeed, assessing the maturity represents a common practice for performance measurement and serves as a valuable tool to assist decision-makers (Danese et al., 2018). Our review of existing S&OP maturity assessment contributions presented in the next section outlines the absence of context-related models that measure S&OP performance regarding contextual critical attributes. Motivated by the recommendation of several authors to design more context-fitted assessments (Bower, 2005; Kristensen and Jonsson, 2018), we contribute to fill this gap by designing a new context-related S&OP assessment jointly with professionals. More specifically, based on the existing literature, on our observation made within an automotive company (OEM) and on expert opinion gathered during workshops, we identified maturity dimensions linked to the high product diversity and integrated them in the assessment. The evaluation grid was submitted to a panel of actors involved in the S&OP process of a large automotive

company. Each dimension has been assessed during the assessment whose results are discussed in this paper.

This paper is organized as follow: The second section will be dedicated to a literature review of existing maturity models and their limits. The third section will cover the construction and design of the new framework. Section four will cover the case study of a major car manufacturer, its results and analysis. The last section will be dedicated for a conclusion and future research.

2. Literature review

In this section, we present the maturity models, then we focus on those dedicated to S&OP and finally we try to explain why context-related frameworks are beneficial.

2.1. Maturity models

A maturity assessment is designed according to a maturity model. It consists on evaluating the performance of a process over a set of performance criteria in order to be positioned at a certain level called 'maturity level'. The practice is a derivation from Capability Maturity Models (CMM) (Paulk, 1995) originally developed for the quality management of software development. The use of maturity models has been since then generalized to reach the supply chain operations research applications and related areas (de Bruin et al., 2005; Vereecke et al., 2018).

Maturity models have been proven useful through their benefits (Lapide, 2005) and can be deployed for three purposes (de Bruin et al., 2005). They can be used as descriptive and serve to give insights related to actual situation of the process with no intention for improvement or relationship to performance. A maturity model can be also used for prescriptive purposes and indicates how to improve the maturity and business performance. The last purpose is comparative and aims to provide a benchmark across industries or regions. Furthermore, maturity models develop a standard roadmap to follow while seeking improvements(Fraser et al., 2002), they serve as educative tools by generating awareness toward the assessed aspects (Wendler, 2012). For more details, an interesting systematic review on business process maturity models has been performed by (Tarhan et al., 2016).

2.2. S&OP maturity models

Sales and Operations Planning (S&OP) is a collaborative tactical planning business process that aligns the demand to production capacities. The process can be evaluated using S&OP maturity models which represent a sub-family of maturity models as their focus is limited to the evaluation of S&OP performance. There have been a countable number of contributions on maturity assessment for S&OP evaluation. They differ mainly by the number of maturity levels and the choice of performance criteria as shown in ***Table 3.1***.

Table 3.1: Existing S&OP maturity models.

Contribution	Dimensions	Maturity levels
(Wing and Perry, 2001)	Information Technology	1. Integrated 2. Collaborative 3. Fully connected
(Lapide, 2005)	Meetings Alignment Integration of IT	1. Marginal 2. Rudimentary 3. Classic 4. Ideal
(Grimson and Pyke, 2007)	Meetings and Collaboration Organization Measurements Information Technology Integration	1. No S&OP 2. Reactive 3. Standard 4. Advanced 5. Proactive
(Cecere, 2012)	Process Goal Focus of the demand model Focus of the replenishment model Focus of the process model	1. Feasible 2. Balanced 3. Integrated 4. Demand driven 5. Market driven
(Wagner et al., 2014)	Process effectiveness Process efficiency People and organization Information Technology	0. Undeveloped 1. Rudimentary 2. Reactive 3. Consistent 4. Integrated 5. Proactive
(Kohler et al., 2016)	Outcome Process focus	1. No shared goals 2. Functional 3. Integrated

	Organization Metrics Time horizon Technology	4. Collaborative 5. Value-driven
(Hulthén et al., 2016a)	DATA Forecast accuracy Resource and Plan adherence Gap Measurements Process Organization People	1. No S&OP 2. Reactive 3. Standard 4. Advanced 5.Proactive
(Pedroso et al., 2017)	Tools: - Metrics - Technology Process: - Integrated Planning - People organization - Process organization	1.Very low 2.Low 3.Medium 4.High 5.Very high
(Danese et al., 2018)	People and organization Process and methodologies Information technology Performance measurement	1.No S&OP 2.Reactive 3.Standard 4.Advanced 5.Proactive
(Vereecke et al., 2018)	Data Method System Performance Organization People	Score from [0,5]

2.3. Context related maturity models

Following an established 'one-size-fits-all' S&OP maturity model have been proven to be inefficient for most cases (Bower, 2005; Kristensen and Jonsson, 2018). Therefore, designing context-related models could help getting accurate assessments.

Among the ten reviewed models, only the contribution of (Wing and Perry, 2001) was successful in establishing a context-related S&OP assessment that evaluates S&OP considering the requirements of a pharmaceutical industry.

Being a critical practice for the automotive industry, we believe that developing a S&OP context-related assessment would yield a better diagnosis for the process and would contribute to the existent literature.

Even if there are few known contributions that assess process maturity by considering critical context attributes (Bagni and Marçola, 2019; Carvalho et al., 2019; Wing and Perry, 2001), the remaining models can serve as a basis to design a framework for maturity assessment in a context of mass customization.

3. S&OP maturity assessment model for mass customization production systems

This paper proposes a new context-related model to assess the maturity of the S&OP for companies operating under a mass customization production system. The model, inspired from the template proposed by (Kohler et al., 2016), has been developed jointly with practitioners and consists of five maturity levels scaling six dimensions. The following sub-sections detail the development phases and the content of the model.

3.1. Research methodology: The model building process

The development of our assessment instrument followed a five-phase approach (***Table 3.2***). It relies mainly on academic contributions, on workshops organized with the process practitioners and on the project team recommendations. The latter joined two academics, a project manager and a S&OP expert.

Table 3.2: Assessment development phases

Phase	Actors	Mean	Input	Output
1. Initiation and planning	Project team	Workshops	Business objectives	Assessment objectives List of interviewees Assessment planning
2. Literature review	Project team	Research Databases	Keywords	State of the art
3. Expert opinion	Project team Practitioners	Workshops	State of the art performance criteria	Context-related performance criteria
4. Template formatting	Project team Practitioners	Excel workbooks Workshops	Chosen criteria/levels Assessment in English	Assessment instrument Assessment in French
5. Test iterations	Project team Practitioners	Excel assessment	Original assessment	Improved versions

3.2. Maturity levels

A maturity level can be defined in practice as the stage at which a company is situated for a given dimension and serves to qualify the actual performance. Conventionally, the higher the stage is, the more performant the process is. The models presented in ***Table 3.1*** range from three levels (Wing and Perry, 2001) to six levels (Wagner et al., 2014). The most used ranking method is the Likert five-point scale (Likert, 1974). Consequently, we used it for our model. A clear benefit of our choice resides in the possibility of comparing our results to most of the existing models.

Table 3.3 summarizes the design of our maturity ranking scale:

Table 3.3: Maturity ranking scale

Level	Description
Level 1 Marginal	S&OP is a marginal process that requires more involvement and development to add significant value to the planning.
Level 2 Functional	S&OP is a functional process limited to basic data and aims for balancing volumes and mix while firefighting short-term issues. The process is very manual and consumes a lot of resources and time.
Level 3 Flexible	S&OP process is satisfying in terms of functioning. The key added value at this level is the integration of financial data that assist decision making and enable effective scenario comparison. The process is more fluid due to the use of more mature and sophisticated IT tools and the focus is on flexibility.
Level 4 Integrated	The process is an efficient stable process that integrates various stakeholders and capable of delivering high quality scenarios to guarantee a robust plan. At this level, the focus switches toward profitability. Decision making is supported by BI analysis and demand forecast relies on strong data management.
Level 5 Strategic	At this level, the process is very sophisticated. An end-to-end integration is enabled, and the process satisfy the company orientations. The focus is thus on strategic development of the company.

3.3. Maturity dimensions

Maturity dimensions constitute the axes upon which a process is assessed. We have identified six dimensions to constitute our model relying on literature and workshops. ***Table 3.4*** provides their description.

Table 3.4: Maturity dimensions and sub-dimensions

Dimension	Description	Sub-dimensions	Description
Outcome	The outcome reflects the extent to which a S&OP is oriented toward achieving good results.	Time horizon for decision making	Mature S&OP focuses more on long and mid-term than on short term. Less mature S&OP is harassed by the short-term issues and operates on a firefighting mode which gives no room for practitioners to think and decide about important tactical subjects.
		Degree of alignment	Alignment is one of the most important criterions for S&OP performance. The process should bring together people from different Business units in order to establish a plan that satisfies the demand and ensure green KPI's (bigger market share, less costs…).
		Components of the plan	The S&OP is about establishing a plan for sales and production. The plan can be limited to volumes, include mix and integrate financial data and flexibilities at higher stages.
Process	This dimension is intended to assess the process design performance.	Level of integration	Integration refers to the participation of internal and external actors. It questions the ability of the process to integrate the stakeholders.
		Meetings	Assesses the efficiency and organization of meetings.
		Transparency	S&OP is a multi-stakeholder process, transparency can be key to alignment and yield high benefits for the process.

		Synchronization	A mature process should be able to synchronize the plans of major actors and put them in-line to get correct and synchronous data.
Organization	Organizational dimension assesses the position of each stakeholder in the process and the level of collaboration.	Ownership	Alignment is crucial for S&OP, thus, clarifying “who owns what” is an important aspect and helps avoid misunderstanding and conflicts.
		Sponsorship	S&OP is a major process that impacts the whole company, top manage-ment sponsorship is key to solve issues and facilitate decision making.
		KPI’s	A strong S&OP is a process that links all functions together toward shared KPI’s and objectives.
Data	A strong S&OP relies highly on the quality of data shared between stakeholders.	Data standardization	This performance criteria measures the level of standardization of data which could be crucial since the process is transversal and data are going to be handled by many departments, so it might be crucial to have a clear communication and common understanding of data by all stakeholders.
		Data quality and sources	Mastering data quality and sources in term of stability, exhaustivity and consistency is an advantage for a forecast-based process.
		Data management	Data are precious assets and should be well managed to boost the performance of the process. Regular updates and historization are important for traceability and for actions follow-up.

Product portfolio management	This dimension was identified by the practitioners as one of the most critical context-related S&OP performance criteria since the composition of the product mix heavily impacts the procurement and production plans.	Aggregation level	This criterion measures the suitability of the aggregation level in product definition. In fact, from one side, it is impossible to discuss and build S&OP at SKU level in the automotive industry since we have billions of SKU's for one model. From the other side, planning with high granular level hides a lot of information since one model can be declined to billions of varieties that are totally different. Therefore, aggregate families at arbitrary levels are constituted, and we aim to measure the satisfaction of stakeholders with the proposed aggregation levels.
		Product definition	Each stakeholder has his own product definition. Salespeople speak the customer language and define a product as options and features while Operations teams speak the suppliers/plants language and define a product as a set of parts. Having an unambiguous link between the two world and a common ground is crucial for S&OP success and alignment.
Information Technology	This dimension assesses the maturity of IT tools.	Level of assistance	This criterion evaluates the use of IT tools to assist elaboration of scenarios and process. The use of IT tools is critical in the case of mass customization since they have to deal with a huge load of data.
		Performance and Ergonomics	IT tools should be performant, intelligent and user-oriented to yield better results and reduce process execution time.

4. Case study

To test the applicability of our model, we conducted a case study within an automotive company. Many authors have affirmed the benefits of conducting real life applications as they help to test the robustness and applicability of developed models (Wendler, 2012). The next sub-sections will define the environment in which our model was tested as well as the results of the study and our analysis.

4.1. Context

The assessed company is a major automotive OEM who owns several brands and have numerous joint ventures with other manufacturers. The group has more than 30 plants, operates in 5 continents, offers 18 different models and produces more than 3 million cars per year. The supply chain department is centralized in the operations headquarter and disposes of two supply chain planning teams: one for engines and powertrains and one for vehicles. Each planning team has his own S&OP. In this study, we focus on the vehicle S&OP for all brands and consider the powertrain and engines team as a stakeholder and a major supplier. In total, five departments negotiate to establish a valid plan: Sales Planning (SP), Supply Chain Planning (SCP), Power Train (PWT), Part Supply (PS) and Cost Controlling and Finance (CCF).

The assessment had two goals: identify the current maturity level of the process and educate about what a better S&OP can be, and what a worst S&OP is.

4.2. Interview process

At the start of the assessment, we briefly mention who we are, why we conduct this study and we present some instructions about the confidentiality and anonymity of the answers. For each performance dimension, we intended not to order the choices corresponding to maturity levels (i.e. first choice is neither the best nor the worst) to avoid possible bias of choosing intentionally answers that reflect a good or a bad image. Therefore, the interviewees had to read carefully all five statements of each dimension and choose the most appropriate one. Moreover, the interview instrument presented in the previous section was not distributed to guarantee spontaneous answers. At the end, we review in the last sheet of the assessment instrument the

choices and we present the results in the form of a dimension-based radar. In total, the average assessment time was around 30min.

Seeking the highest possible rate of answers, we followed a hierarchical top-down approach. We started by interviewing the top managers who served as ambassadors for the assessment in their teams and provided us with a list of subordinates capable of filling the assessment. One author assisted all interviewees to answer their questions. He also recorded comments that were not directly related to the questionnaire items. This opening, combined with previous interviews performed with the practitioners, supported the analysis resulting from the quantitative formatting of the answers.

All interviews took place at the company operations headquarters and were face-to-face. The total number of interviewees was twenty-eight. Twenty-seven persons belong to the five up-mentioned departments where twelve of them held top-managerial positions and fifteen held operational positions. One interviewee was an external expert hired by the company.

4.3. Results and Analysis

The results section focuses on the difference of perceptions between departments and hierarchical levels. It provides insights on global trends for each dimension for each actor. In fact, we believe that alignment is a major requirement for S&OP. Therefore, disparities in perceptions represents an interesting and original lever for analysis. Additionally, due to confidentiality restrictions, we cannot publish the results scores.

4.3.1. *Department result*

In general, the aggregated results of all dimensions show that the SP department detains the highest S&OP maturity score, while the PS department detains the lowest score. This can be explained by the position of the SP teams as clients of the whole process while the PS teams represent the major supplying unit and deal with a huge product diversity derived in thousands of parts and suppliers. As a result, they carry the burden of shortages and are accountable for volume gaps. Additional interviews with their managers reveal that they have to deal with short term issues and are always under the pressure of ‘fire-fighting’ shortages.

For the Outcome dimension, all S&OP stakeholders, except for the SP teams, agreed on the same score. The SP teams tend to be more optimistic about the achievements of the S&OP while the remaining departments provided a poorer evaluation. We believe that the higher perception of the outcome given by the SP is correlated to the design of S&OP process that position them as clients 'to be satisfied'.

The Process dimension results are distributed between departments. SP and SCP teams are aligned on the same score. These two departments work very closely which explains their alignment on process maturity. However, Part Supply dept. is the least satisfied while the CCF dept. is the most satisfied. This can be explained, as for the general results, by the complexity of product variety and the burden carried by the PS teams versus relatively far position of the CCF teams whose involvement is limited to financials.

The results of the IT dimension show that the main S&OP stakeholders seem to be aligned on the same level of satisfaction toward the quality of IT tools except for the CCF teams. They seem to be less satisfied. The lack of S&OP financial data and the limited contribution of CCF teams to the process can explain this.

The Data dimension shows an interesting pattern characterized by the clear disparity between department's perception to data quality. Remarkably, we can clearly observe that the more a department is involved in the S&OP process and close to data sources, the better it evaluates the data quality. The given score gets worse in the same direction of the information flow. SP teams, detainer of the first demand data signals, have the best perception. The demand is then amended and sent to SCP teams, which express lower satisfaction regarding data quality, and so on, until reaching the PS teams, who gave the lowest evaluation. This pattern can refer to a lack of transparency or a poor data transfer tools between departments.

The Product portfolio results show that the Powertrain teams are the most satisfied while the supply chain planning teams represent the least satisfied entity. To understand the root causes behind these results, one should know that in terms of diversity, PWT teams deal with a limited number of references (less than 10^4 different SKU) while the SCP teams deal with a product diversity that goes up to 10^{20} for some car models. On the other hand, SP teams score higher than SCP teams. To understand this behavior, we need to consider the fact that a major task of SCP teams consists on

disaggregating the high granular sales demand into the SKU level to get accurate procurement needs. Thus, they must decide the exact mix of the plan among 10^{20} varieties. ***Figure 3.1 (left)*** illustrates the dept. radar results. Graduations are removed to preserve confidentiality.

4.3.2. *Hierarchical results*

The aggregated hierarchical results show that the top managers see the process differently compared to their subordinates. Top managers tend to be more optimistic for all the dimensions except for the outcome where they appear to be more pessimistic about the intended results of the process. We believe that such disparity is natural and can be explained by two things: the relatively high-level distant position of managers compared to daily practitioners and by a managerial attitude supposing they provided what's needed to do the job but wanting teams to perform better. ***Figure 3.1 (right)*** summarizes the hierarchical results.

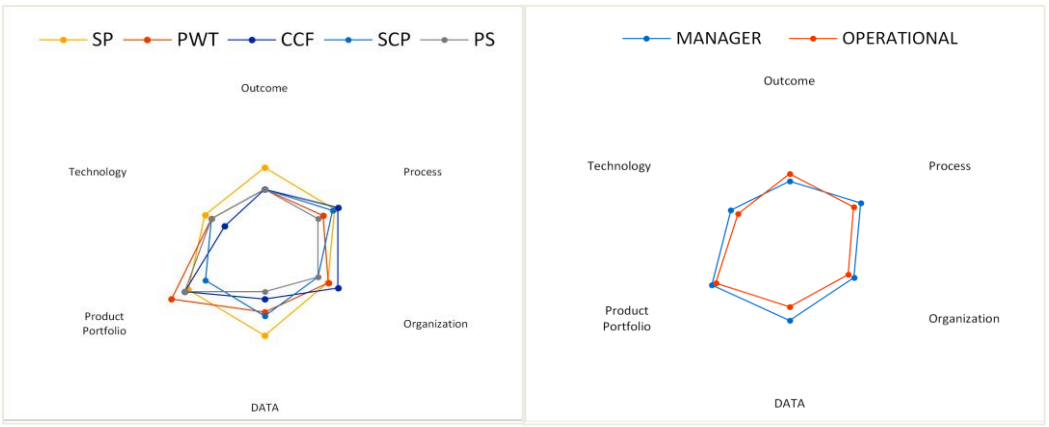

Figure 3.1: Dimensions' result radar by department (left) and by hierarchical level (right)

5. Conclusion

Assessing the performance of a business process using maturity models is a common practice in both academic and professional environments. Motivated by the lack of context-related frameworks in a sufficiently mature body of literature full of generic models, our paper aimed to provide a new S&OP maturity model that considers context-related attributes. We believe that maturity assessments should target the process main pain points related to the industry particularities. The developed model

is fit for industries that deal with a high level of product diversity and relies on both academic and professional literature since it was designed considering practitioner opinion. The study output was tested and implemented in a major automotive OEM. The results presented in the previous section show how the different process stakeholders evaluate each dimension. Through the assessment, we shed the light on two main aspects: the impact of diversity as a critical context-related attribute and the interactions between different actors of the process, more precisely, how the position and the tasks of each actor affect the evaluation score. These results gave us a better understanding of the S&OP process by picturing it through the eyes of its actors.

