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Abstract: In mass customization production systems, end-products diversity proceeds from the combination of hundreds of alternative components (ACs) involved in the final assembly stage. Since diversity is very important, forecasts cannot be done directly at the end-product level for production planning purposes. Thus, it is generally agreed in a mass customization context that Master Production Schedules (MPSs) have to be defined for each AC rather than each end-product. Nevertheless, some issues may hamper this approach. First, the MPSs have to be consistent with the technical and commercial constraints that prevent some ACs combinations. Second, due to longer lead times resulting from globalization, production planning must accommodate with uncertainty over the frozen horizon. To address these issues in the automotive sector, a new way to represent product through the concept of the Alternative Services (ASs), which refers to the alternative commercial features offered to the customer, has been introduced by some carmakers. This paper proposes a description of this approach and discusses its relevance regarding the issues of the classical production planning process. Some suggestions are proposed to overcome the limitations of the approach based on the ASs.

Keywords: mass customization, planning Bill of Materials, generic Bill of Materials, alternative services, master production schedule, forecast, automotive industry

1. INTRODUCTION

Over the last five decades, many organizations have switched from mass production to mass customization in order to better meet customer expectations. This has resulted in an explosion of end-product diversity that far outstrips the annual production capacity (Pil & Holweg, 2004). The automotive industry is a perfect example of this context since a car results from the combination of thousands of alternative components. According to Anderson & Pine (1997), the automotive industry is one of the few industries that have pushed the envelope further in implementing mass customization. Accordingly, all the examples referred to in our paper are drawn from a simplified but real automotive case study.

End-product diversity is at the origin of production and material requirements planning issues especially for components whose lead time exceeds the frozen horizon. The classical Bill of Material (BOM) explosion mechanism that relies on end-product forecasts provided by the sales department is not manageable in a high diversity context. Indeed, due to the millions of potentially manufacturable products, it is impossible to obtain directly reliable forecasts at end-product level. This paper proposes to describe the approach used in the automotive sector for sales and production planning based on an original representation of product diversity. This approach is discussed and compared to another alternative that deals with demand uncertainty over the frozen horizon.

From a production standpoint, millions of end products may be obtained on an assembly line through the combination of alternative components and a few physical postponement operations (such as painting…). We assume that an alternative component (AC) is a variant chosen from a set of alternative components (SAC) that are used in the same assembly line workstation. Obviously, end products assembled on a given line share many components but those components that are systematic do not impact the end-product variety. For instance, a variety analysis of a Renault assembly line shows that vehicle production involves around 700 systematic components and as many SACs. The 700 SACs account for a total of more than 1,900 ACs.

Because of huge product variety, forecasting is difficult in practice either at end product level or at alternative component level. Thus, the particular context of mass customization has led automakers to devise a new approach for production planning and diversity representation. This solution hinges on functional product description that reflects the customer perception through what we call "alternative services" (ASs) rather than the organic perception directly based on components. In this new perception, a car can be completely defined by the choice of one AS in each different Set of Alternative Services (SASs) just like what customers do through the online configurators. The use of each AC on the assembly line is related to a certain combination of ASs called "predicates". The link between ASs and ACs, which remains needed for operational matters, is done through the predicates. The transition from a functional perception to an organic one is described in (Chatras *et al.*, 2015).

The sales departments can only make their forecasts at this functional level, which is the only one that can be understood by customers. Based on the definition of predicates for each AC, the determination of the list of all the ACs from the list of all the ASs of a car is straightforward within the frozen horizon. Unfortunately, the calculation of AC forecasts from AS forecasts over the frozen horizon is not so easy because of the numerous AS combinations and incompatibilities. In this paper we describe and analyze two possible ways to solve the methodological problem of drawing MPS that arises from the mass customization. Starting from the AS forecasts, the first proposal aims at drawing up MPSs independently for each level 1 item of the BOM (i.e. alternative components level) while the second proposal aims at drawing up MPSs for level 0 items of the BOM (i.e. end product level). The second solution is the current solution adopted by several carmakers to deal with this issue.