The next steps of our work will focus on diversity management and organizational transformations to benefit the process and enable better alignments. We are preparing and testing a model that reconnect Operations to Sales and complete the loop of S&OP interactions. We do so by equally dividing the diversity management tasks and by defining an appropriate aggregation level that suits different stakeholders and handles diversity. Our solution is intended to benefit the organizational aspects of S&OP since it provides a decision support tool and enhances collaboration and communication between actors of the process.

At the end, there is no doubt that this study would suffer from several limits. First, the number of interviewees was limited because we only had the chance to interview the corporate head operations site employees. Second, our case study was limited to one OEM, yet for a model to be used comparatively it must be applied to many other industries characterized by high diversity. Such generalization would enhance the robustness of the model. Finally, the evaluations are highly subjective and depends on personal opinions. The study could benefit from other techniques like fuzzy set theory to recalculate the scores.

Chapter 4. Optimal product family aggregation for Sales and Operations Planning in a mass customisation context

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Abstract:

Sales and Operations Planning (S&OP) is a multi-actor tactical planning process that balances, on a mid-term horizon, aggregated sales demand and supply capabilities to deliver reliable production plans. To obtain accurate sales demand, individual products are generally grouped into homogenous sets, or product families, according to their market behaviour and technical features. In Mass Customisation (MC) context, the product portfolio is described using a unique combination of attributes derived from a set of features. This paper introduces the planning aggregation level concept, which refers to a subset of features used to constitute product families. In such a situation, multiple aggregation levels may exist and deliver different performances from the point of view of the actors involved in the S&OP. A multi-objective model is designed to identify the best aggregation levels considering features linked to critical supply capabilities and useful for demand forecast. The model is implemented on various data instances provided by a large automotive manufacturer. Compared to the current choices made by the studied company, the results highlight the existence of aggregation levels offering a better planning performance and guaranteeing more cross-functional alignment.

***Keywords*:** Sales & operations planning; Mass customisation; Planning aggregation level; Product family; Cross-functional alignment; Multi-objective optimization

1. Introduction

Market volatility, globalisation, and disruptive regulations are common challenges for the supply chain management. Furthermore, industrials are struggling with the new consumption habits of customers seeking mass customised products and shorter delivery lead times (Marino et al., 2018). This trend has resulted in an extremely large variety of products, which consequently has altered the different operations of companies (Um et al., 2017). Much effort has been made to conciliate large volumes, high variety, distant suppliers, and short delivery lead times under favourable economic conditions. Modularity, commonality, and delayed differentiation were the most popular and effective approaches widely applied in the automotive sector in particular (ElMaraghy et al., 2013). Despite such efforts, sales, manufacturing and engineering business process are still negatively impacted by product variety (Lyons et al., 2020). Even if it may increase sales opportunities, (Huffman and Kahn, 1998) underline how a wide assortment of products can negatively influence customer satisfaction by introducing confusion. Chong et al. (1998) point out that variety increases supply chain complexity, production and inventory costs, as well as lead-times. Thonemann and Bradley (2002) show that when setup times are significant, the negative effect of product variety can be substantial on both production costs and lead-times. Syam and Bhatnagar (2015) consider that variety increases both set-up and variable production costs essentially through the interaction effects between products. More recently, Wan and Sanders (2017) underline the negative impact of product variety on inventory levels due to exacerbated forecasts bias. From a production planning and scheduling perspective, variety introduces complexity through product interactions, multiple constrained capacities and increasing uncertainty that prevent achieving cost-effective production (Jiao et al., 2007; Kolisch, 2000). In addition to the efforts made in products and production systems design, Assemble-To-Order (ATO) strategy has largely been adopted to limit the impact of diversity, particularly on inventory and lead-times (ElMaraghy et al., 2013; Olhager, 2003). ATO strategy consists of positioning the order penetration point at the assembly level while anticipating the requirements for modules and basic components (Olhager, 2003; Pil and Holweg, 2004). In such manufacturing environment applied to the automotive industry, sales demand consists of final customer and dealer detailed orders as well as aggregated forecast on mid-term horizons essential for capacity and material requirements planning (Meyr, 2009).

Distant suppliers, product variety, assembly processes complexity, demand uncertainty and capacity limitations at all the supply chain stages call for more coordination and functional alignment (Laurent Lim et al., 2014).

Sales and operations planning (S&OP) appears as a central process to achieve this coordination. S&OP is the process that links strategic plan to daily operations plans and balances demand and supply to create mid-term horizon plans (Grimson and Pyke, 2007). S&OP is a key tactical process for cross-functional intracompany and supply chain intercompany coordination regardless of the industrial context (Tuomikangas and Kaipia, 2014). In a MC context, coordination through S&OP is both necessary and challenging since a common negotiation basis has to be found to avoid the potential conflicts of interest that may occur between the actors involved in the process, especially sales and operations teams (Rexhausen et al., 2012). S&OP is often applied to product families rather than to individual stock keeping units (Grimson and Pyke, 2007). This can be explained by the tactical nature of the decisions to be made on horizons that range from few months to one year with a monthly granularity (Pereira et al., 2020) and by the need to mitigate demand forecast errors by grouping items (Zotteri et al., 2005). Indeed, according to (ElMaraghy et al., 2013), grouping similar products into families is a fundamental enabler of production planning in the MC context. Thus, a common negotiation basis to build a consensus-based operations plan relies on the way products are grouped into families to express sales demand and to evaluate its compliance with the available capacities at all the supply chain stages (i.e. supply capabilities).

When product variety is obtained through combinatorial or optional modularity as in automotive industry (Alford et al., 2000; Salvador et al., 2002), the number of individual stock keeping units may raise astronomic numbers (Hu et al., 2008; MacDuffie et al., 1996; Pil and Holweg, 2004) even when peripheral equipment or delayed differentiation accessories are not considered. Instead of grouping all the potential stock-keeping units into aggregated sets in a bottom-up fashion, product families are built through common attributes related to some of the products' features (Chatras et al., 2016b). Each possible combination of the attributes related to these features constitutes a product family. A product feature can be seen as a general characteristic of the product (body style, engine, gearbox, etc.) while an attribute refers to a specific instance of a given feature. For example, gasoline, diesel, electric, and hybrid are attributes of the

feature engine. Taking the up-mentioned features as a basis to construct product families, a particular product family is defined as the set of products that have the same attributes of body style, engine and gearbox. The number of resulting product families, which corresponds to the number of authorized combinations of the features' attributes, is qualified as variety. To remain compliant with the tactical nature of the S&OP and to mitigate forecast bias and inaccuracy, the planning variety must not be too large and thus the number of features used to construct the product families must be limited.

We introduce in this paper the concept of aggregation level which refers to the set of features used to generate the product families that are considered to express the sales demand during S&OP in MC context. The choice of these features is decisive since they are supposed to represent a common basis to characterize both sales demand and supply capabilities. When sales department expresses a demand using a certain aggregation level, the operations team must be able to check demand against available capacities in order to evaluate the feasibility of the sales request and eventually propose an amended version of it. This second step of the S&OP, called supply review, can be correctly done only if the aggregation level reveals some valuable information about the constraints that weigh the most on the supply capabilities. To illustrate, let's consider the previous aggregation level made of the features: body style, engine and gearbox, and a set of supply capabilities that limit the monthly production volume of sunroof cars. Since the constrained capacity concerns a particular feature (i.e., roof type) that is not part of the aggregation level, it is impossible to check accurately and directly its compliance using the aggregated sales demand. In practice, the operations team needs to perform a data disaggregation that consists of computing the mix rate of sunroof cars relying only on historical data if known or an arbitrary estimation if not. This rate is then applied to the original sales demand at the aggregate planning level to check whether the requested volumes are compliant with the available monthly sunroof capacity. The use of historical mix rates in volatile markets is very risky and can generate bias with costly consequences (Laurent Lim et al., 2014; Wan and Sanders, 2017). When the global production volume per period is limited, a positive bias on a given attribute automatically generates a global negative bias on the other attributes of the same feature and vis-versa. Hence, a bias, whether positive or negative, can generate overstocks, costly emergency measures to avoid shortages or bullwhip effects linked to frequent adjustments of the production plans (Chatras et al., 2016b; Giard and Sali, 2013; Sali and Giard, 2015).

To enhance the S&OP cross-functional alignment, this paper proposes an original approach to identify the best subset of features to include in an aggregation level by considering both sales and operations expectations. The main issue addressed by this paper may be formulated as follows:

In a MC context, what are the products' features to consider as an aggregation level to ensure a relevant demand formulation from a sales point of view and ensure supply capabilities are well considered in the S&OP?

Because product variety results from a combination of many features that may or not be relevant for demand formulation or affected by a constrained capacity, identifying an aggregation level that addresses the capability matters while remaining suitable and accurate for medium-term demand planning is a multi-objective combinatorial problem. Despite the criticalness of the subject, only a few studies discussed the product family from a production planning perspective in MC context.

This paper contributes to filling this gap by identifying the properties of a good aggregation level and by proposing an analytical model to identify efficient aggregation levels with regard to both operations (by including features that reveal critical constrained capacities) and sales (by including features that are relevant for demand formulation) points of view. The problem is solved using a lexicographic resolution approach where each objective function refers to one of the two criteria mentioned previously. The model was implemented using real data from a large European automotive company to challenge the current aggregation levels used for various car models. Compared to the current choices made by the company, the results highlight the existence of aggregation levels offering a better planning performance and guaranteeing more cross-functional alignment.

The remainder of this paper is organised as follows: the second section will be dedicated to a review of the literature on the main concepts used to conduct this study. The third section describes some relevant aspects observed in the studied company and introduces three general properties for a good planning aggregation level. The fourth section translates these properties into a multi-objective model. The fifth section presents and discusses the results obtained after applying and solving the proposed model in a case study. The last section highlights the major perspectives and limitations of the study.

2. Literature review

The subject discussed in this paper concerns several research fields related to the industrial context (MC), the business process (S&OP) and the central addressed problem (product family). We propose in this section to explore these three fields to position our contribution and extract from the literature useful knowledge for the study.

2.1. Mass customisation

The concept of MC emerged in the late 1980s and refers to the ability to provide customized products through flexible industrial processes in high volume and reasonably low cost (Davis, 1989; Hart, 1995). Following the customer-centric philosophy, MC relies on the involvement of the customer in the value chain and the product specification (Duray et al., 2000; Lyons et al., 2012). Based on the degree and the stage of the customer's involvement, Fogliatto, Da Silveira, and Borenstein (2012) identify eight generic levels of MC, ranging from pure customisation (individually designed products) to pure standardization. When the customer involvement point is located at the assembly stage, variety is obtained through the combination of standard and independent modules and production is carried out according to an ATO strategy (Chatras and Giard, 2016; Pil and Holweg, 2004; Salvador et al., 2002). Modularity emerges as one of the main means of achieving MC (Duray et al., 2000). Modular products platforms emerged as a way to streamline modular design costs by providing a common basis for a wide variety of products (Daaboul et al., 2011; Gershenson et al., 2003; Meyer and Lehnerd, 1997; Siddique et al., 1998).

Modularity has been widely studied in the design theory literature which describes its forms (Pine, 1993; Ulrich and Tung, 1991), analyses its benefits (Gershenson et al., 2003), studies its central role in product architecture (Huang and Kusiak, 1998; Muffatto and Roveda, 2002) and develop new frameworks for its implementation (Albers et al., 2019; Siddique and Boddu, 2004).

Other fields of study have focused on the efficiency of business processes in the context of MC and modular design of products by measuring the impact of variety on operational performance (Berry and Cooper, 1999; Squire et al., 2006; Thonemann and Bradley, 2002; Van Den Broeke et al., 2015; Zhang and Tseng, 2007) or by

providing insights about specific issues in sales demand (Randall and Ulrich, 2001; Wan and Sanders, 2017), manufacturing (Hu et al., 2011), production planning (Chatras et al., 2016b; Laurent Lim et al., 2014), scheduling and line-balancing (Boysen et al., 2007; Yao and Deng, 2015; Yao and Liu, 2009) to name a few. The modular design of the products has a direct consequence on the structure of the master data used in operations management. Indeed, products are no longer depicted individually through a Bill Of Material (BOM) that leads to data explosion (Olsen and Sætre, 1997), but rather they are described through a set of functional features and their alternative attributes that can be chosen by the customer. The concepts of modular BOM and generic BOM have been introduced in the literature to provide representations that are compliant with high variety products (Hegge and Wortmann, 1991). In a modular BOM representation, a product is described through a set of standard components and several lists, each corresponding to a particular module, of possible alternatives of which only one is active for a given item. In Generic BOMs, the alternatives offered to the customers are modelled through a hierarchical representation of the corresponding functional features. Modular BOMs can be used only when the modules are perfectly independent, and the interfaces are completely standardized. This situation is described in the literature under the concept of integrality (Ulrich, 2003) which is not always guaranteed in practice since certain combinations of modules may require particular connection components that prevent the direct mapping from functional to physical elements (MacDuffie, 2013). Emphasizing the limits of these approaches, particularly in the automotive sector, Chatras, Giard, and Sali (2016) propose an alternative representation based on a dual physical and functional description of the products which, unlike what is proposed in generic BOMs, is not based on a pre-established hierarchy. They show that production planning processes are particularly affected by these representations which introduce new issues. Our contribution falls within this field of the literature by addressing the issue of production planning in a MC context.

2.2. Sales and operations planning

Production and supply planning is a critical decision practice for industrial manufacturers largely discussed in the literature (Lalami, Frein, and Gayon 2017; Olhager 2013; Staeblein and Aoki 2015, etc.). Planning can be defined as the consequence of a hierarchy of top-down decisions (Gelders and Van Wassenhove,

1982; Özdamar et al., 1998). The practice consists of defining production plans by deciding upon the use of supply capabilities to satisfy a sales demand over different time horizons, starting from strategic decisions and moving to daily operational scheduling decisions (Fontan et al., 2005; Gelders and Van Wassenhove, 1982; Pereira et al., 2020).

S&OP is the process that links strategic plan to daily operations plans. This multi-actor tactical planning decision process consists of defining a roadmap for projected future production and a company commercialisation strategy by balancing sales demand and supply capabilities, while considering the financial and strategic orientations. Plans are established regarding aggregated product families and generally updated every month over a tactical planning horizon (Blackstone and Cox, 2005; Grimson and Pyke, 2007). The resulting planning is rolling over a horizon of several months (up to 18 months) (Antônio Márcio Tavares Thomé et al., 2012).

Tuomikangas and Kaipia (2014) highlight that connecting different decision levels facilitates collaboration, which benefits S&OP and which in return would benefit the whole supply chain performance. A recent review by (Pereira et al., 2020) discussed many studies providing analytical models to reduce the objectives related to the overall production cost, emissions costs, labour costs, etc. These models considered parameters linked to production, procurement, distribution and sales. Arguably, the success and convenience of the S&OP is very dependent on the degree of alignment between the different actors (Feng et al., 2008; Gelders and Van Wassenhove, 1982; Antônio Márcio Tavares Thomé et al., 2012) who often have contradictory objectives. Numerous authors have stressed the importance of alignment in supply chain tactical planning (Goh and Eldridge, 2019; Oliva and Watson, 2011; Tuomikangas and Kaipia, 2014; Wagner et al., 2014). More evidence regarding the importance of alignment for tactical planning could be found in maturity assessment studies, which have considered alignment at a S&OP as an important performance criterion (e.g. Ghrab and Sali, 2020; Grimson and Pyke, 2007).

An important challenge to effective alignment through S&OP resides in the high product variety (Blecker and Abdelkafi, 2006; ElMaraghy et al., 2013). Indeed, one of the prerequisites of the coordination is to clearly define the unit of analysis on which the arbitrations between sales demand and supply capabilities will focus. The unit of analysis in S&OP is the product family (Grimson and Pyke, 2007) which has to reveal

the main business goals and constraints while remaining sufficiently aggregated. Considering the particular product representation in MC introduced by (Chatras et al., 2016b), our contribution helps to clarify this concept and tries to provide valuable insights on how to define and use aggregation criteria suitable for S&OP.

2.3. Product family

From a design theory approach, product family refers to a set of products that are derived from a common platform supporting specific features. According to (Meyer and Lehnerd, 1997), a platform can be seen as “a set of subsystems and interfaces developed to form a common structure from which a stream of derivative products can be efficiently developed and produced”. Efforts in this area have focused on the commonality/distinctiveness trade-off to identify product families, leading to a wide piece of contributions (Gershenson et al., 2003; Kota et al., 2000; Mikkola and Gassmann, 2003; Thevenot and Simpson, 2006; Van Wie et al., 2007).

From a production planning perspective, some empirical rules for aggregating products into families have been provided in the literature. These rules mainly relay on similarity criteria used to group products into homogenous subsets. Hax and May (1973) use the setup costs as similarity criteria to anticipate scheduling issues in a hierarchical planning and scheduling system. Liberatore and Miller (1985) consider seasonality patterns for demand forecast purposes. Adopting a manufacturing point of view, Herrmann et al. (1994) and Kanyalkar and Adil (2005) propose an aggregation based on similar industrial resources and/or similar processing times to take advantage of repetitions. Following the same logic, Hasan et al. (2018) analysed the complexity of the assembly systems to identify similar process patterns. Kashkoush and ElMaraghy (2016) focused on analysing operational parameters linked to, among others, machines, processes, and the BOM structure in the context of MC.

All these contributions are based on the implicit assumption that unit products can be qualified through the used similarity criteria. In MC context, this qualification is difficult to achieve given the particular structure of the products described through generic features. The combinations of these features may lead to very heterogenous products using distinctive components and absorbing different amounts of resources. Much more research efforts have to be made to propose product family aggregation strategies for production and planning purposes in MC context. By proposing an

original aggregation analytical approach considering both sales and operations points of views, our contribution take part of this effort.

3. Context and problem description

Because this paper is related to MC context in the automotive sector and is inspired by the particular case of a European automotive company, it seems important to describe some key concepts useful for understanding the problem and the environment in which it arises. The first part of this section introduces three key concepts that will be helpful for both describing and solving the problem. The first concept, linked to the combinatorial variety, invalidates a certain number of planning practices applicable to situations where catalogues are made up of a few hundred or thousands of products at most. The second concept refers to the functional description of the products in the particular context of the studied company. The third concept discusses the planning process addressed through its specificities in MC context and in the light of the practices observed in the studied company. The second part of this section identifies the challenges related to the choice of the aggregation level and introduces three essential properties: sales significance, supply significance and compactness. These properties are essential to understand the modelling and resolution approach proposed in *section 4*.

3.1. Background

3.1.1. *Product variety*

Driven by customisation and the customers' desire for individual and unique products, the automotive catalogues have exploded in terms of proposed variants. The last 15 years have seen an enormous evolution of product variety. Just taking the Clio as an example (a popular hatchback made by Renault), a comparison of the data from *Table 4.1* and the data provided by Pil and Holweg (2004) shows that the total number of variations has evolved from 10^5 to 10^{30}. This product variety results from the numerous possible combinations of features that a customer can select to configure his car (Alford et al., 2000). Although limited by some technical and marketing compatibility constraints, the variety that results from these possible choices can be qualified as

combinatory (Salvador et al., 2002). These compatibility limitations will be discussed in the next subsection.

Table 4.1 gives recent data (2020) regarding the number of variants for different car models.

Table 4.1: Product variety for different car models

Model	Product variety
Twingo	10^{16}
Trafic	10^{19}
Clio 4	10^{30}
Master	10^{47}

To give the reader an idea of the magnitude of such product variety, consider the example of the *Trafic* model, which is a light commercial vehicle (LCV). The company data shows more than 10^{19} final products available for sale in the catalogue for one specific country. Considering an average volume of 330K LCVs sold yearly, and an average three-year commercialisation lifecycle, if it is assumed that each produced car is entirely unique, the probability of producing a specific car will be around 10^{-13}. Moreover, 10^{9} Tb of storage space would be needed to store the full product definition for each variety on a hard drive.

Note here that the extremely large storage space needed for a full description of all the potential cars would make the use of classical BOM approaches for product representation technically impossible (Chatras et al., 2016b). As a result, a specific functional definition of the product is used and discussed in the next sub-section.

3.1.2. *Product functional description*

The studied company has established a functional representation that describes a car as a combination of attributes derived from a set of features (Chatras et al., 2016b). Instead of storing the entire product catalogue, only the features and their corresponding attributes are stored in their systems. Data from the previous example shows that on average, a car can be defined by ~150 features. Note that the number of features increases with the product complexity, while the number of attributes depends on the feature's degree of customisation.

A feature can be seen as a functional characteristic of the product. For example, some common car features are the engine, roof, wheels, colour, and equipment level. Each

feature *j* has a set of n_j possible alternative attributes. For example, white, red, and blue are some possible attributes for the feature colour. To define a specific product, each feature must take one and only one attribute. For example, a car can never have two attributes for the feature engine. Therefore, a product is completely described through the union of unique attributes for each feature. Regarding such a structure, an aggregated product level could be defined as a subset of features. A very aggregated level would only refer to a single feature (e.g. car model). However, a more detailed and less aggregated level would use more features (e.g. a combination of car model/body shape/engine).

The resulting variety that can be offered in a product catalogue is thus the multiplication of the number of attributes for each feature minus the non-authorised combinations. The non-authorised combinations are the result of technical and commercial compatibility constraints. For example, assume we have four attributes for the feature type of engine and two attributes for the type of gearbox. The total unconstrained variety is 4x2 = 8 car variants. Now assume that for some technical reason defined by engineering departments, only one gearbox attribute could be considered for a given engine attribute. Consequently, an engine could only be assembled with the authorized gearbox. Therefore, the resulting constrained variety is restricted to 4 where 4 combinations were forbidden by the constraint on the gearbox. In this case, the feature engine induces the feature gearbox.

From a planning perspective, knowing only the type of engine in the previous example, we could automatically deduce the type of gearbox. Therefore, we could elaborate that the engine feature induces the gearbox feature. In such a case, integrating only the engine feature in an aggregation level is enough to cover the capacities expressed using the gearbox feature.

In the same way, the attributes of the features can be used to define a capacity. A capacity is expressed by the combination of attributes that characterise the population of cars impacted by such a capacity. For example, assume that line L only assembles cars of model X, which can be equipped with one of the three engines: E1, E2, or E3. Note here that E1, E2, and E3 are attributes for the feature engine, and that X is an attribute of the feature car model. Assume that, for a technical reason, the daily line production capacity is limited to 100 cars equipped either by E1 or E2. According to the functional product description system, this capacity "C" would be written as follows: *C: X AND (E1 OR E2) ≤ 100* (i.e., the total number of produced cars that are equipped

with the combination of attributes X AND E1 or X AND E2 cannot exceed 100). This kind of logical expression used to describe the left term of a capacity is referred to as the 'expression of a capacity'. In a real case, the expression of a capacity may involve a dozen of attributes related to several features.

3.1.3. *Planning process*

Interviews with key players of the S&OP within the studied company as well as internal process descriptions, showed that the current S&OP configuration consists of four steps: sales review, supply review, pre-S&OP, and executive review. One may refer to (Ghrab and Sali, 2020) for more details about these steps and their maturity for the specific studied company.

In terms of process, demand data are typically provided by the sales team to the operations team at the chosen planning aggregation level. Then, the operations team conducts a review to verify that the sales demand complies with the supply capabilities (i.e., capacities). To do so, a partial data disaggregation operation might take place. It consists of computing volumes for some features linked to capacities that do not appear in the original aggregation level. This step is done using historical rates. For example, assume that the sales demand is expressed using only the engine as aggregation level. If there is a critical capacity on a type of radio for a specific engine, the operations team needs to know the sales demand not only for each engine but also for the combination radio/engine. Therefore, the original sales demand will be expressed according to theses combinations while respecting the original volumes by engine and using historical data to determine the repartition of radios by engines. The reviewed data is aggregated again to the original form of data, and an answer is communicated to the sales team at the end of the supply review phase. The disaggregation-aggregation process is described in *Figure 4.1*.

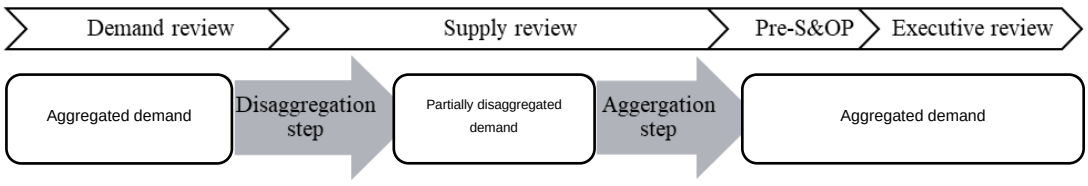

Figure 4.1: Sales demand aggregation-disaggregation process

The task of disaggregation-aggregation is time-consuming for operations team and introduces a large bias since it relies on historical information, which is usually inaccurate in a market known for its high volatility and recurrent disruptions. Therefore,

defining an appropriate planning aggregation level is crucial under such circumstances. Indeed, when more features involved in the expressions of the supply capabilities are taken into account from the sales side, less bias will be introduced in the process by the disaggregation step. Nevertheless, the aggregated nature of the demand review step prevents a consideration of all the features. A choice must therefore be made.

3.2. Properties of a good planning aggregation level

Based on observations made in the field, an attempt was made to better understand the issues associated with the choice of an aggregation level and to define a series of good properties that will serve to qualify what is a 'suitable aggregation level'. The quantitative translation of these desirable properties will serve as a basis for the construction of the model presented in *section 4*.

In the studied company, the current choice for the planning aggregation level was defined through an empirical consensus, whose origins were difficult to date, between the sales and operations teams. What is interesting to note is that the consensus focused exclusively on features linked to sales view. The current aggregation level is composed of features related to 'major' functionalities, seen or chosen by the customer, and of features that give approximate insights about the expected commercial margins of a product. It includes, for example, the features engine, equipment level, and gearbox. While these choices were empirical and could be easily criticised, they could not be totally neglected for two main reasons. First, the sales demand relies on market studies and benefits from strong demand channels sustained by their sales network recommendations and requests. Second, the stability of the aggregation level can be based on this core of features. As a result, including the maximum number of sales preferred features is beneficial for a good aggregation level. Note that the remainder of this paper will use the term 'sales features' to designate these features.

Based on the above explanations, a trivial key property for a good planning aggregation level can be deduced:

A good aggregation level must be significant from a sales perspective by considering sales features.

We call this property 'sales significance'.

On the other side, critical capacities are defined regarding features linked to constrained supply capabilities. The term ‘supply features’ is used to denote them. As previously explained, the operations team must extrapolate the sales demand based on historical data to obtain the anticipated volumes for some of the specific critical capacities and thus review the sales demand according to these limits. This procedure may introduce a significant bias in the predicted values because the operations team lacks expertise with demand evolution and the historical data are usually unreliable, especially in volatile markets. This inaccuracy could lead to two situations. First, the extrapolated volumes could be overestimated, and thus the related capacities might look overloaded, which could lead to an unnecessary distortion of the original forecast mix to meet the constrained capacities by cutting some volumes or to an unnecessary investment to increase the capacity. Second, the extrapolated volumes could be underestimated. In this case, while the sales demand seems to be compliant with the capacities, shortages may occur later when the real demand arrives, and costly emergency deliveries may be triggered to avoid missing sales opportunities.

Consequently, considering the constraint-linked ‘supply features’ by analysing the supply capabilities would help avoid inaccurate extrapolations and thus ensure better alignment between the two main actors of the S&OP, along with better integration between the tactical and operational levels. The second good planning aggregation level property can be deduced from this short analysis:

A good aggregation level must be significant from a supply chain perspective by considering supply features.

We call this property ‘supply significance’.

Another important aspect that characterises a planning aggregation level is the effort needed to prepare the sales demand at that level. We measure the planning effort as the number of product families resulting from the aggregation level. As a general rule, the more the planning variety is high, the larger is the number of product families and the more effort is needed to prepare demand data for all these families. It can be established that the sales team would naturally seek a low planning variety by pushing toward very aggregated levels using a small number of features. Indeed, the compactness of the aggregation level ensures better forecast accuracy and offer more flexibility to sales team by postponing detailed demand expressions to the short-term.

As a result, a third property for a good planning aggregation level could be derived:

A good aggregation level should ensure, besides sales and supply significance, a maximum level of compactness to guarantee a better accuracy of the sales demand and less demand preparation effort.

We call this property 'compactness'.

Regarding these three properties (i.e., sales significance, supply significance and compactness), it can be observed that they have contradictory objectives. More sales significance means selecting more sales features linked to sales preferences, which might lead to less use of supply features representing critical capacities and thus supply significance. In addition, selecting more features, whatever part (sales or supply) they serve, negatively impacts the compactness by increasing the variety.

Considering the context and problem description, this paper intends to provide a quantitative approach based on a multi-objective model that identifies suitable aggregation levels considering the previously defined properties. The problem to be modelled can be summarised as follows:

What are the sets of features that represent an efficient compromise with regard to the sales significance, supply significance and compactness?

The following section proposes a multi-objective optimisation model that can be used to select the best planning features regarding the sales, supply, and compactness considerations in order to constitute an aggregation level.

4. Model

A good planning data aggregation level is meant to satisfy and align the different actors of the process (mainly sales and operations teams). The analytical model developed in this section aims to identify subsets of features that contribute to making an aggregation level an effective compromise of the properties mentioned in *section 3.2*.

The antagonism of the decision criteria, on the one hand, and the combination character linked to variety, on the other hand, led us to choose a multi-objective model formulation for the problem as going to be discussed in *section 4.2.* to identify a Pareto front made up of effective aggregation levels, a lexicographic resolution approach will be presented in *section 4.3*. The results obtained from the application of this model on actual data will be discussed and compared to the current situation in *section 5.*

4.1. Notations

The remainder of the paper uses the notations summarised in *Table 4.2*.

Table 4.2: Model notations

Notation	**Description**
Indices and sets	
C	Supply capabilities set
F	All features set
S	Sales features subset
M	Total number of supply capabilities
N	Total number of features
i	Supply capabilities indices, *i = 1.. M*
j	Features indices, *j = 1.. N*
Parameters	
b_{ij}	$\begin{cases} 1, \text{ if capacity } i \text{ includes feature } j \\ 0, \text{otherwise} \end{cases}$
$Coo_{j,k}$	$\begin{cases} 1, \text{ if the feature } j \text{ induce the feature k} \\ 0, \text{otherwise} \end{cases}$
t_i	Number of features present in the expression of a capacity *i* $(\forall i\ t_i \geq 1)$
cs_j	$\begin{cases} 1, \text{if } j \text{ is a sales features} \\ 0, \text{otherwise} \end{cases}$
cr_i	Criticalness weight for capacity *i*
n_j	Size (number of attributes) of feature *j* $(\forall j\ n_j \geq 1)$
ε	Small positive number
B	Large positive number $(\forall i\ B \geq t_i)$
MaxVar	Maximum variety resulting from the current aggregation level
Decision variables	
Y_j	$\begin{cases} 1, \text{ if feature } j \text{ is selected} \\ 0, \text{otherwise} \end{cases}$
Z_i	$\begin{cases} 1 \text{ if capacity } i \text{ is covered} \\ 0, \text{otherwise} \end{cases}$
A_j	$\begin{cases} 1 \text{ if feature } j \text{ is selected and is not induced} \\ 0, \text{otherwise} \end{cases}$

The model is fed by five major inputs linked to the properties of a good planning aggregation level. The first input represents the list of *sales features* **S**. This list is used to compute the sales significance binary coefficient $\boldsymbol{cs_j}$. The second input refers to the list of *supply capabilities* (i.e. capacities) ***C*** expressed using features as explained in *section 3.1.2*. This list is used to create a binary matrix where the features ***j*** defined as column names and capacities ***i*** as rows ID. Each $\boldsymbol{b_{ij}}$ takes the value 1 if the feature ***j*** is

present in the expression of the capacity ***i*** or 0 otherwise. The third input holds the values of the computed capacity criticalness scores, $\boldsymbol{cr_i}$. The $\boldsymbol{cr_i}$ score is measured pre-optimization as the relative level of a capacity compared to the total demand. The fourth input represents the list of induction links between the features. This list is used to calculate the binary induction matrix $\mathbf{Coo_{j,k}}$ where both columns and rows are defined by features. The coefficient $\boldsymbol{Coo_{j,k}}$ takes the value 1 when the feature ***j*** induces the feature ***k*** or 0 otherwise. The final input provides the number of attributes $\boldsymbol{n_j}$ for each feature ***j***. The $\mathbf{n_j}$ values are used to measure the variety size for an aggregation level.

On the other hand, the model is based on three binary decision variables. The variable $\boldsymbol{Y_j}$ defines if a feature ***j*** will be selected to constitute the resulting aggregation level. The variable $\boldsymbol{Z_i}$ decides whether a capacity ***i*** is considered by the resulting aggregation level. A capacity is considered by the aggregation level if all the $\boldsymbol{Y_j}$ associated to the capacity features are set to 1. Finally, since the features are interconnected and some of them could be totally deduced from others, the $\boldsymbol{A_j}$ variable is defined to only select non-induced features.

4.2. Multi-objective model

4.2.1. *Objective function*

The aggregation level selection model is a multi-objective mixed integer linear program, where the first two properties derived in *section 3.2* are formulated as optimisation objectives, while the compactness property is considered as a model constraint. Therefore, the problem objective functions are formulated as follows:

$$OF_1 = Min \sum_j (1 - cs_j) \times A_j$$

$$OF_2 = Max \sum_i cr_i \times Z_i$$

The first objective function ($\mathbf{OF_1}$) is linked to the preferences of the sales team and tries to achieve the first property by measuring the number of *non-sales features* present in the aggregation level. To ensure sales significance, this number must be minimised.

The second objective function ($\mathbf{OF_2}$) represents the second property, which is linked to the preferences of the operations team. It measures the rate of critical capacities

considered by the selected aggregation level. To ensure supply significance, this rate must be maximised.

4.2.2. *Model constraints*

The optimisation model tries to choose a set of features to achieve ***OF₁*** and ***OF₂*** without exceeding a certain threshold of compactness that corresponds to the maximum variety manageable in the process. To this end, the following constraints were derived to ensure the proper calculation of the model's decision variables.

The first model constraint (**MC1**) forces Z_i to be equal to 0 if at least one feature ***j*** involved in a capacity expression ***i*** is not selected among the features of the aggregation level (i.e. $Y_j = 0$).

$$\sum_{j=1}^{N} b_{ij} \times Y_j - t_i \geq B(Z_i - 1), \forall\, i = 1..M \ (\mathrm{MC1})$$

The second model constraint (**MC2**) sets Z_i to 1 if all the features ***j*** involved in a capacity expression ***i*** are selected to constitute the aggregation level (i.e. $Y_j = 1$).

$$\sum_{j=1}^{N} b_{ij} \times Y_j - t_i \leq (\mathrm{Z}_i - 1), \forall\, i = 1..M \ (\mathrm{MC2})$$

On the other hand, two constraints are derived to take in consideration the links that exist between the correlated features. The first constraint (**MC3**) introduces the decision variable A_j to identify the non-induced selected features. The second constraint (**MC4**) sets the Y_p of the induced features ***p*** to 1 if their inducer ***j*** is selected.

$$\forall\, j \in OBJ, -B * A_j \leq \sum_{\mathrm{k}\epsilon\mathrm{OBJ}} Y_k * Coo_{k,j} - Y_j \leq B * (1 - A_j) - 1, \qquad B\ big\ (MC3)$$

$$Y_p \geq Y_j * Coo_{j,p}\ \forall\, p, j \in OBJ\ (MC4)$$

The last model constraint (**MC5**) is derived from the compactness property detailed in *section 3.2*. The compactness constraint guarantees that the resulting variety from the selected features does not overcome the current variety. Because the variety results from the combination of the features' attributes, the constraint can be simply expressed as follows: $\prod_{j|A_j=1} n_j \leq MaxVar$.