In the next section (Section 2), we describe the MPS definition problem within the context of mass customization. Sections 3 and 4 are dedicated to the description and analysis of MPSs construction respectively at the AC and end-product levels. This paper ends with a conclusion (Section 5) that provides some strategic perspectives to overcome the current issues of production planning encountered in the mass customization sectors.

2.THE MPS DEFINITION PROBLEM IN THE CONTEXT OF MASS CUSTOMIZATION

In a mass customization context, defining the MPS for the assembly line requires a prior definition of overall production volume for each period of the planning horizon. Because this type of assembly line is characterized by fixed cycle time, the periodic production volume is directly deducted from overall production time derived from the number of shifts for the period. In order to manage teams and also part supplies, this information must be planed over the planning horizon. We will suppose this to be known for purposes of this paper.

The large diversity obtained by combining ACs from different SACs makes it difficult to define the MPS at the end-product level. This difficulty can be lifted since it is not mandatory to use the finest level of combination (i.e. end product) for procurement planning. Indeed, the diversity induced by some cheap and easily obtainable ACs pertaining to SACs used for postponement (stickers, paintings…) can be ignored in the planning process. Despite the huge remaining end-product diversity, some companies still use an MPS at this level. This solution is discussed under Section 4.

The alternative solution that consists in defining MPSs at the AC level is easy to implement when the information (BOM coefficients and total production volume per period) used for those components is reliable. Each MPS is related to a SAC and defined through the combination of the planning BOM (Stonebraker 1986) and a periodic production volume considered as known. Beyond the frozen horizon, the planning BOM related to a SAC are considered as average usage rates related to each AC. Assuming these BOM coefficients (i.e. average usage rates) are reliable, two MPS calculation approaches beyond the frozen horizon are possible.

- In the first approach, the requirements for a period beyond the frozen horizon are calculated as the total production volume for the period multiplied by the AC BOM coefficients. This calculation is based on the assumption of a certain demand. In order to limit the propagation of disruptions in the upstream part of the supply chain due to demand uncertainty that leads to MPS rolling changes, it is important to dispose of safety stocks for those ACs.
- In the second approach, AC demand beyond the frozen horizon is considered known in probability. The planning BOM coefficients for a SAC are used as a vector of a multinomial distribution in which the number of trials is the total number of cars produced for the period (Camisullis and Giard 2010, Sali and Giard 2015). AC demand in a given period beyond the frozen horizon can be seen as a random variable following a binomial distribution and the safety stock calculation can be done by defining a replenishment level associated with a predetermined shortage risk. In this context, it can be shown that the gross requirements of any component in the BOM are random variables defined as a weighted sum of binomial random variables (Sali and Giard 2015).

The relevance of those two approaches is based on the quality of the planning BOM coefficients' forecasts. When the number of SACs is low and there are no combination constraints between ACs, one can easily define planning BOM coefficients' forecasts from their demand records using for instance the exponential smoothing technique when structural changes in demand are slow. If there are constraints that limit the free combination between ACs, the use of these approaches is possible only if the structural characteristics of demand are stable.

Because of the product diversity and the multiple combinatory constraints between ACs, many companies of the automotive sector propose a new representation of end products through a list of ASs instead of a list of ACs (Chatras *et al*. 2015, Astesana *et al*. 1995). This representation hinges on functional product description that reflects customer perception rather than the classical organic description that reflects the engineering perception. Limited in number, the ASs allow an easier management of the combinatory constraints and thus facilitate the planning process at this level.