This constraint must be linearized before using it in the model. Logarithmic transformation can be used to obtain the following formulation (**MC5**). The linearization steps are provided in the ***Appendix4.1.***

$$\sum_{j=1}^{N} \log(n_j) \times A_j \leq \log(MaxVar) \quad (MC5)$$

4.3. Lexicographic resolution method

Different approaches can be used to deal with multi-objective optimisation problems (Marler and Arora, 2004). We distinguish the approaches that seek to optimize a single synthesis criterion such as weighted sum or goal-programming from approaches that aim to identify a set of effective solutions and form a Pareto front. Given the nature of the problem in which it is a question of identifying several alternatives to the current situation combined with a need for post explanation of two incomparable objectives (i.e. sales vs. operations objectives), it is this second type of approach that has been adopted in our case.

More precisely, we opt for a lexicographic resolution method widely used to solve these kinds of problems and capable of providing solutions belonging to the Pareto front.

The principle of this resolution method is to iteratively search for the optimal solution for one of the objective functions while constraining the second objective with the results of the previous iteration. Each iteration, therefore, consists of solving a mono-objective mixed-integer linear program. The iterative resolution is repeated until the problem becomes unfeasible.

We choose to solve **OF_1** and iteratively apply a constraint on **OF_2.** This choice is motivated by the fact that the minimization of **OF_1** reduces the number of non-sales features and thus selecting solutions that guarantee minimum variety. Indeed, an algorithm based on the maximization of **OF_2** would lead to solutions rich in supply features with a tendency to quickly saturate the constraint of variety.

Consequently, (**OF_2**) is replaced by the following constraint (**MC6**):

$$\left(\sum_{i \epsilon MTC} cr_i * Z_i\right)^k > \left(\sum_{i \epsilon MTC} cr_i * Z_i\right)^{k-1}, \; for\; k \in iterations \;\; (MC6)$$

This principle is applied through the following procedure, which returns a list of optimal solutions. Some of these solutions, which can easily be identified through a post-optimal dominance analysis, guarantee the pareto optimality.

$k = 0$ *(iteration counter)*

$L = [\ \ ]$ *(list of optimal solutions)*

Resolve the mono-objective problem regarding objective function (OF_1).

Set $\dot{Z}_i^k$, $\dot{A}_j^k$ *and* $\dot{Y}_j^k$ *to the optimal values of the decision variables obtained in iteration k.*

$L = \left[\left(\dot{Y}_j^k, \dot{A}_j^k, \dot{Z}_i^k\right)\right]$

While the problem is feasible do:

$k = k + 1$

Introduce the constraint (MC6) in the model: $\sum_{i=1}^{M} cr_i \times Z_i^k \geq \sum_{i=1}^{M} cr_i \times \dot{Z}_i^{k-1} + \varepsilon \ \ (MC6)$*, where* Z_i^k *is a decision variable in iteration k*

Resolve the mono-objective problem regarding objective function (OF_1)

Set $\dot{Z}_i^k$, $\dot{A}_j^k$ *and* $\dot{Y}_j^k$ *to the optimal values of the decision variables obtained in iteration k*

Append $\left(\dot{Y}_j^k, \dot{A}_j^k, \dot{Z}_i^k\right)$ *to L*

Return L

Note here that the model is iterated by updating the right-hand side of the constraint (MC6) at each iteration *(k)* using the values of the left-hand side calculated at the previous iteration *(k-1)*. The ε was added to guarantee that the objective function (**OF_2**) is improved at each iteration.

The model was tested with different configurations, including various scenarios ranging from extreme one-objective achievement to alignment consensus. The configurations of these scenarios, as well as the results, are presented and discussed in the next section.

5. Case study

The model and resolution method presented in Section 4 were tested on actual data made available by the research partner. Several scenarios for different product ranges were analysed. Section 5.1 summarizes the scenarios studied. Section 5.2 details and reviews the results observed for each scenario.

We used CPLEX 12.9 IDE to code and execute the resolution algorithm on a computer equipped with an Intel i5 6th Gen 2.4GHz CPU and 8Gb RAM. The execution time for the different instance is given at *table 4.3* presented at the following subsection.

5.1. Problem parameters

A numerical study was performed on a variety of four car models belonging to different market segments. The proposed model was implemented on each car model to obtain a list of optimal solutions that constituted alternative compromises to the current aggregation level. *Table 4.3* presents the problem parameters related to each one of the four instances selected for the analysis.

Table 4.3: Case study parameters

Car model	Nb of features	Non-induced sales features	Supply capabilities	Current variety (*MaxVar*)	Execution time (s)
Small	246	9	40	159344640	10,49
Bestseller	207	10	39	4462920	9,16
Electric	171	6	11	23328	9,52
Premium	214	8	35	2640000	10,26

The number of features refers to all the features used for a complete description of a product. An aggregation level containing all the features leads to a planning variety which is identical to the product total variety mentioned in table 4.1.

The current aggregation level is exclusively made of sales features where the current variety (*MaxVar*) is the variety resulting from the combination of non-induced *sales features*. The number of possible combinations is calculated based on the product catalogue available for all countries. This catalogue is defined according to engineering and global marketing compatibility constraints. The market-specific constraints are discarded as they could lead to confusion in the choice of the aggregation level. Therefore, *MaxVar* could be considered as an upper-bound of the current variety.

5.2. Results and discussion

The results discussed in this section were derived from three main performance criteria linked to the first objective function (**OF_1**), which measured the number of non-*sales features* figuring in the chosen aggregation level ($\sum_j (1 - cs_j) * A_j$), to the second objective function (**OF_2**), which measured the ratio of covered criticalness of supply capabilities $\left(\frac{\sum_i \mathrm{cr}_i * Z_i}{\sum_i cr_i}\right)$, and finally, to the compactness property measured for the strongly pareto efficient solutions as the ratio of a solution point generated variety compared to the maximum current variety $\left(\frac{\sum_j \log(n_j) \times A_j}{\log(MaxVar)}\right)$.

Recall that a good solution would select a set of features that detains most of the currently used *sales features* to ensure stability, covers most of the supply capabilities to decrease the potential need to amend the sales demand, and finally does not generate additional variety compared to the current situation.

Following the lexicographic procedure, a set of solutions, presented in *Figure 4.2* as blue points, was obtained for each data instance. All these solutions could be considered as weakly or strongly pareto efficient. The orange line represents the pareto frontier drawn through the strongly pareto efficient solutions while the yellow line represents the ratio of variety generated by these solutions.

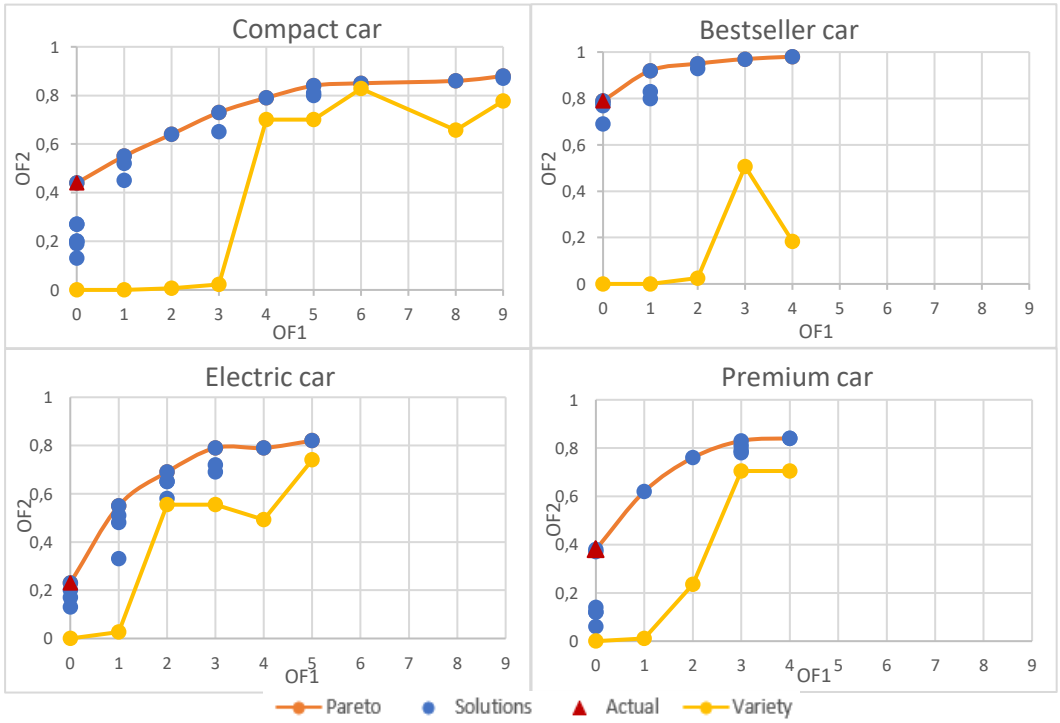

Figure 4.2: Pareto frontier for different car model

(*blue: identified solutions, orange: Pareto front, red: current solution, yellow: Pareto solutions' resulting variety)*

5.2.1. *Current situation*

The performance measure of the current situation is represented by a red triangle and is situated at the bottom left of the pareto front. The currently used aggregation level contains all the *sales features* and therefore corresponds to a lower bound of $\mathbf{OF_1}$ ($\mathbf{OF_1}$ = 0). On the other hand, since all relevant *sales features* (non-induced) are present in the current aggregation level, the $\mathbf{OF_2}$ score of the red triangle is situated at the pareto front and corresponds to the best possible solution for $\mathbf{OF_1}$ = 0. The blue dots on the same vertical axis (i.e., when $\mathbf{OF_1}$ = 0) and below the current solution (red triangle) represent solutions composed of subsets of relevant *sales features*.

Comparing the results of the different instances, one could observe that except for the *Bestseller* model, which has a current situation coverage score $\mathbf{OF_2}$ = 79%, the remaining car models scored and $\mathbf{OF_2}$ ranged between 23% and 44% with the current aggregation level (i.e. $\mathbf{OF_1}$ = 0). More precisely, the *Electric* model held the lowest $\mathbf{OF_2}$ score (23%), followed by the *Premium* model (38%) and finally the *Compact* model (44%). The interpretation of the $\mathbf{OF_2}$ score means for the *Electric* model, for example, that the currently used aggregation level makes only 23% of the weight of supply capabilities visible (which refers to 2 among 11 capacities). Such a score means that the demand expressed according to this level of aggregation must undergo a history-based data aggregation-disaggregation process for all the remaining 9 supply capabilities to be able to verify their compliance with the requested demand. This result illustrates the low supply significance of a level of aggregation composed exclusively of *sales features*. Luckily, not all instances exhibit the same behaviour. The *Bestseller* car has a good $\mathbf{OF_2}$ score for the current aggregation level. This reveals a possible tendency to make uniform aggregation level choices based only on supply capabilities for the best-selling vehicles. This intuition must be confirmed by further analysis.

5.2.2. *Alternative solutions*

A general observation made on all the instances proves that the alternative solutions provided by the model are at least better than the current solution at $\mathbf{OF_1}$ = 0. Indeed, the different instances' charts show a blue dot under each red triangle, which means that these alternatives solutions using a subset of *sales features* provide the same $\mathbf{OF_2}$

score compared to the current solution. On the other hand, the variety yellow curve shows that these solutions generate far less variety compared to the current solution. These strongly pareto efficient solutions demonstrate that not all the existing *sales features* are useful for the supply review phase. Therefore, we could use fewer features while guaranteeing the same coverage of supply capabilities, and unquestionably, less variety.

More interesting solutions could be found for $\mathbf{OF_1}$>0. The analysis of the pareto front shape shows that introducing small changes to the current choices can lead to significant improvements in the supply significance of the aggregation level. Specifically, the solutions corresponding to $\mathbf{OF_1}$=1 show that a slight deterioration of $\mathbf{OF_1}$ can have a significant impact on the visibility of critical supply capabilities measured by $\mathbf{OF_2}$. More precisely, the introduction of one non-*sales feature* results in an $\mathbf{OF_2}$ improvement of 8% for the C*ompact* model, 13% for the *Bestseller* model, 24% for the *Premium* model and 32% for the *Electric* model. Such a compromise is likely to minimize the risk associated with disaggregation and aggregation operations.

The shape of the pareto curve shows a disparity between the different vehicles. The length of the pareto's forehead (given by the maximum value on the abscises axis that represents $\mathbf{OF_1}$) can be explained by the diversity of capacities related to each vehicle. The more different the expressions of the capacities, the more non- *sales features* are needed to cover them. For example, the *Compact* and *Bestseller* car models have almost the same number of supply capabilities (40 and 39 respectively). However, the *Compact* car model introduces 9 features to reach 87% of $\mathbf{OF_2}$ where the last 4 features only add 3% to the $\mathbf{OF_2}$ score while the *Bestseller* car model introduces only 4 non-*sales features* overall which improve $\mathbf{OF_2}$ by 19%.

On the other hand, the initial slope of the pareto front tells us about the relevance of the current aggregation level. The steeper this slope, the more interesting it is to introduce a new feature. For example, the slope of the pareto front of the *compact* vehicle is relatively small while its length is greater compared to other vehicles. This reflects, for the *compact* vehicle, the need to introduce into the aggregation level a large number of non-*sales features* to achieve a good level of $\mathbf{OF_2}$. On the other hand, the initial steep slope of the pareto front for *Electric* and *Premium* vehicles shows that a significant improvement in $\mathbf{OF_2}$ is achieved by introducing only a few non-*sales features* into the aggregation level.

An interesting solution would be for example to select levels that guarantee an $\mathbf{OF_2} \approx$ 80%. This would mean to introduce at most 4 non-*sales features* for the *Compact* model, 3 for both *Electric* and *Premium* model and 0 for the *Bestseller* model. In order to guarantee less variety, these solutions assume discarding any *sales features* that could be considered as useless from a supply significance perspective.

5.2.3. *Variety size*

The yellow curve represents the relative variety generated by the pareto curve solutions. One could observe that all the new solutions are at least better than the current situation thanks to the model constraint on the generated variety (**MC5**). Indeed, the current situation solutions represent a variety upper bond which refers to a ratio of variety equal to 1.

Contrarily to the pareto curve, the relative variety curve shows no correlation between the use of more non-*sales features* and the relative size of the generated variety. This behaviour is explained by the non-incremental feature selection. The model constraints (**MC1)** and (**MC2)** force the grouping of features to match a complete expression of a supply capability. Consequently, adding one non-*sales feature* could change many features from the previous selection and does not necessarily mean that a new feature is added to the same previous selection. Many features could change between two successive solutions to increase the coverage of capacities expressed with a totally different set of features, which would explain the non-linear change of the variety curve.

In conclusion, without loss of generality, it can be established that by making slight changes to the current situation, it is possible to provide the operations team with a sales demand expression more useful for the supply review phase and thus to ensure a better alignment of the players involved in the S&OP process without profoundly changing the actual habits. This first result constitutes a decision-making tool for designing an aggregation level that efficiently balances the sales and operations objectives while respecting an upper bound for the resulting planning variety. It remains up to the decision-makers, regarding the different provided solutions, to choose the most convenient aggregation level.

6. Conclusion and perspectives

S&OP is an important aggregate planning process that relies heavily on the alignment and coordination between its major actors. On the other hand, extremely large product variety is a customer-oriented trend that strongly affects the planning performance. One of the challenges of S&OP in the MC context is to establish a common negotiation basis that allows both sales demand expression and supply capabilities matching. The choice of a relevant aggregation level to form product families is thus a crucial issue. The empirical choices made to select a planning aggregation level were proven to be inefficient by favouring one actor at the expense of the others. This paper provides an analytical decision support tool, based on a multi-objective optimisation model, for cross-functional alignment. Different properties of a good aggregation level were defined, and related optimisation objectives were derived. The proposed model was tested using real data from a large European automotive company. The data were collected, treated, and implemented in the model to test the hypothesis. The results are promising. First, it was possible to measure the performance of the current situation regarding different objectives. Second, new aggregation levels, which may be good candidates to replace the current solutions and enable better alignment, were identified. Third, a comparative study was conducted of different car models with different characteristics.

Although the proposed model provided valuable insights regarding aggregate planning performance, it was necessary to simplify the real problem by some hypotheses.

First, the criticalness score of the supply capabilities was computed using simple volume formula. This score represents a major input for the problem and heavily impacts the choice of the features. Therefore, defining accurate criticalness scores considering inherent capacity criteria could help to select more interesting features.

Second, the product variety was computed based on a global product catalogue that does not consider the market-specific compatibility constraints. Therefore, the computed resulting variety represents an upper-bound to the real variety. Taking into account market or country-specific constraints could only be done on market or country-level demand data, but not on an S&OP aggregate data. If so, an aggregation level for each market or country will be defined, which could not be relevant for an aggregate tactical planning purpose.

Third, this study was limited to sales and operations objectives, but they are not the only actors involved in S&OP. It was felt that these two major actors were sufficiently representative and could be a manageable challenge for this first attempt to solve a planning aggregation level problem in the MC context. However, thanks to the flexibility of the optimisation model, a more extensive study could be conducted by integrating objectives related to other actors (finance, marketing…). To this end, further investigations must be made to clearly identify what are the good properties of an aggregation level for each introduced actor. The proposed model may thus be enriched by translating these properties into objective functions and/or model constraints.

Fourth, future research could profit from integrating context-specific features to obtain better performance and visibility. For example, features linked to regulations like the Corporate Average Fuel Economy (CAFE) could be pinned in the proposed aggregation level to help provide accurate calculations of this key performance indicator, define a better mix and avoid large penalties.

Furthermore, a global property not discussed in this paper concern the stability of the choice of the aggregation level. The frequent update of the aggregation level could create confusion among demand preparation teams. In the present model, the stability is partially guaranteed by the sales significance property that maximises the use of common sales features. More consideration could be given to introducing specific stability criteria in the model. This issue could also be addressed from an organisational perspective to limit the update frequency of the aggregation level as long as there are no major changes in demand or supply capabilities (e.g. update each 6-12 months).

Finally, from a technical point of view, the proposed model using the lexicographic optimality method as a resolution technique considers the maximum planning variety as a constraint. A future study could strongly benefit from transforming this into an optimisation objective.