To move from a functional to an organic perception, which is essential for scheduling, production planning and procurement purposes, a system of predicates serves to identify a list of compatible ACs from a list of compatible ASs. A predicate is a logical expression associated to an AC that indicates the specific combinations of ASs implying its use (i.e. the AC). The ASs involved in a predicate determine the use of the associated AC. Since it is possible to move from a functional to an organic description of the product through the predicates, let us see how the planning process can be performed at the level of the ASs. The planning BOM method, initially applied at the AC level, can be used at the AS level. In fact, this method is more adapted to SASs since they are fewer than SACs and correspond to a customer and sales standpoint whereas SACs correspond to a physical perception. For production planning and procurement purposes, several scenarios illustrated in table 1 must be distinguished:

- If AC procurement lead time is shorter than the frozen horizon, no MPS needs to be drawn up beyond the frozen horizon. Accordingly, the definition of systematic MPS component is purposeless since it uses known information (i.e.: production volume and planning BOM coefficient).
- If AC procurement lead time is beyond the frozen horizon, an MPS beyond the frozen horizon is required. In that case, two scenarios are possible:
  - AC is determined by a single AS. In this situation, the forecast is straightforward based on the planning BOM of the AS (i.e. the periodic production associated with the average usage rate of the AS within the SAS to which it belongs). The planning BOM of the AC is the same as the planning BOM of the AS.
  - AC is determined by several ASs from different SASs. In this situation, the definition of the AC planning BOM coefficient is a hard problem, even if all the AS planning BOM coefficients have been forecasted. Indeed, the presence of several ASs that belong to different SASs in the logical expression of a predicate is a real issue we address below through a simple example inspired from a real case in the automotive industry.

Table 1 : Typology of problems for defining level 1component MPSs

Lead time	Systematic components	Number of SASs that determine the SAC: 1	Number of SASs that determine the SAC: ≥ 2
≤ Frozen period	Synchronized supply or production possible but not mandatory	Synchronized supply or production prefered	Synchronized supply or production prefered
> Frozen period	Easy supply based only on the forecasts of production volume	Supply based on the planning BOM of the unique SAS	Supply based on a complex replanishement policy that has to be defined

Table 2 highlights how each alternator (i.e. A_1, A_2 and A_3 that constitute a SAC) is defined by a combination of ASs that belong to the motorization and cooling system services. The three predicates associated to the three ACs are given under the table.

Table 2 : Determination of alternators via the motorization and cooling system services

		SAS Motorization (MO)					
		MO_1	MO_2	MO_3	MO_4	MO_5	MO_6
SAS Cooling System (CS)	CS_1	A_1					
	CS_2				A_2		
	CS_3						A_3

$A_1^{-1} = (MO_1 \vee (CS_1 \wedge CS_2)) \vee (MO_2 \wedge CS_1)$
$A_2^{-1} = (MO2 \wedge CS2) \wedge (MO3 \wedge (CS1 \wedge CS2)) \wedge (MO4 \wedge (CS2 \wedge CS3)) \wedge (MO5 \wedge CS2)$
$A_3^{-1} = (MO5 \wedge CS3) \wedge (MO6 \wedge (CS2 \wedge CS3))$

Using a standard probability notation, table 3 describes the calculation of the alternator coefficients based on the motorization and the cooling system services. The calculations using the twelve variables of the table (i.e. colored cells in the table) are given under the table grouped by a hug. As the marginal probabilities P(MO_i) and P(CS_j) are assumed to be known, defining the planning BOM coefficients consists in finding a solution for the following system with 9 equations and 12 variables.

$$\begin{cases} P(CS1) = P(MO1 \wedge CS1) + P(MO1 \wedge CS2) + P(MO3 \wedge CS1) \\ P(CS2) = P(MO2 \wedge CS2) + P(MO3 \wedge CS2) + P(MO4 \wedge CS2) + P(MO5 \wedge CS2) + P(MO6 \wedge CS2) \\ P(CS3) = P(MO4 \wedge CS3) + P(MO5 \wedge CS3) + P(MO6 \wedge CS3) \\ P(MO1) = P(MO1 \wedge CS1) + P(MO1 \wedge CS2) \\ P(MO2) = P(MO2 \wedge CS1) + P(MO2 \wedge CS2) \\ P(MO3) = P(MO3 \wedge CS1) + P(MO3 \wedge CS2) \\ P(MO4) = P(MO4 \wedge CS2) + P(MO4 \wedge CS3) \\ P(MO5) = P(MOE \wedge CS2) + P(MO5 \wedge CS3) \\ P(MO6) = P(MO6 \wedge CS2) + P(MO6 \wedge CS3) \end{cases}$$