Chapter 5. Critical capacities' assessment: a conceptual classification framework

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Abstract:

The supply capabilities represent an important input for the sales and operations planning (S&OP). They refer to the different supply chain capacities and are assessed during the supply review phase to check the feasibility of the sales demand regarding the resource limitations before the operations plans are validated. Mutually connected, the supply capabilities define guidelines to the S&OP while the validated plan provides feedback on their utilization. In a context of mass customisation, the product aggregation level at which sales demand and supply capacities are compared corresponds to a subset of product's features that serve to construct products' families. The choice of the features to include in the aggregation level determines which capacities are accurately checked at the supply review. Therefore, to avoid infeasible plans leading to short-term costly emergency measures, the most critical capacities must guide the choice of the aggregation level. The criticalness of a capacity is multi-dimensional and can be measured in different ways. This paper proposes a new conceptual critical capacity assessment (CCA) model which can be used to identify the capacities to consider in priority to select the appropriate aggregation level used for S&OP data. The proposed capacity criticalness measure is a combination of a capacity impact score (i.e., consequences of insufficient capacity to meet the demand) and its flexibility (i.e., the ability to mitigate a constrained capacity).

Keywords: capacity management, capacity assessment, S&OP, mass customisation, aggregation level

1. Introduction

Capacity planning represents an important component of the sales and operations planning process (S&OP (Antônio Márcio Tavares Thomé et al., 2012). The effective management of capacities is proven to be an important lever for a company's competitiveness and efficiency (Gyulai and Monostori, 2017). Indeed, the volatile and ever-changing market demand has always been a challenge for manufacturing companies yielding more pressure on the ability of existing resources to adapt to future trends and to meet the predicted changes (Laurent Lim et al., 2014).

Capacity management represents the field of the study that deals with the proper definition and update of capacities to match the evolution of the demand while minimizing costs and respecting the desired service level (Gyulai and Monostori, 2017; Klassen and Rohleder, 2002). Common to almost any industry, capacity management was documented in the literature for numerous sectors like air transportation industry (Dixit and Jakhar, 2021), chemical industry (Naraharisetti et al., 2006), automotive industry (Gyulai and Monostori, 2017) to name a few. It aims to ensure the best use of internal capacities and the presence of the right resources to answer the various demand evolutions (Olhager et al., 2001; Sabet et al., 2020).

One of the major planning processes where we tackle decisions linked to constrained capacity issues is the S&OP (Feng et al., 2010; Antônio Márcio Tavares Thomé et al., 2012). The S&OP process has emerged in the 80ties as "an extension of the aggregate production planning, integrating mid-term decisions from procurement, production, distribution, and sales in a single plan"(Pereira et al., 2020). In order to work effectively, the process reposes on three types of inputs: demand data, capacity data and financial data (Antônio Márcio Tavares Thomé et al., 2012). The demand data refers to the sales plan and is prepared by the sales team. The capacity data (also called the supply data) refers to the level limitation for the available resources of the different supply chain processes and is provided by the different operations units (procurement, production, distribution, etc.). We use the term *supply capabilities* to denote all the capacities linked to the various supply chain operations. Finally, the financial data refers to the available budget and is provided by the cost controlling and finance teams.

Positioned on the edge of tactical planning (Pereira et al., 2020), S&OP is a decision process that maintains the balance between aggregate capacity plan and aggregate sales demand through monthly updates of the annual business plan (Antonio Márcio

Tavares Thomé et al., 2012; Zhang et al., 2014). Consequently, capacity and demand are treated at an aggregate level, dealing with the most important resources rather than all individual resources and based on forecasts of product families rather than individual products (Olhager et al., 2001).

Without doubts, aggregation of data is a must at tactical planning levels (Zotteri and Kalchschmidt, 2007). However, aggregation comes with the risk of losing important information (Orcutt et al., 1968). Regarding the supply capabilities plan, the aggregation of the demand data might hide important information regarding critical resources that could fail to meet the demand in the future. Consequently, the supply plan could be distorted due to unforeseen constraints on capacities and lead to a mismatch between the demand and the supply. This risk is even higher in a context of mass customisation (MC) (Davis, 1989; Hart, 1995). The high level of variety enabled by MC increases the number of possible aggregation levels (i.e. product families) (ElMaraghy et al., 2013), which makes choosing an appropriate level challenging.

To avoid such risk, an aggregation level choice model that selects the safest level based on the criticalness of supply capabilities was developed (Ghrab et al., 2021). The criticalness score of each supply capacity was calculated using simple volume formula. Due to the importance of criticalness score to the model, we believe that the capacity criticalness score could use a more accurate assessment that include more capacity inherent criteria to yield better results. Besides, the high number and variety of constrained capacities present in modern industries making complex products could use a better classification (Gyulai and Monostori, 2017). Therefore, focusing on a selection of the most relevant capacities based on their criticalness could be useful for a tactical aggregated level. To do so, we thrive to develop a new capacity criticalness assessment tool using a set of capacity-related criteria identified in the literature.

Consequently, two research questions will be discussed in this paper:

1- "What are the characteristics that qualify the criticalness of a capacity?"
2- "How to classify the supply capabilities according to the identified criteria?"

To answer these questions, we follow a three-step methodology. First, we study the existing literature in a quest for criteria that characterize the system capacities and for existing capacity criticalness assessment tools. Then, we try to design a conceptual framework to classify the capacities by their criticalness using the identified criteria. The goal of this step is to use the criticalness score for the S&OP aggregation level

selection model providing more valuable information regarding the importance of the system capacities. Finally, the last step consists of defining the use cases of the framework and the related new process.

This paper will be organized as follow: the following two sections will try to answer the two research questions. Section 2 will span the literature to identify the different types of supply capabilities and their most common criteria. Section 3 will try to provide a more complete definition for capacity criticalness and develop a new capacity assessment method using the identified criteria. The last section will be dedicated to providing insights regarding future work and improvements to the current study.

2. Capacity types and relevance criteria

This section will focus on identifying the different supply chain capacity types and their characteristics as defined in the literature. The final aim is to prepare the inputs for the classification of the capacities at the third section.

2.1. Capacity types

Within the scope of the S&OP process, supply capabilities exist all over the supply chain processes driven by the planning process, this means according to the SCOR model (Huan et al., 2004): source, make and deliver. Consequently, the presence of these capacities impacts the decision making at procurement, production and distribution levels. Many quantitative optimization models have pointed out the impact of the constrained capacities on the S&OP decision making during the last two decades (Pereira et al., 2020).

As shown in the previous section, the supply capabilities are identified and studied during the S&OP process to verify the feasibility of the sales demand (Grimson and Pyke, 2007; Antonio Márcio Tavares Thomé et al., 2012). Therefore, they could be categorized according to the resources and requirements of each supply chain process. Indeed, the capacities could be associated with the activity they represent.

We have analysed different articles from the literature regarding decision model of S&OP that used the supply capabilities in their designs (Lahloua et al., 2018; Martínez-Costa et al., 2014; Pereira et al., 2020; Antônio Márcio Tavares Thomé et al., 2012). We have identified nine different major capacity types present at different supply chain

levels linked to suppliers, subcontractors, machines, human labour, transportation and warehousing.

The following table 5.1 shows the types of capacities for each supply chain process:

Table 5.1: Capacity classification by type

Supply chain level	Capacity type	Examples
Procurement	Supplier capacity	(Chen-Ritzo et al., 2010; Feng et al., 2008; Antônio Márcio Tavares Thomé et al., 2012; Van Landeghem and Vanmaele, 2002)
	Inbound transport capacity	(Feng et al., 2008; Antônio Márcio Tavares Thomé et al., 2012; Wang et al., 2012)
	Warehousing capacity	(Feng et al., 2008; Wang et al., 2012)
Production	Machine capacity	(Feng et al., 2008; Ponsignon and Mönch, 2014; Antônio Márcio Tavares Thomé et al., 2012; Van Landeghem and Vanmaele, 2002; Wang et al., 2012)
	Human-labour capacity	(Antônio Márcio Tavares Thomé et al., 2012)
	Subcontractor capacity	(Goli et al., 2019; Hahn and Kuhn, 2012; Van Mieghem, 1999)
	Warehousing capacity	(Feng et al., 2008; Laurent Lim et al., 2014; Wang et al., 2012)
Distribution	Outbound transport capacity	(Ahumada and Villalobos, 2011; Feng et al., 2008; Laurent Lim et al., 2014; Antônio Márcio Tavares Thomé et al., 2012)
	Warehousing capacity	(Feng et al., 2008; Laurent Lim et al., 2014; Nemati et al., 2017b; Wang et al., 2012)

The procurement capacities could be defined as the limitations imposed by external suppliers on manufacturing companies' inbound flow of raw materials (Guan and Philpott, 2011) or parts (Zhang et al., 2011). In terms of volume, these capacities could take the form of a minimum or a maximum ordering quantity (Chang, 2007). Three types of procurement capacities were identified:

- *Supplier capacity*: it represents the limitation of what could be delivered by the suppliers. For example, the monthly volume of spare parts.
- *Inbound transport capacity:* It refers to the volume of raw materials or parts that could be delivered per period of time. This capacity depends on the type of transportation means (Truck, train, aeroplane, ship, etc.) (Bevrani et al., 2017; Feng et al., 2008).
- *Inbound warehousing capacity:* it refers to the limit of storage capacities at the company's inbound level. For example, the maximum number of stored parts or of the maximum volume of raw materials storage. This capacity could also be represented as the holding costs of procurement (Nemati et al., 2017b).

At the next level comes the production-related capacities which could be defined as a limitation to the final product's production rate and could be defined by four types of capacities:

- *Machines capacity:* they refer to the volume of production that could be delivered by the production equipment.
- *Human labour capacity:* they refer to the production level that could be guaranteed by the available employees. These capacities are especially important in manual assembly industries. Despite being linked to the production process, human labour could be sometimes considered as a procurement capacity since the workers could be external or temporary (Pereira et al., 2020). This capacity level may also vary during the production ramp-up phase (Becker et al., 2017).
- *Subcontracting capacity:* it represents a form of purchased production capacity and refers to subcontracting the production of final products to external companies (Goli et al., 2019; Hahn and Kuhn, 2012; Van Mieghem, 1999).
- *Production warehousing capacity:* similarly to the procurement warehousing capacity, it refers to the storage capacity with the difference of storing final products instead of bought out parts (Nemati et al., 2017a).

Finally, the distribution capacities refer to the limitations on the final product delivery to customers or to final distribution points and define what will could really reach the market. These capacities could be divided into two categories:

- *Outbound transport capacity:* they refer to the capacity of delivering final goods to the customer using one or different transportation mode.
- *Outbound warehousing capacity:* like the production warehousing capacity, these capacities provide storage space closer to the final customers.

One should note that the presence of these different capacity categories is conditioned by different parameters including the type of the industry, the distance between suppliers and customers, the company strategy and economic conditions.

2.2. Capacity criteria

During an S&OP cycle, two types of decision can be made to balance the demand and the available capacities in case of a mismatch between their levels (Olhager et al., 2001):

- Adjust the supply level to match the sales plan by updating the blocking capacities.
- Adjust the demand level to match the supply capacities by postponing the production of the additional volumes to the following time periods or by cutting them.

The choice of the appropriate decision depends on the flexibility of the capacity to adjustments and on its impact on the demand in case of a shortage. These two notions are linked to different criteria that characterize each type of capacity and might impact the decision of qualifying a capacity as critical in case of shortage.

Supply chain capacity criteria have been mostly treated by quantitative models rather than qualitative ones due to the parametric nature of the capacity management decisions (Sabet et al., 2020). Most of the existing studies model the capacities as a cost or volume function (e.g. Feng et al., 2008; Fu et al., 2020; Gyulai and Monostori, 2017). Sabet et al. (2020) suggested other criteria to be used for the capacity management decision making such as the capacity maximum level or location, the link of the capacity to the product or the processes and finally, political, environmental or financial decisions. While these criteria seem relevant for capacity decision problems,

they fail to provide answers to the question of capacities criticalness classification rose by this paper.

We dedicate this section to present different criteria that characterize the supply chain capacities retrieved from a dispersed body of literature where we classify them in two assessment dimensions: criteria linked to the impact of the capacity shortage on the supply chain and criteria linked to the flexibility of the capacity to change. One should note that a highly critical capacity is characterized by a high impact on the sales demand and weak flexibility toward change while a non-critical capacity has a small impact on the sales demand and is highly flexible to change.

2.2.1. *Capacity impact*

We define the impact as the gravity of the consequences of a capacity shortage on the adherence to the demand plan. We propose a combination of two criteria to define this dimension: the relative level and the demand change durability. It is worth noting that the higher the impact on the sales demand is the more critical the capacity subject to constraint is.

Relative level:

The capacity level represents the limitation of a specific resource for a specific period of time (Goldratt, 1988). For example, the Theory Of Constraints (TOC) developed by (Goldratt and Cox, 1984) is one example of methodologies that rely only on the throughput metric (i.e. level) to classify the capacities by their order of appearance as bottlenecks. The level criterion is present in most of the existing models (e.g. Feng et al., 2008; Lim et al., 2017; Sabet et al., 2020; Wang et al., 2012).

While this metric is important, it is not enough for capacity assessment in a context of MC where many product variants are provided but only a few of them have important volume ratios compared to the total demand (ElMaraghy et al., 2013; Laurent Lim, 2014). In such a case, the capacity level criterion does not provide valuable information on the relative impact of shortage regarding that capacity on the whole sales demand.

Therefore, we define the relative level as the measurement of the demand ratio subject to a capacity. The relative level criterion relies on both the capacity level and the total volume of the sales demand for a specific product and period. For example, 100 cars/day is the production level for *assembly line 1* while 200 cars/day is the total requested sales demand. Therefore, the ass*embly line 1* capacity could impact half of the total demand if not fulfilled. Other capacities could be dedicated to specific product

varieties and thus impact a small portion of the total demand if compromised. For example, sunroof assembly station capacity is only dedicated to cars that will be equipped with a sunroof. The relative level criterion was used to assess the supply capabilities for the S&OP aggregation level selection model developed in (Ghrab et al., 2021)

Demand change durability:

The demand change durability criterion refers to the length of the change in the capacity associated demand. The demand increase or decrease could be temporary or permanent (Gyulai and Monostori, 2017; Olhager et al., 2001). Therefore, the decision of changing the capacity level is more impactful in the case of a permanent demand change compared to the case of a temporary demand spike.

One important example could be derived from the automotive industry which recently witnessed an important change in the demand regarding the energy mix motivated by new regulation of emission (CAFE and ban of diesel cars from European capitals (Wang and Miao, 2021)). The regulation penalties pushed toward a long-term increase for electric and hybrid engines demand versus a long-term decrease for diesel and gasoline engines demand.

2.2.2. *Capacity flexibility*

We define the capacity flexibility dimension as the easiness of making a change to the capacity level when it fails to meet the demand (i.e. become constrained). Therefore, a highly flexible capacity could be updated easily (increase or decrease of the level) while a poorly flexible capacity refers to a hard ability to change. As a result, for equivalent impact, a highly flexible capacity is less critical compared to a poorly flexible capacity. The flexibility dimension is defined as a combination of four criteria.

Investment cost:

One of the most used criteria to make a decision regarding the change of the capacity level is the investment cost. There are several contributions concerned with capacity investment problems (Gyulai and Monostori, 2017; Hahn and Kuhn, 2012; Sabet et al., 2020, etc.). Since the demand is subject to a dynamic change, capacities under constraint need to be updated regularly to follow the demand level (Olhager et al., 2001). The update of the demand could either be cheap or expensive which might affect the decision to change. Some constrained capacities do not need additional investment to be levitated however others could be very expensive to update. For

example, adding a new production line needs tremendous investment to be put in place while on the other hand, increasing the procurement capacity by buying more parts from a supplier who has enough capacity could decrease the unitary price of the part and decrease the capacity cost (Ventura et al., 2020).

Change lead-time:

In order to assess the degree of change flexibility, cost measurements are not enough. Some needed capacity investments could be hard to realize if they take a long time to be put in place. Therefore, we define the change lead-time criterion as the time needed for a constrained capacity level to be changed. Like the previous criterion, the lead-time needed for capacity level change is important for investment and strategic capacity management decision (Gyulai and Monostori, 2017; Hahn and Kuhn, 2012; Sabet et al., 2020). For example, building a new assembly line in the automotive industry to increase assembly capacity is a project that needs months to be put in place while recruiting additional subcontracting temporary workers to increase the human labour capacity could be obtained within a fortnight (ElMaraghy et al., 2013).

Rarity:

The rarity criterion is linked to the number of alternative solutions which can replace the constrained capacity subject to a shortage that could endanger the fulfilment of the sales demand. If a constrained capacity is unique and all the demanded quantities pass through it, then its flexibility is low compared to the case where the demand linked to a constrained capacity could be easily replaced by other alternatives. For example, a unique supplier problem (Chen-Ritzo et al., 2010; Thomas et al., 2008) or a unique production unit (Lim et al., 2017) are examples of rare resources.

Procurement lead-time*:*

The procurement lead-time is a specific characteristic limited to the procurement activity and refers to the time spent by a product between a supplier and a buyer. The lead-time depends on the position of the supplier and on the type of transportation mode (Laurent Lim et al., 2014). In case of shortage, it is harder to change the demand level for distant suppliers (Aiassi et al., 2020).

To sum up, the following table presents some examples of academic contributions discussing the presented criteria.

Table 5.2: Capacity classification by criteria

Dimension	Criterion	Examples
Impact	Relative level	(Feng et al., 2008; Laurent Lim et al., 2014; Sabet et al., 2020; Wang et al., 2012)
	Demand change durability	(Gyulai and Monostori, 2017; Olhager et al., 2001)
Flexibility	Investment cost	(Gyulai and Monostori, 2017; Hahn and Kuhn, 2012; Sabet et al., 2020)
	Change lead-time	(Gyulai and Monostori, 2017; Hahn and Kuhn, 2012; Sabet et al., 2020)
	Rarity	(Chen-Ritzo et al., 2010; Lim et al., 2017; Thomas et al., 2008)
	Procurement lead-time	(Aiassi et al., 2020; Laurent Lim et al., 2014; Wang et al., 2012)

3. A conceptual framework for capacities classification:

This section is intended to develop a conceptual classification model for the supply chain capacities based on the criticalness criteria (i.e., impact and flexibility) identified in the previous section.

The identification and review of the supply capabilities is a critical step for the S&OP process and serves to guarantee a feasible plan and to provide feedback for strategic capacity update (Olhager et al., 2001; Volling et al., 2013).

In general, the S&OP process goes through four major steps (Dittfeld et al., 2020; Honstain, 2007; Lapide, 2004; Wallace and Stahl, 2008). First, a demand review phase consists of preparing and presenting an aggregated sales demand. Second, a supply review phase consists of identifying and presenting the major capacities. Third, a reconciliation phase is conducted to balance the sales and the capacities plans. Finally, an executive S&OP meeting is held to make a decision regarding major balancing conflicts and officialise the final plan. There are other variants of S&OP designs that introduce additional steps. For example, many models start with a product review step

(Bower, 2005). Nevertheless, all the reviewed models included the supply review phase. The following figure illustrates the four process steps.

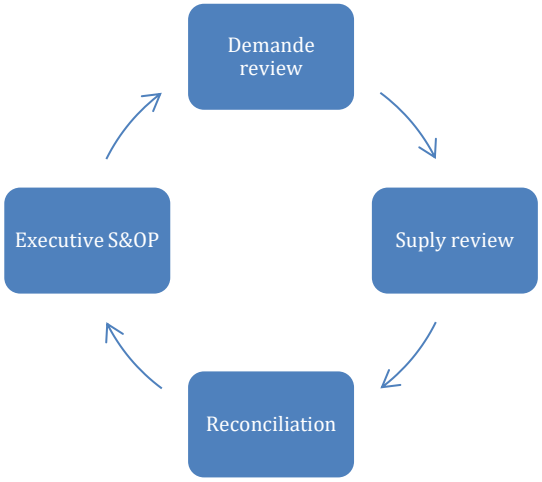


Figure 5.1: S&OP four-step cycle

Within the supply review phase, the resource planning translates the production plan into a resource requirement plan (Olhager et al., 2001). Consequently, many decisions on capacity are taken by opposing the aggregate sales demand to the aggregate capacity plan with the aim to match demand and supply while trying to reduce costs and respect the allocated budget (Sabet et al., 2020).

The capacity decisions depend today mainly on the level and the cost criteria. We try to improve these decisions by using more relevant criteria. Therefore, a capacity assessment model based on the flexibility and the impact of the constrained capacity will be defined in the next section.

3.1. Capacity assessment

The capacity criticalness assessment is a poorly discussed subject in the operations management literature. Except for the theory of constraints (Goldratt and Cox, 1984) and its extensions (de Jesus Pacheco et al., 2020; Tulasi and Rao, 2012), there is little if none relevant contributions that deal with the problem of supply chain related capacity assessment and classification.

The TOC received great interest from academics and practitioners in the last three decades (de Jesus Pacheco et al., 2020; Rahman, 1998; Tulasi and Rao, 2012). Representing one of the main theories that contributed to prove the importance of constraints for operations management, the TOC is a management and operations

philosophy that focuses on identifying and leveraging the system constraints. The approach has been effectively applied to manufacturing processes and procedures to improve organizational effectiveness (Blackstone 2001; Draman 1995).

In practice, the TOC thrives to identify bottlenecks and leverage them by order of appearance (Goldratt, 1988). This means that first, a bottleneck will be leveraged, then, a new one will appear and leveraged after the first one, etc. Following such logic, the capacities are ordered only regarding their throughput (i.e. volume) criterion. Besides, this method assumes to explore all the constrained capacities and try to leverage them with no consideration of how difficult the change could be.

In this paper, we don't focus on leveraging the constraints, we rather focus on measuring the criticalness score of the capacities subject to constraints to ensure their integration in the S&OP data aggregation level. The computed scores will be used as an input to the optimization model developed in (Ghrab et al., 2021).

With the scarcity of contributions on the subject in production planning literature, we looked at related fields. One popular criticalness assessment tools is the Failure Mode and Effect Analysis (FMEA) method (Liu et al., 2019). FMEA is a practical risk assessment tool that relies on the expert judgement to give an idea on the risk level of a system. In order to classify risk sources in priority order, a risk priority number (RPN) is calculated as the multiplication of three dimensions: the occurrence (O), the severity (S) and the detection (D) (i.e. RPN = O x S x D, Liu et al., 2019). The method was first introduced in the 1960s within the aerospace industry and applied to the naval aircraft flight control system (Bowles and Peláez, 1995). Then it was generalized to reach many industries (Liu et al., 2019).

Using the same logic, we design a new capacity criticalness assessment (CCA) model dedicated to the evaluation of the supply capabilities. Our approach considers the demand capacity mismatch as a risk indicator that appears when a capacity becomes a constraint and fails to meet the requested demand. Accordingly, the notion of failure used in the original FMEA will be replaced in our case by the notion of a capacity becoming constrained due to an excessive level of demand. Therefore, we compute a capacity criticalness score (CCS) the same way an RPN is computed for the FMEA method. In other words, we can suppose that the impact (I) could be simulated to the severity (S) score and the flexibility (F) could be considered as the detection score (D).

However, we don't directly evaluate the impact (I) and flexibility (F). We rather evaluate the elementary scores for each criterion linked to I and F where a score is given for

each impact and flexibility criterion, then I and F are computed as the multiplication of these elementary scores. In other words, $I = i_1 \times i_2$ where i_1 is the evaluated score for the criterion *relative level* and i_2 represents the relative score evaluated for the criterion *demand change durability*. The same logic applies to the flexibility dimension where we measure $F = f_1 \times f_2 \times f_3 \times f_4$. Finally, the global CCS will be calculated as the multiplication of scores attributed to each dimension (CSS = I x F). The following table identifies the analogy used on the FMEA method to design our approach.

Table 5.3: Analogy with the FMEA method

Method	FMEA	CCA
Evaluated risk	Process or tool failure	Capacity becoming constrained
Assessment dimensions	Occurrence	N/A
	Detection	Flexibility
	Severity	Impact
Evaluated score	RPN = O x D x S	$I = i_1 \times i_2$ $F = f_1 \times f_2 \times f_3 \times f_4$ CCS = I x F
Evaluation method	Expert judgment	Expert judgment

In terms of process, a capacity assessment meeting should be included in the S&OP process to evaluate periodically the capacities facing the risk of being constrained and prepare anticipated solution scenarios. During this meeting, the CCS will be calculated using the impact and flexibility dimensions evaluated for each capacity. The frequency of the suggested meeting will depend on the evolution of demand and capacity. Finally, the aggregation level will also be updated accordingly with the CCS as an input associated with each capacity expression if needed.

In order to guarantee enough stability for the aggregation level, the frequency of these meetings must be minimized. Minor changes in the demand shape or capacities availabilities should not trigger a meeting to update the capacities scores or the aggregation level.

Nevertheless, a change of the capacities scores does not necessarily mean a change in the aggregation level composition since the model proposed in (Ghrab et al., 2021)

is sensitive to the relative criticalness rather than an absolute score of each supply capability.

The new proposed S&OP process will be as follows. The green rectangles represent the new arbitrations to include as preparation steps for the usual S&OP meetings.

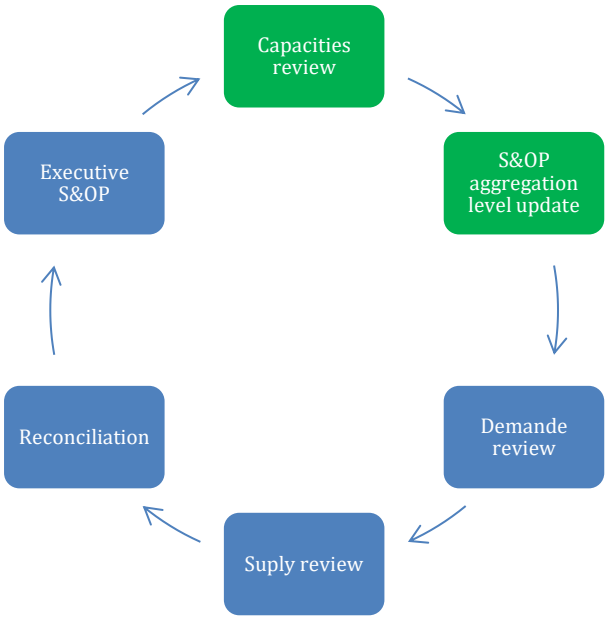


Figure 5.2: Suggested six step new S&OP cycle

3.2. Capacity classification framework

Based on the impact and flexibility scores defined in the previous section, we propose a four-category matrix as a visual tool to help better visualize the differences between the evaluated capacities. To do so, we suggest an evaluation scale based on three levels. More precisely, we consider each criterion i_x (where x $\in$\{1,2\}) or f_x (where x $\in$\{1,2,3,4\}) to be evaluated on three levels: *low(1), medium(2) or high(3).* Accordingly, each criterion takes the values 1, 2 or 3. Thus, $1 \leq I \leq 9$ *and* $1 \leq F \leq 81$. A threshold is set to separate categories for both axes as the median score (5 for the impact axis and 41 for the flexibility axis). The resulting matrix is described in the following figure:

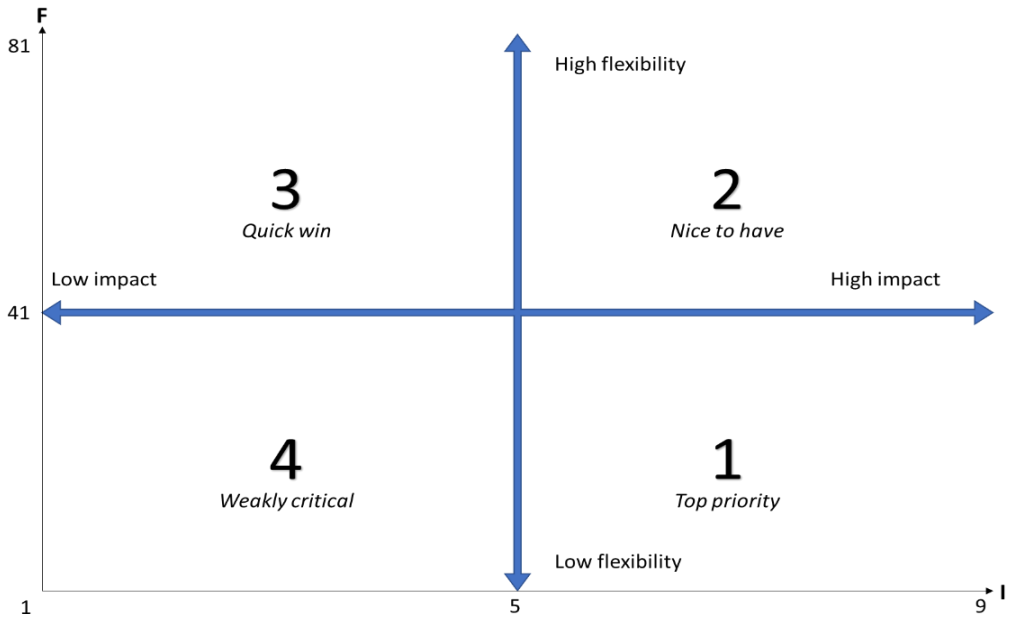


Figure 5.3: Capacity classification matrix

The capacities classified in each of these categories will be subject to a different type of decision:

- The first category represents the capacities characterized with a high impact on the sales demand combined with low flexibility toward change. These capacities are structural resources to the supply chain and are very important to the aggregation level definition due to their impact. Besides, they could not be modified easily in case of shortage. Therefore, they must be monitored closely and integrated into the aggregation level selection level as a *Top priority.*
- The second category concerns supply capabilities that have high flexibility and a high impact. These capacities have a very important impact on demand planning but are easy to change. Therefore, integrating them in the S&OP process aggregation level is a *nice to have* but not mandatory since they can be updated rapidly in case of a demand-supply mismatch. However, they should be updated and monitored at a short-term horizon because they could have a great impact on the S&OP plan quality if they fail to meet the requested demand level.
- The third category is concerned with capacities that have a low impact on the sales demand but benefit from the advantage of being easy to change. Thus, they could be defined as *quick wins* where an improvement could be yielded easily from their change. This type of capacities should be monitored closely to avoid compromising

the production plan in case of shortage. However, including them in the aggregation level selection model does not seem important since they can be updated shortly.

- Finally, the fourth category has opposite characteristics compared to the first category. Hence, it concerns capacities characterized by a weak impact on the sales demand while being hard to update in case of shortage. These capacities could be classified as *weakly critical*. Therefore, they could be discarded from the aggregation level selection model.

The developed matrix provides a simple and easy visualization of each capacity category which could help make a quicker decision making. However, this representation is not static since some capacities could change position on both axes when demand or resources availability changes over time. For example, the demand mix change could favour some specific products on behalf of other alternatives (Chatras et al., 2016a). Consequently, the change of the capacity level to absorb the new demand could result in more impact since its relative level would increase. Besides, one should be aware that the proposed evaluation scale is given as an indication. The real scale and threshold should be defined by the process experts participating in the capacity evaluation meeting the same way for the FMEA method.
In the following section, we provide archetype examples from the automotive industry that discusses some basic types of capacities.

3.3. Archetype examples

In order to give the reader a better understanding of the representation matrix, we prepared the following example inspired by typical cases that we have observed in the automotive industry.

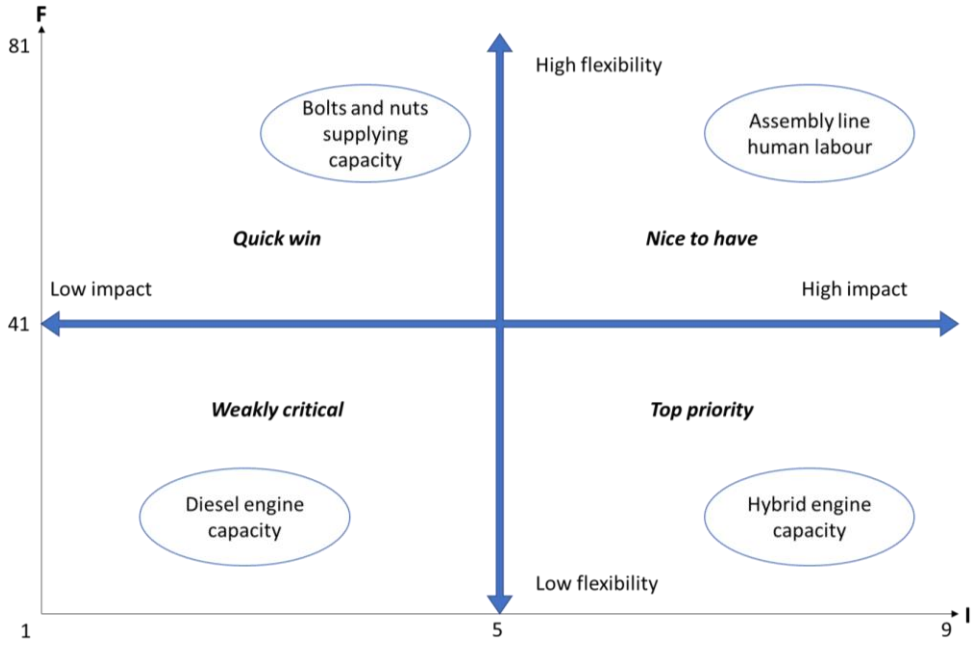


Figure 5.4: An automotive industry capacity classification example

- Hybrid engine capacity versus diesel engine capacity: these two examples illustrate the impact of the permanent change of the demand. As explained in section 2.2, the environmental CAFE policy has created a permanent change in engines demand mix by decreasing the sales of diesel engine cars while increasing sales for hybrid and electric engine cars. Besides, engines are present in each sold car, therefore their relative level is high. Consequently, we can establish that hybrid engines have a high impact while diesel engines have a low impact. On the other hand, the engines capacities are usually expensive production lines which require a good amount of time to be changed, and they are produced in-house which increases their rarity. Therefore, both engines capacities are considered as weakly flexible.
- The bolts and nuts capacity is a good example of high flexibility relatively low impact capacities. Indeed, despite being in every car, standard bolts and nuts associated demand does not change rapidly compared to other less frequent and less standard components. Therefore, they could be easily anticipated which position them as exerting relatively low impact on the sales demand. Contrarily, the bolt and nuts capacity is highly flexible since these parts are usually standard which makes buying them more capacity not expensive, easy to obtain in a short time, provided by many suppliers.

- Assembly line human labour capacity: this capacity is considered as relatively flexible and highly impactful in the case of a long-term demand change. Indeed, regarding the capacity impact in case of shortage, the assembly line is the main resource used to assemble all the cars of the specific model and usually is the only one, therefore its relative level is high. As a result, it could be very impactful. From a flexibility perspective, all the criteria associated to the assembly line human labour are manageable: the capacity could be changed in a relatively fast manner, does not require a high cost or a high obtention lead-time and could be easily obtained from dedicated recruitment companies.

These cases are in no manner an exhaustive representation of the different possible situations but rather a simple illustration of the classification tool. More interesting cases could be found in examples applied to other capacity types of industry sectors.

4. Conclusion

Capacity management represents an important challenge for flexible supply chain planning. It helps to achieve better plans and provide more realistic feasibility answers to the sales demand. Motivated by the lack of capacity assessment methods, this paper has the ambition to assess the criticalness of available supply capabilities using the different types and criteria qualifying the criticalness of a capacity shortage. These criteria were used to provide a new capacity classification method.

The proposed model provides a capacity criticalness score measure and suggests four categories to classify the supply capabilities based on two dimensions: impact and flexibility. Each dimension is defined through a combination of three criteria identified in the S&OP decision-related academic literature where each criterion characterizes a capacity or its associated demand level. In terms of process, the developed method introduces a new step to the S&OP cycle that, in the way of the FMEA meetings, uses the expert judgement to identify a score for each criterion and compute a global capacity criticalness score based on both dimensions scores.

On the other hand, a visualization matrix is proposed to better position each capacity according to the scores of the two dimensions. The visual classification could be useful to prioritize in a different manner the capacities to include in the S&OP aggregation level selection model (Ghrab et al., 2021). Besides, it could be used to provide

feedback to investment strategy teams in order to better define the short, mid and long-term capacity investment strategies. Indeed, while initially developed to evaluate the criticalness of capacities for the S&OP aggregation level choice, the CCA model could be useful for the capacity management literature and capacity investment prioritizing decisions since it provides a quantitative score measuring the flexibility of a capacity to be updated in case of shortage.

One should note that the provided model is at a conceptual level and constitutes our first attempt to assess the criticalness of a capacity using multiple criteria. Thus, we identified interesting improvement areas for future research.