Table 3: planning BOM coefficient definition for alternators based on motorization and cooling system services

		SAS Motorization (MO)						
		MO_1	MO_2	MO_3	MO_4	MO_5	MO_6	MO_{Set}
SAS Cooling System (CS)	CS_1	P(MO1∧CS1)	P(MO2∧CS1)	P(MO3∧CS1)				P(CS_1)
	CS_2	P(MO1∧CS2)	P(MO2∧CS2)	P(MO3∧CS2)	P(MO4∧CS2)	P(MO5∧CS2)	P(MO6∧CS2)	P(CS_2)
	CS_3				P(MO4∧CS3)	P(MO5∧CS3)	P(MO6∧CS3)	P(CS_3)
	CS_{Set}	P(MO_1)	P(MO_2)	P(MO_3)	P(MO_4)	P(MO_5)	P(MO_6)	100%

$P(A1) = P(MO1 \wedge CS1) + P(MO1 \wedge CS2) + P(MO2 \wedge CS1)$
$P(A2) = P(MO2 \wedge CS2) + P(MO3 \wedge CS1) + P(MO3 \wedge CS2) + P(MO4 \wedge CS2) + P(MO4 \wedge CS3) + P(MO5 \wedge CS2)$
$P(A3) = P(MO5 \wedge CS3) + P(MO6 \wedge CS2) + P(MO6 \wedge CS3)$

We are therefore faced with an underdetermined system that accepts an infinity of solutions, which doesn't allow the calculation of the alternator planning BOM coefficients. The under-determination is systematic when an AC is determined by two or more ASs belonging to different SASs. In our example, in order to define the alternator MPS beyond the frozen horizon, one needs to add three additional constraints (i.e. three equations to the previous system) or add an optimization function. Both solutions imply a measure of arbitrary decision to solve the problem.

As mentioned above, in a mass customization context the MPS could be defined for components of level 1 in the BOM (i.e. ACs level) (Section 3) or for end products (Section 4). We identified two possible uses of planning BOM coefficients to define an MPS: a deterministic approach and a stochastic one. In the MPS definition for components of level 1, the stochastic approach beyond the frozen horizon is adopted. To our knowledge, this approach is a novelty since it is not yet used by practitioners. In the end product MPS definition, which is the method used by some carmakers, the deterministic approach is adopted.

3. DEFINING MPSs FOR LEVEL 1 OF THE BOM

Table 1 shows that the MPS definition at the level 1 of the BOM is simplified by the setting aside of the systematic components and those whose lead time does not exceed the frozen horizon. Thus, the problem arises for the ACs not included in these two categories.

The probabilistic approach of MPS definition beyond the frozen horizon described in the previous section can be used in the presence of AC BOM coefficient forecasts. Two cases can be distinguished:

- Case 1. AC BOM coefficients are calculated from the ASs which determine them.
- Case 2. AC BOM coefficients are calculated on the basis of their time series without reference to ASs. In this case, it is useless to make forecasts for ASs that determine these ACs.

Case 1 - SAC BOM coefficients calculated from AS coefficients

The first case requires knowing BOM coefficients associated to the ASs that determine the relevant ACs through the predicates. Two possibilities have to be distinguished:

- AC is determined by a single AS. The BOM coefficient forecast for this AC is determined by those of the relevant AS. One may then use the probabilistic approach referred to under Section 2, using an arbitrarily weak risk of stockout, to determine component production launches, required to fully or partly cover random requirements. This approach has been implemented on cases drawn from real situations in the automotive industry (Sali and Giard, 2015). The stochastic approach yielded clearly better results than the deterministic approach based on end-product MPS definition.
- AC is determined by several ASs belonging to different SAS. In this situation, the BOM coefficient forecast problem is more complex as shown at the end of Section 2. As mentioned, one possible solution to calculate the AC BOM coefficients consists in introducing an objective function to optimize under constraints. In the example of table 3, the values of the variables $P_1(MO_j \wedge CS_i)$ can be calculated in order to minimize an indicator that measures a distance between these forecasts and the last values $P_0(MO_j \wedge CS_i)$ historically recorded. This method is illustrated by a numerical example in table 4. The objective function used in this example is $\text{Min}\sum_j \left[P_1(MO_j \wedge CS_i) - P_0(MO_j \wedge CS_i)\right]^2$. The left-hand part of table 4 corresponds to the "historical" table of the AC BOM coefficients (i.e. joint coefficients of combined ASs). The right-hand part provides the forecasted AS BOM coefficients (i.e. marginal distributions of the motorization and cooling system services) and the solution which minimizes the selected criterion, under constraints of respect of the margins (see equations under table 3). Note that this method is used here locally and thus differently from what will be described under Section 4. Indeed, for the definition of AC BOM coefficients within each SAC, only the BOM coefficients of the ASs involved in the relevant predicate are used. The AS BOM coefficients are independently reused as many times as necessary for the different SACs.

Table 4: example of determination of alternator BOM coefficients based on motorization and cooling system services using the minimization criterion

Initial coefficients $P_0(CS_i \wedge MO_j)$

		SAS Motorization (MO)						
		MO_1	MO_2	MO_3	MO_4	MO_5	MO_6	MO_{Set}
SAS Cooling System (CS)	CS_1	0,020	0,080	0,110				0,210
	CS_2	0,070	0,120	0,060	0,050	0,110	0,080	0,490
	CS_3				0,110	0,100	0,090	0,300
	CS_{Set}	0,090	0,200	0,170	0,160	0,210	0,170	1,000

$P(A_1)=0,17$; $P(A_2)=0,56$; $P(A_3)=0,26$

Forecasted coefficients $P_1(CS_i \wedge MO_j)$

SAS Motorization (MO)							
MO_1	MO_2	MO_3	MO_4	MO_5	MO_6	MO_{Set}	
0,02667	0,06667	0,10667				0,200	Forcasted structure of cooling system
0,07333	0,10333	0,05333	0,04333	0,09334	0,08333	0,450	
			0,12667	0,10666	0,11667	0,350	
0,100	0,170	0,160	0,170	0,200	0,200	1,000	
Forecasted structure of motorization							

$P(A_1)=0,1667$; $P(A_2)=0,5267$; $P(A_3)=0,3067$

Case 2 - Calculation of SAC BOM coefficients based on time series

Where ACs are determined by more than two ASs, the above approach becomes unwieldy. The MPS should then be prepared at AC level and the solution consists in performing direct BOM coefficient forecasts on the ACs. Rather than using the last observed BOM coefficients values for a given AC, one may use for instance a simple exponential smoothing technique, well adapted in the case of slow changing demand structures. $\mathrm{P}(\mathrm{AC}_i)$ is thus replaced by $\hat{\mathrm{P}}_{t'>t}(\mathrm{AC}_i) = \alpha \cdot \mathrm{P}_t(\mathrm{AC}_i) + (1-\alpha) \cdot \hat{\mathrm{P}}_{t-1}(\mathrm{AC}_i)$ for the periods beyond *t*. In these calculations, the constraint $\sum_i \hat{\mathrm{P}}_{t'>t}(\mathrm{AC}_i) = 1$ guarantees that the sum of BOM coefficients is equal to 1 within the same SAC. This is guaranteed at the initialization of the calculation process of the exponential smoothing that uses BOM coefficients whose sum must be equal to 1. This condition is fulfilled since the same smoothing coefficient is used for all the ACs of the same SAC. The exponential smoothing technique is adapted to slow demand structure changes and short procurement lead times, failing which, the sales department should adopt a different forecasting technique.