First, a next challenge could concern the use of more accurate evaluation techniques to measure each criterion criticalness score and counter the drawbacks of the highly subjective FMEA expert judgement (Liu et al., 2019). Also, the developed method measures the criticalness of each capacity individually without considering the combined effect of multiple shortages on multiple capacities. Such an effect could be far more important than a sequential criticalness assessment.

Second, the study could benefit from sophisticated multi-criteria decision models to compute the flexibility and the impact dimensions' scores instead of using a simple formula based on the multiplication of each criterion score.

Finally, a real-world case study could help provide finer feedback on the quality of the framework and provide more relevant improvement tracks.

Chapter 6: General conclusion

Planning is a multi-level-multi-actor major supply chain process. It represents a mandatory practice for companies operating in volatile markets and complex globalized supply chains. The process helps manufacturers define a clear roadmap to organize their supply chain major operations and to reduce the delivery lead-time of their products by anticipating the demand.

On the other hand, despite the complexity it drives, MC has emerged as a popular production paradigm that regroups the cost benefits of mass production and the commercial advantages of high product variety. Consequently, MC gained great success among manufacturers and became the reference production model for many pioneering industries.

While the two concepts are popular in many industry sectors and received a lot of interest from both practitioners and academia, they were often discussed separately despite the strong relationship between them. Indeed, MC heavily relies on planning to operate properly in volatile markets and globalized supply chain.

Therefore, our thesis readdresses the joint problem of planning under a MC production system and tries to understand and solve the challenges it could drive.

To do so, we performed a complete case study on a large automotive company struggling with its mid-term planning process heavily impacted by the MC production system. Indeed, global automotive manufacturers are a fitted example for the study. They adopt an aggressive MC production strategy and strongly depend on planning to manage their globalized supply chain operations from procurement to delivery.

We focus on the tactical decision level through the study of Sales and Operations Planning (S&OP) which represents the reference process for mid-term planning. Indeed, S&OP has shown great importance in anticipating major changes of demand and in aligning the company toward a unique shared plan while respecting different economic conditions compatible with the company's strategic objectives. However, despite the important role it plays, the S&OP process has shown a weak performance across industries and failed to fulfil its promises.

This dissertation tries to investigate the failure issues and to provide practical solutions. To meet that challenge, the main body of this dissertation, composed of a general introduction, four research papers and a general conclusion, try to cover several problem aspects.

More precisely, the general introduction presents the frame of the study by listing the motivations and the context, provides a succinct definition for the basic theoretical concepts mobilized for this work, and finally formulates the problem and objectives of the study. The following chapters discuss the problem sequentially and represent two peer-reviewed contributions and two working papers. The first two chapters (chapter 2 and 3) discuss an explorative research phase detailed in two conference papers. The fourth chapter represents an InProgress journal paper and covers two research phases: problematization and design. The fifth chapter represents a new conceptual working paper that aims to reinforce the robustness of the model provided in the fourth chapter by providing a new calculation method for capacity criticalness measures.

From an epistemological perspective, the thesis followed a Research Intervention methodology constituted of three phases to address the planning performance problem and propose convenient solutions. The details of each phase are given hereafter:

Phase 1

The explorative research phase aims to explore the theoretical models of S&OP as well as the practical implementation of the process in the studied company. Therefore, it comprises two steps.

First, a theoretical exploration step consisted of reviewing the academic literature toward the S&OP process. Chapter 2 discusses this first research direction where we try to answer the following research question: "*Why do the existing S&OP models fail to deliver good performance in mass customisation environments?"*

We addressed the planning problem by reviewing the existing S&OP models and their performance. In this first exploratory approach, we tried to investigate the reasons behind the observed weak performance of the S&OP practices in a context of diversified MC. To do so, we derived some theoretical hypothesis to explain the observed negative impact of MC on tactical planning. More precisely, we linked the bad performance to the ambiguous definition of the data aggregation level during the S&OP meetings historically defined as "family level". The conclusions of the first exploration lead to consider the necessity to redefine the S&OP process configuration regarding the data aggregation level.

Second, we conducted an empirical explorative diagnosis of the implemented process using a S&OP process maturity assessment to confirm the observations and hypothesis of the previous step. The development and the results of the maturity assessment were presented and discussed in chapter 3, where we tried to answer the question: "*What is the maturity of the currently implemented process and what are the major pain-points?*"

We performed a literature review of the existing maturity assessment tools where we observed an absence of assessments able to measure the hypothesis derived at the first step discussing the impact of data aggregation level on the performance of the process. Thus, we designed our assessment tool in collaboration with the S&OP teams and we deployed it within the corporate S&OP teams. Finally, we discussed the results obtained for each dimension by business unit to derive a hypothesis regarding the major process pain-points. The assessment of the process maturity on different performance dimensions by different actors confirmed our first observations regarding the weak performance of the S&OP process. The identified pain-points were very

helpful to understand the problem at hand and represented a foundational step to build a relevant problem definition that constituted the aim of the second research phase.

Phase 2

The second research phase benefits from the conclusions of the first explorative research phase and identifies a problem with the sales demand aggregation level.

The investigation of the data aggregation problem in the case of the S&OP process represented the first part of chapter 4 and tried to answer the following question: "*How does the data aggregation affect planning and what are the metrics that serve to measure the quality of an aggregation level?*"

The automotive industry is characterized by its highly diversified catalogues of finished products, which offers the customers millions of configuration possibilities that vary significantly according to time, commercial actions, engineering developments, etc. This internal instability of the product portfolio, generally invisible to the customer, coupled with the volatility of the demand, weighs heavily on the planning process because its consequences are multiple and sometimes difficult to anticipate, strongly impacting the performance of the supply chain. Indeed, since supply capabilities are limited and usually shared by many products, any change in the demand could impact the efficiency of operations. The feasibility of a production plan, therefore, depends on the quality and interpretability of the information transmitted by the sales team and discussed during the S&OP process. The success of the latter, because of its cross-ownership, relies heavily on the data quality and the coordination between the involved actors. Indeed, we demonstrate that the data quality is strongly impacted by the choice of the planning data aggregation level. Good data will thus promote cross-functional alignment through a good consideration of the issues of each stakeholder.

Technically, aggregation corresponds to a logic of grouping finished products into larger sets that can be assimilated to product families. Due to the complexity of the finished products driven by the large number of sub-components, several levels of aggregation exist. Consequently, the choice of the aggregation level is bounded by a fine level (i.e. very detailed level) adapted to industrial needs, and a macroscopic level suitable for accurate forecasts but providing little information. Consequently, macroscopic aggregation levels require multiple unreliable data aggregation-

disaggregation operations to verify the compliance of the supply capabilities with the planning demand.

Thus, the challenge of this thesis is to build an approach that identifies a common data expression based on the choice of the right aggregation level to adopt within the framework of a S&OP process. The provided solution must ensure maximum flexibility to the sales team and allow anticipating the most critical supply capacity issues.

To characterize what a good aggregation level is, we derived three performance properties where two properties are linked to the distinct preferences of each major process actor and aim to guarantee a cross-functional alignment whilst the third property refers to a shared feasibility objective. More specifically, the first property linked to the preferences of the sales team is defined as *sales significance* and supposes that a good level should contain enough sales features to be relevant. Similarly, the second property linked to the preferences of the operations team is defined as *supply significance* and supposes that a good level should be significant from an industrial perspective, which means expressed using features linked to critical supply capabilities. The last property is a common property defined as *compactness* and refers to respecting a maximum planning variety during S&OP. The aggregation compactness property represents a prerequisite at a tactical decision level.

Accordingly, three metrics were derived from the above properties. The first metric referring to the sales team preferences' property measures the number of the non-sales features in an aggregation level. The second metric linked to the operations team preferences' property measures the rate of critical supply capabilities covered by the selected features. Finally, a third shared metric referring to the compactness property was designed to measure the generated variety resulting from a specific aggregation level.

The problem definition phase revealed a more general problem linked to the need to coordinate between different actors that deal with data at different aggregation levels. In such a recurrent situation, identifying a common data expression is usually made arbitrarily satisfying the preferences of one actor at the expense of the others. A solution for the identified problem was provided in the third phase.

Phase 3

The last research phase consists of designing and testing a new model to solve the problem formulated in phase two based on the issues identified in phase one. To do so, we use the metrics and inputs defined at phase two to populate the model and identify the most suitable configuration of the aggregation level that satisfies the different properties identified in the previous phase.

The last research question discussed by this phase was formulated as follows: "*What is the best aggregation level that improves the performance of the S&OP process in a mass customisation context?*"

In this final phase, we tried to identify the best set of features that constitute the planning aggregation level using a model designed as a multi-objective optimisation program. The model uses a list of sales features and a prioritised list of critical supply capabilities as inputs to the optimisation. Then, it tries to select a group of features that on one hand, satisfies the sales significance property by minimising the number of non-sales features while on the other hand, pushes toward a selection that increases the supply significance property by maximizing the rate of covered critical supply capabilities. The selection of features is performed under the constraint of compactness which guarantees an upper bound of features' planning variety.

The execution of the model on different data instances representing different car models shows that the current choices are not well defined. Worse, the current choices generate useless variety compared to an alternative solution with equivalent performance regarding the first two properties. In terms of organisation, the analysis of the obtained results shows that the current choices favour one actor on behalf of the other. Such a situation could threaten the alignment between the process actors. The provided model suggests alternative solutions with better performance and enough stability compared to the original selection.

An attempt to improve the inputs of the model is presented in the last contribution where an improved calculation method of the supply capabilities criticalness scores is suggested based on multiple criteria derived from a planning perspective.

6.1. Contributions

The conducted study was fruitful and delivered multiple contributions relevant to both academic and practitioner communities.

The observations and investigations of the studied process shed the light on the rarely discussed planning aggregation level, a concept that holds multiple challenges for planning in the context of MC. A general problem linked to the aggregation level conflicts was exposed when data is expressed at different levels for different actors working together. These conflicts of data aggregation levels coupled with the existence of multiple actors holding different objectives is a widely present issue. Our dissertation has focused mainly on the case of an S&OP process subject to a mass customisation production paradigm. The obtained solution is the result of multiple research phases detailed hereafter.

The first contribution showed that the S&OP needs to be revisited for the weak performance it delivers and identified a gap regarding the problem of aggregation level definition in the context of mass customisation.

The second contribution identified alignment issues between different stakeholders driven by data quality issues. The results showed a process design that satisfies one actor on behalf of the others. Additionally, the study highlighted the absence of context-related assessment grids that could be very useful in a specific context compared to ‘one-size-fits-all’ generic grids. Therefore, a new S&OP assessment tool was provided. It offered the same advantages as generic assessment tools and added context-specific maturity dimension linked to product variety. Consequently, it could be applied to a wide variety of industries.

The third contribution provided three measurable properties that define the quality of an aggregation level in the context of MC. These metrics were designed to guarantee a good balance between two major involved process actors, to respect a reasonable variety, and above all, to reach a cross-functional alignment, critical for S&OP success. A multi-objective optimization model was developed using these metrics to identify alternative solutions to the currently used aggregation level with respect to the identified properties. The model results showed that the current choices are not the best where a neat improvement of the supply significance property could be observed

when we authorize a small deterioration of the sales significance property. Indeed, some results show that the introduction of one feature not originally used by sales can increase the visibility of supply capabilities by over 30% for some car models. To the best of our knowledge, the proposed mathematical model is the unique approach that selects a planning data aggregation level considering the preferences of the process actors in a context of MC. Most importantly, it has the advantage of transferability to a wide spectrum of problems that deal with complex products and different decision-makers where a choice must be made regarding the expression of data in a way that respects their preferences.

Finally, the fourth contribution provided a good opening for an interesting subject linked to the characterization of the supply capabilities criticalness. The provided model discusses a more relevant calculation method for capacity criticalness inspired from a well-established assessment tool. The paper prepared the terrain for future work on an improved capacity assessment model. Besides the direct use in the aggregation level selection model, the developed framework could be extended to help making better capacity investment decisions.

6.2. Limitations and future research directions

In order to improve the current study, we identify the following research limitations which could be turned into interesting future research directions if properly exploited.

On a technical level, the use of simple definitions for some parameters was a major limit to the model. For example, we used a simple binary parameter to identify sales features with no reference to their relative importance. In the same way, a simple formula was used to compute the criticalness score of the supply capabilities. These two important inputs could yield better model results by using more sophisticated mathematical techniques. For example, the sales significance metric could use a specific score for each sales feature regarding its importance to the sales team or the customer rather than a simple binary score. On the other hand, the supply capabilities criticalness score could be improved according to the new calculation method introduced in chapter 5 not yet implemented in the model. In terms of stability, the model could use additional criteria to guarantee the stability of the choices over time.

From an organizational perspective, since neither the outcomes nor the consistency of the approach was known prior to the study, we chose to focus only on two major process actors for an easier representation and interpretation of the results. The study could be extended by integrating more actors and defining a more exhaustive list of metrics that take into account the preferences of more players. Typically, alongside the active S&OP process actors, we can integrate an uncommon player. The legislators could be added to the study as an external impacting player with their game-changing regulations. For example, we believe that the corporate average fuel economy standard (CAFE) regulations are a good example. Indeed, the CAFE metric focuses on the average emissions amount of the sold products. If a certain threshold is reached, a penalty is paid for each additional unit. This average could be managed by defining a mix that favours the sales of low emission products which in our case could be defined using specific features (for example, type of energy, engine, etc.). Therefore, considering the legislator as a major player in the S&OP process could be very beneficial to comply with the regulations and avoid additional costs.

Also, in terms of organization, further work could focus on the practical implementation of the developed model which was not discussed in this dissertation. In particular, the owner and the frequency of the aggregation level update task should be defined, tested, and validated using real data.

Finally, another interesting research direction that we have explored consists of focussing on the procurement activity by considering the criticalness of the bought-out parts as an input for the problem. In this approach, we try to identify the set of features that maximizes the coverage of critical parts the same way we did with the critical supply capabilities. Indeed, since the parts use the same product definition system used for the demand expression or for the supply capabilities (i.e. features and attributes), we can add a new objective of critical parts coverage using the same model. By doing so, the maximization of the critical parts coverage could provide more visibility on critical parts, like for example distant ones. Although the idea seems to be simple, a prior task of defining the criticalness of the parts should be performed. Besides, we observed that the expression of the parts using the same functional definition is not always reliable since the same part could be expressed in different manners which could require the first task for complex parts' data wrangling.

To sum up, we feel that this thesis has reached its major initial objectives. First, by contributing to the scientific literature toward planning and MC and showing the importance of the choice of data aggregation level in the context of MC. Second, by developing and testing a robust decision support tool to help decision makers get relevant answers regarding the current choices and explore alternative solutions for a better organizational alignment.

Appendix

Appendix 1.1: Original thesis proposition

FICHE DE PROPOSITION DE SUJET DE THESE CIFRE

Direction : Direction de la Supply Chain Alliance

Service : Projet R3

Tuteur proposé : P. Becamel / A.Bénichou Tél : 44330 /44988

TITRE : Demand Driven Supply Chain ; segmentation produit et gestion opérationnelle différenciée

1- Thème de recherche (dans les grandes lignes ; si vous le souhaitez, vous pouvez joindre une explication complète en annexe)

La supply chain de Renault gère une complexité croissante de véhicules et de pièces sur un périmètre géographique toujours plus large. Elle se dote actuellement d'outils qui lui permettront prochainement d'être plus connectée et d'avoir des données plus exhaustives (aux niveaux opérationnels, tactiques et stratégiques).

L'enjeu de cette thèse est de définir les modèles de décision pour maximiser la satisfaction client et la création de valeur en segmentant les produits et en appliquant des stratégies

supply chain différenciées : équilibres « Built to stock/ built to order » ; stocks de flexibilité intermédiaires ; délais clients différenciés ; voire pénuries ponctuelles ;….

2- Argumentez l'intérêt du travail de recherche pour l'Entreprise : contribution aux axes R&AE de l'entreprise et target value associée.

Comme de nombreuses entreprises industrielles, Renault monte en puissance sur ses outils supply chain. Ceci concerne notamment le S&OP (sales & operational planning), ainsi que plusieurs projets de digitalisation (TMS, WMS,…). Ces changements vont amener une masse croissante de données et permettre une gestion plus fine de la supply chain.

Dans un environnement toujours plus complexe, nous devons définir, modéliser & prioriser :

- Les critères de segmentation produits,
- Les stratégies opérationnelles de la supply chain,

Ces solutions sont critiques pour

- Etre au meilleur niveau de Satisfaction délai client
- Garantir les Stocks et le coût logistique minimal

3- Description des missions

- Etude et benchmark du contexte : industrie automobile et activités comparables
- Identification et quantification des leviers de l'analyse : lead-time, stock, coûts,
- Liste de réponses stratégiques : délais, stock, capacités, contraintes, pénurie
- Modélisation et étude de stratégies d'optimisation multi-critères,
- Organisation opérationnelle.