Two complementary remarks can be made. The value of the smoothing coefficient can be adjusted periodically to minimize the forecasting errors. In addition, the use of a linear filter generates oscillations known as the Slutsky-Yule effect, which induce a skew in the forecasts (Kendall, 1976). This skew can be easily neutralized by increasing forecasts by the quantity corresponding to the standard deviation of forecast errors. This avoids undervaluation if the forecast is on the high part of an oscillation (which can be known only latter), at the cost of building excess safety stock in the contrary case. Direct BOM coefficients forecasts using a simple exponential smoothing were subject to a real time three-month benchmark in an automotive assembly plant, on the supply of wiring harnesses which are determined by several ASs. A comparison with the system in place based on the deterministic approach described in section 4, showed a clear superiority of the probabilistic approach based on direct forecasts (Camisullis *et al.,* 2010).

4.DEFINING MPS FOR LEVEL 0 OF THE BOM

Some carmakers (Renault and PSA…) propose a process that gradually transforms the sales information in stages, expressed at SAS level, to draw up an MPS at end-product level. To move from SAS level forecasts to end-product forecast level, the ASs from different SASs are iteratively combined to gradually expand the definition of an object which, ultimately, becomes a finished product. The combination of the ASs representing the different SASs gives rise to successive resolutions of equation systems that are generally under-determined as previously shown. The final result of this iterative process, called "enrichment process" by one of the manufacturers that uses this approach, is a forecast expressed in Completely Defined Vehicles (CDV). Let us briefly examine this iterative process.

At each step of the enrichment process, the resolution of the equation system consists in choosing a particular solution among the infinite number of possible solutions. To select a particular solution, one must define a selection criterion that may be for example, as proposed in the previous section, the minimization of a difference between the forecasts (i.e. decision variables) and the last observed values (i.e. historical values). To pursue the logic of calculating the coefficients at a higher level of AS combination (eg. combination involving three SASs), $\mathrm{MO}_i \wedge \mathrm{CS}_j$ combinations such as $\mathrm{P}(\mathrm{MO}_i \wedge \mathrm{CS}_j) > 0$ are considered as ASs that pertain to a set that can be qualified as a Meta-SAS. This iterative process therefore aims to gradually expand, at each period of the planning horizon, the sales forecasts expressed at the ASs level. Table 5 illustrates the calculation of coefficients associated with combinations of ASs from the SASs Motorization, Cooling system and Commercial Region (prohibited combinations $\mathrm{MO}_i \wedge \mathrm{CL}_j$ are not included in the Meta-SAS combining the Motorization and Cooling system SASs).

The existence of alternative components determined by several SASs involves multiple steps in the enrichment process. The extreme case is that of an AC determined by ASs from all the SASs. In practice, this method leads to forecasts expressed at end-product level (i.e. level 0 of the BOM) excluding postponed components. Without any improvement, the described enrichment process would be difficult to implement in practice. Indeed, at the last stage of enrichment, the number of decision variables reaches the diversity of end products. To work around this problem, ASs are combined into groups of strongly dependent SASs. The notion of interdependency between SASs refers to the existence of technical and/or commercial constraints between ASs belonging to these sets (see Chart 1). Meta-SASs formed from interdependent SASs include combinations of ASs whose coefficients are calculated using the previously illustrated optimization method. By grouping SASs into Meta-SASs, which by construction have more limited dependency between them, it becomes possible to calculate coefficients by combining two by two the elements of the Meta-SASs. The coefficients obtained are then used to generate, for each period of the planning horizon, CDVs that are characterized over all the SASs. The total number of CDVs per period is equal to the total periodic production of the assembly line.

Table 5: Example of BOM coefficient determination for a combination of three ASs belonging respectively to the Motorization, Cooling System and Commercial Region SASs