4- Compétences requises du futur thésard

- ***Connaissances spécifiques*** :

- Modélisation, Simulation, Optimisation mathématique
- Data analytics
- Planification et ordonnancement de production

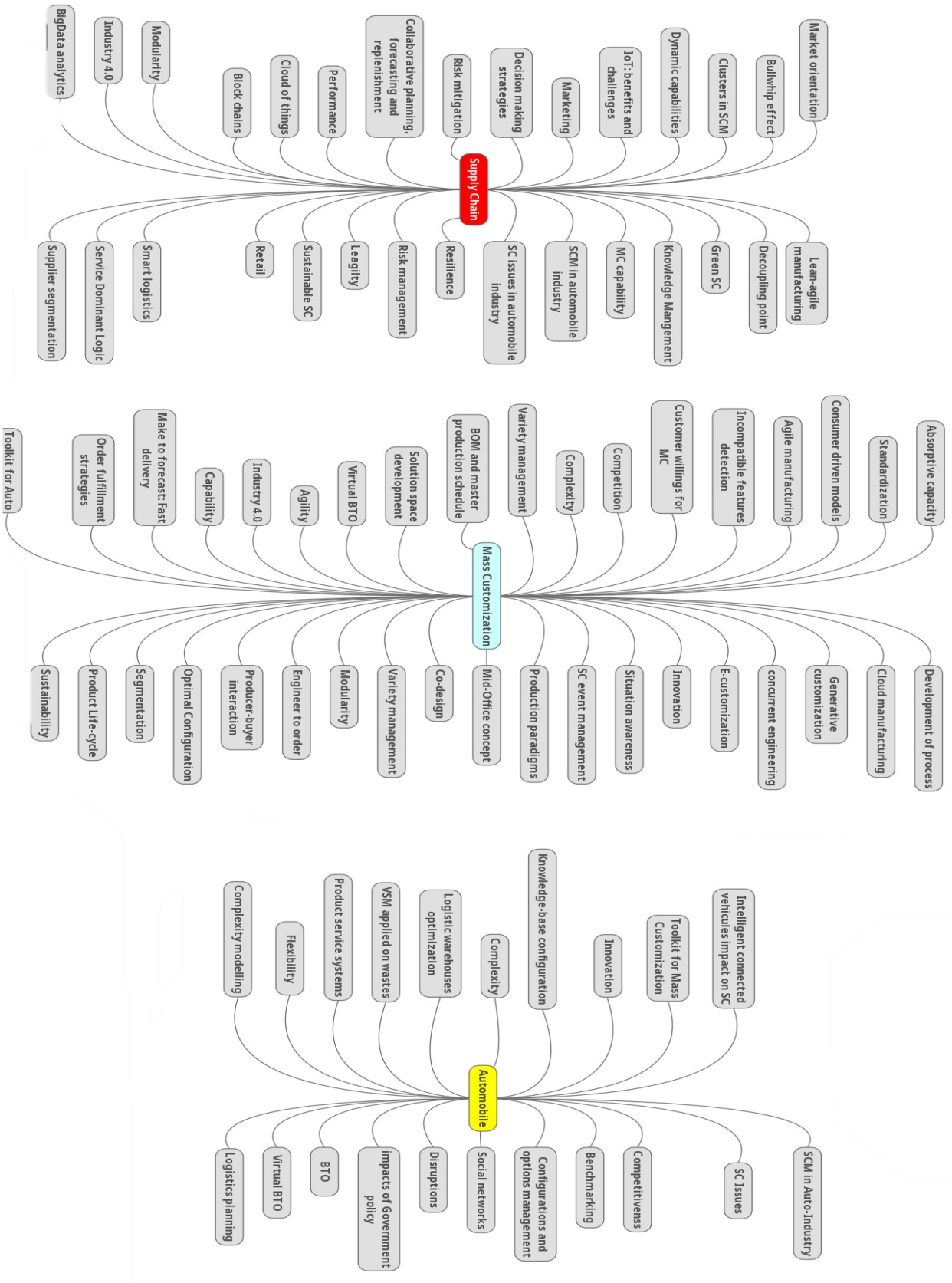
➢ ***Formation souhaitée*** :

- Ingénieur généraliste, Option Génie Industriel ou Supply Chain
- Master Recherche en Supply Chain, Génie Industriel ou Recherche Opérationnelle

➢ ***Aptitudes personnelles souhaitées*** :

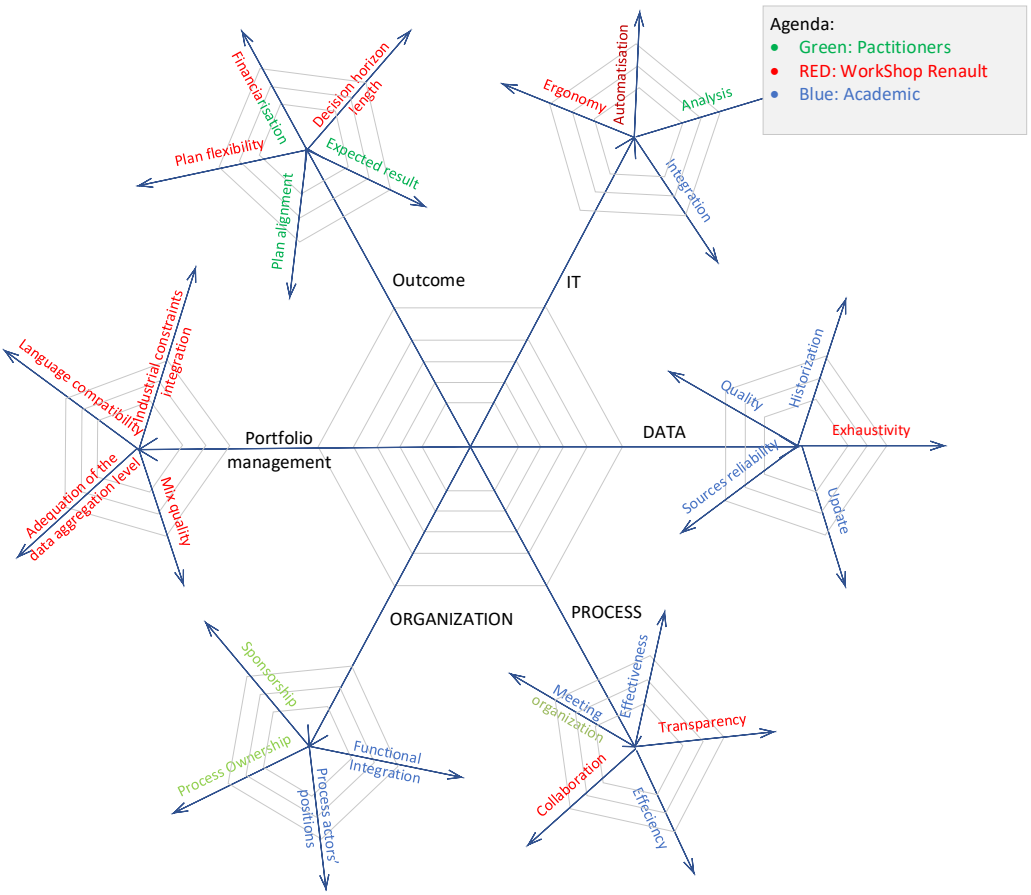
- Dynamique
- Rigoureux
- Autonome et transversal
- Capacité à travailler dans un environnement multi-culturel
- Attrait pour la supply chain et le monde industriel
- Anglais courant

Appendix 2.1: Mind map of the literature review



Appendix 3.1: New kit grid

	Sub-dimension	References
Outcome	Expected result	(Cecere, 2012; Kohler et al., 2016)
	Plan alignment	(Kohler et al., 2016; Lapide, 2005)
	Financiarisation	(Kohler et al., 2016)
Process	Meetings organization	(Grimson and Pyke, 2007; Lapide, 2005)
	Effectiveness/Efficency	(Wagner et al., 2014)
Organization	Functional integration	(Grimson and Pyke, 2007; Wagner et al., 2014)
	Process actors' position	(Pedroso et al., 2017; Wing and Perry, 2001)
	Sponsorship/Ownership	(Kohler et al., 2016)
DATA	Quality/Reliability	(Hulthén et al., 2016b)
	Update/historization	(Vereecke et al., 2018)
IT	Analysis	(Kohler et al., 2016)
	Automatisation	(Danese et al., 2018)
	Integration	(Lapide, 2005; Tuomikangas and Kaipia, 2014)



Appendix 3.2: Interview kit

	Outcome	**Process**
Stage 1	The desired result is to avoid shortages. There is no formal S&OP process or shared objective. The plan validated at the end of the S&OP does not harmonize the objectives of Sales and the SC. There is no alignment between the industrial, commercial and financial forecast plans. Manufacturing and sales plans are based on the volume of historical orders per business unit (Country, region). The decisions are taken in firefighting mode to resolve operational short-term supply-demand balance problems.	Lack of a consistent and stable process to steer planning. The S&OP cycle is not clearly defined; meetings are held on an ad-hoc basis. The process only integrates the first order actors of the S&OP (Production, Stock, Sales) S&OP is interpreted as follows: S corresponds to sales and OP corresponds to the capabilities of the SC.
Stage 2	The result is a volume-based operational plan using sales forecasts and limited industrial / supply capacities. No financial figures taken into account to guide the choices of manufacturing and sales plan. The objectives of S&OP are expressed by taking into account demand forecasts and / or the industrial capacities. The decisions are taken to mainly deal with short-term operational problems (1- 3 months), majorly in firefighting mode, they also extend to cover major events in the medium term (4-12 months).	A coherent process which integrates the major players in the S&OP cycle is implemented and is respected by the participating players. The heaviness of the process and the desynchronization of the actors imposes a time difference between the established plans. The process put in place does not provide enough transparency, which affects trust between the process actors. The collaboration concerns the internal actors of the SC but remains limited. The participation of other external stakeholders in the SC, in particular finance and costt controlling, is very limited. S&OP is interpreted as follows: S corresponds to the sales plans and OP corresponds to the supply plans.

Stage 3	The result of the S&OP is a monetized plan which respects the constraints while trying to satisfy demand as much as possible. The emphasis is this time on the monetization of the plans and the integration of financial indicators. The main focus is on the medium term, but a few decisions are made to manage the short term.	The process is established to involve all the major players in the S&OP cycle. The process is streamlined with the strengthening of transparency and the synchronization of actors. The collaboration is widening and is mainly internal to the company, with Ad-Hoc points with suppliers. S & OP is interpreted as follows: S = sales and marketing plans, with input from the supply chain group, and OP represents the integrated supply chain capabilities for planning, supply, manufacturing and delivery.
Stage 4	The expected result is to make financial decisions that integrate risks and opportuinities. As the plans are monetized, attention is focused on capacity flexibility and the volatility of demand in order to make investment decisions. The benefits of S&OP are more quantitative, such as higher customer satisfaction and greater market share. S&OP's decisions cover the medium-term planning horizon, beyond the current quarter.	The process is described as fluid, synchronous, global and transparent. The established process allows a total synchronization of the S&OP cycle to reach a final response at the end of the month. Suppliers' flexibility is reinforced by the availability of financial resources for a profitable response. The Sales & Operations Execution (S&OE) function emerges with weekly or bi-weekly meetings to ensure alignment with the tactical plan generated during monthly S & OP meetings and to make short-term corrective compromises. S & OP is interpreted as follows: S reflects sales and marketing, and the OP reflects the extended capabilities of the supply chain for a profitable response.
Stage 5	Decision making is coordinated across the business and the network to create value throughout the planning horizon. Emphasis is placed on long-term strategic plans for Business and Supply Chain. The benefits of S&OP are more strategic, such as supporting the company's growth plans. Other benefits include higher percentages of	The S&OP process is oriented to guarantee profitability and growth, and is based on all the actors of the company. S&OP has evolved into a fully integrated business planning tool, intended to facilitate decision-making in all functions and horizons. The collaboration is evolving towards more

	successful product marketing, improved launch and faster time to market. The result of the cycle allows decisions to be made on the medium to long term.	strategic relationships with partners in order to create global value. S & OP is interpreted as follows: S reflects network strategies and solutions aimed at creating new value. OP reflects the network strategies orchestrated to create demand.

	Organization	**DATA**
Stage 1	The main actors involved in the process lack training. S&OP represents a marginal and sequential process not recognized by most of the company's functions. Governance and the pilot are not clearly defined.	The data is generally incomplete. The data are presented on several heterogeneous supports and are difficult to consolidate. The sources of the demand data are inconsistent and unreliable. Sometimes the data collected is not archived.
Stage 2	Process Owners by major player (Sales and SC) S&OP are defined. Exchanges in short loops within the major business families (Sales and SC) are implemented, but rigid inter-business boundaries exist and complicate reconciliation. The representativeness of actors other than SC and Sales is very limited. Sponsorship by top management is in place.	The data collected is relevant, however is not uniform, unreliable and takes time to consolidate. The demand collection channels are stabilized, additional information on risks / opportunities is presented but not fully exploited. Data collection is weakly automated. Data archiving is in place.
Stage 3	Collaboration and transparency are reinforced by effective short loop exchanges. Broadening of the circle of S&OP actors to integrate finance and cost control. The role of the 'Global S&OP process owner' which guides the adoption of S&OP is created. Shared KPIs are in place, but we often have problems with shared responsibilities. There is still some vagueness about the limits of each function and its responsibilities.	The sources of demand data are well defined, consistent and the collection is often complete. The data is not exhaustive to answer all questions concerning the request. The history is maintained and updated systematically at each new planning cycle. The demand signals are demand forecasts with Risks and Opportunities translated into industrial flexibility.
Stage 4	The organization satisfies internal players and is structured to allow very close collaboration. Shared KPIs are implemented and respected.	The data is qualified as relevant, exhaustive and complete. The data is enriched by external sources and partners to build a complete picture. Demand sensing capabilities are improved

	Most of the tensions over ownership and responsibility have disappeared. The intervention preimeter for each function is well established.	through collaboration with customers. Risk and Opportuinities are controlled, reliable, predictable in advance and efficiently exploited.
Stage 5	The organization satisfies the major players and guarantees an overall performance of the process with regard to the strategic challenges of the company. The position of each actor is very well defined. S&OP sponsorship is provided at the highest level of management by a CEO or a COO.	The collection of demand data is automated and AI techniques are used to suggest corrections. The data is automatically ingested and saved on the servers. The data sources are reliable and controlled.

	Product Potfolio Management	**Information Technology**
Stage 1	Lack of consensus on programming items. The S&OP cycle strives to balance demand and supply expressed in two different languages.	Almost no IT tool to support S&OP planning. We rely on manually filled Excel files. The calculations are performed manually with no control tools .
Stage 2	Two languages to define a product still exist, but we manage to find a perfect translation for the passage from one language to another. Each actor (S or OP) has their own level of aggregation and arbitrary conjectures are always necessary when developing the plan. Many references are proposed but never produced.	Planning tools appear and are connected to the company's Legacy tools. Data collection is automated by interconnected systems. The role of IT tools is limited to consolidating data and sometimes extends to checking their accuracy. We rely a lot on Excel for the balancing of demand and supply and a hypothetical analysis (what-if) limited to volumes, without financial quantification. Lack of BI tools to support analysis.
Stage 3	The S&OP players are aligned on a level of aggregation by consensus that is suitable for the stakeholders. The level of aggregation is frozen over time and is not regularly updated. The analysis of the product offer is improved, most of the references proposed are considered in the planning. Reliable history-based conjectures are made in order to complete the request.	We rely more on IT tools to assist in the construction of monetized and achievable scenarios. Excel remains the system of choice for hypothesis analysis (what-if). Technology translates volume plans into revenue plans. The technology enables better BI analysis and generates KPIs along the value chain.

Stage 4	The S&OP players are aligned on a level of aggregation that makes it possible to cover most of the internal capacity constraints. The level of aggregation chosen ensures a good compromise between costs, system constraints and representativeness of demand. Fine historical and statistical analyzes are carried out to define the right product portfolio. The level of aggregation is frozen over time and is not regularly updated. The extrapolation of demand is made jointly by Sales and Operations teams in order to produce a complete demand which translates into very clear supplier needs.	The tools deployed make it possible to automatically establish achievable scenarios taking into account the limits of flexibility. The tools designed make it possible to improve transparency and collaboration between S&OP stakeholders. Extensive BI analysis are implemented to assist stakeholders in their decision-making. The IT functions developed translate the volume plans into income and profit forecasts. Demand forecasting is significantly improved with AI techniques. The technology supports the declination of S&OP tactical plans into operational plans.
Stage 5	The diversity resulting from the S&OP process is representative of the composition and variety of actual demand. The choice of the level of aggregation is the result of an arbitration offering the best profitability and which takes into account internal and external capacity constraints. A perfect command of the language of each BU is guaranteed.	The technology supports the modeling of scenarios over different time horizons. Business Intelligence tools measure current performance and predict future performance. The technology provides a more dynamic S&OP process, including rapid monitoring and rescheduling in case of an impredictable event. The technology supports demand change scenarios and assesses their impact on business objectives. Technology enables consistent alignment between operational decisions and strategic objectives.

Appendix 4.1: Linearization of MC5

The original product variety constraint is formulated as follows:

$$\prod_{j|A_j=1} n_j \leq MaxVar \qquad (1)$$

Because $A_j \epsilon \{0,1\}$, (1) can be written as follows:

$$\prod_{j=1}^{N} 1 - A_j + n_j \times A_j \leq MaxVar \qquad (2)$$

The base e logarithm is applied on both sides of (2):

$$\sum_{j=1}^{N} \log\left(1 - A_j + n_j \times A_j\right) \leq \log(MaxVar) \qquad (3)$$

Because $A_j \epsilon \{0,1\}$, we have the following:

$$\begin{cases} when\ A_j = 0 \Rightarrow log\left(1 - A_j + n_j \times A_j\right) = 0 = A_j \times log\left(n_j\right) \\ when\ A_j = 1 \Rightarrow log\left(1 - A_j + n_j \times A_j\right) = log\left(n_j\right) = A_j \times log\left(n_j\right) \end{cases}$$

Thus, (3) is equivalent to the following:

$$\sum_{j=1}^{N} log\ (n_j) \times Y_j \leq log\ (MaxVar) \qquad (MC5)$$

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RÉSUMÉ

La planification des ventes et des opérations, ou S&OP, est un processus tactique largement diffusé dans l'industrie. Il consiste en l'alignement cyclique des principales fonctions de l'entreprise sur un seul et même plan de vente et de fabrication. Ce plan est le résultat d'un consensus permettant de concilier les objectifs commerciaux, exprimés en volumes de ventes par familles de produits, et les capacités à tous les niveaux de la chaîne logistique. Dans un contexte de personnalisation de masse, la grande diversité des produits compromet l'alignement des acteurs en raison du décalage qui peut exister entre la granularité des contraintes capacitaires et celle de la demande. Pour établir une maille de négociation commune aux principaux acteurs impliqués dans le processus S&OP, cette thèse propose une méthodologie, basée sur une approche de modélisation quantitative, permettant d'identifier un niveau d'agrégation adapté à l'expression de la demande et à l'analyses des principales contraintes capacitaires dans un contexte de personnalisation de masse.

MOTS CLÉS

Planification des ventes et des opérations, personnalisation de masse, famille de produits, niveau d'agrégation, alignement inter-fonctionnel

ABSTRACT

Sales and Operations Planning (S&OP) is a popular tactical planning process widely used in the industry. It consists of aligning different business actors on a shared plan expressed at product family level by negotiating a balance between aggregate demand and supply capabilities. In the mass customisation (MC) context, this alignment is threatened by the high variety of the products that extends the gap between the aggregate expressions of demand and capacity leading to unfeasible plans or unnecessary adjustments. To establish a common negotiation ground, this thesis proposes a methodology, based on a quantitative modelling approach, to define an appropriate S&OP data aggregation level to serve as a reference for data expression and supply review in MC context. The proposed solution guarantees better data quality and improves the alignment between the different process actors.

KEYWORDS

Sales and operations planning, mass customisation, product family, aggregation level, cross-functional alignment.