Initial coefficients

		Meta-SAS (Motorization, Cooling System)												
		CS_1 MO_1 P(CS1∧MO1)	CS_1 MO_2 P(CS1∧MO2)	CS_1 MO_3 P(CS1∧MO3)	CS_2 MO_1 P(CS2∧MO1)	CS_2 MO_2 P(CS2∧MO2)	CS_2 MO_3 P(CS2∧MO3)	CS_2 MO_4 P(CS2∧MO4)	CS_2 MO_5 P(CS2∧MO5)	CS_2 MO_6 P(CS2∧MO6)	CS_3 MO_4 P(CS3∧MO4)	CS_3 MO_5 P(CS3∧MO5)	CS_3 MO_6 P(CS3∧MO6)	$CS \wedge MO_{Set}$
Commercial Region	CR_1	0,020	0,050	0,070	0,090	0,080	0,060	0,010	0,015	0,060	0,070	0,005	0,070	0,600
	CR_2		0,050	0,050		0,040	0,020	0,040	0,080	0,025	0,010	0,080	0,005	0,400
	CR_{Set}	0,020	0,100	0,120	0,090	0,120	0,080	0,050	0,095	0,085	0,080	0,085	0,075	1,000

Forecasted coefficients

		Meta-SAS (Motorization, Cooling System)													
		CS_1 MO_1 P(CS1∧MO1)	CS_1 MO_2 P(CS1∧MO2)	CS_1 MO_3 P(CS1∧MO3)	CS_2 MO_1 P(CS2∧MO1)	CS_2 MO_2 P(CS2∧MO2)	CS_2 MO_3 P(CS2∧MO3)	CS_2 MO_4 P(CS2∧MO4)	CS_2 MO_5 P(CS2∧MO5)	CS_2 MO_6 P(CS2∧MO6)	CS_3 MO_4 P(CS3∧MO4)	CS_3 MO_5 P(CS3∧MO5)	CS_3 MO_6 P(CS3∧MO6)	$CS \wedge MO_{Set}$	
Commercial Region	CR_1	0,027	0,000	0,000	0,073	0,000	0,000	0,000	0,017	0,083	0,127	0,107	0,117	**0,550**	**Forecasted structure of Commercial Region**
	CR_2		0,067	0,107		0,103	0,053	0,043	0,077	0,000	0,000	0,000	0,000	**0,450**	
	CR_{Set}	**0,027**	**0,067**	**0,107**	**0,073**	**0,103**	**0,053**	**0,043**	**0,093**	**0,083**	**0,127**	**0,107**	**0,117**	1,000	
		Forecasted structure of (Climatisation,Motorization)*													

*Forecast coefficients obtained at the last iteration (see. Table 4)

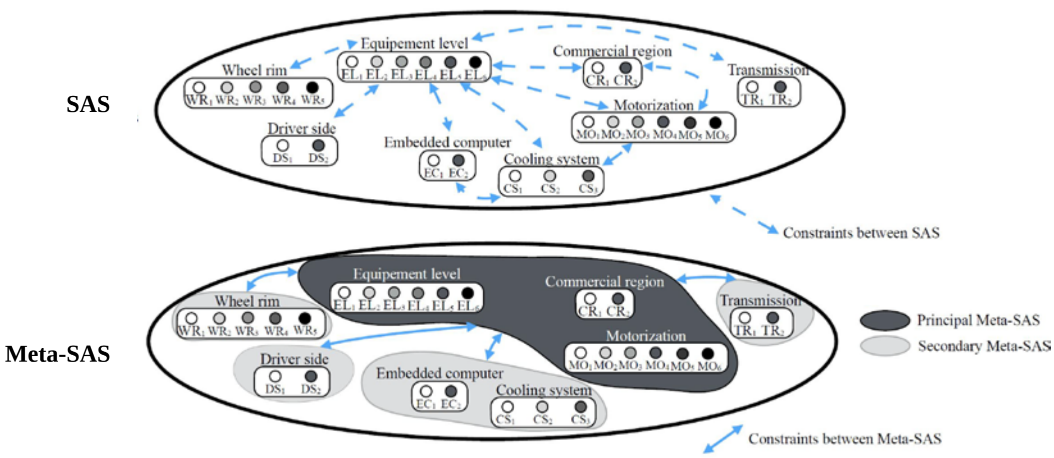
In accordance with the time-driven technical and commercial constraints, a CDV is one of the possible ASs combinations representative of all the SASs. A CDV has no physical existence, but is a reflection of what could be a real finished product assembled at a given time. It may be considered as a virtual product. By construction, a CDV respects the commercial and the technical constraints. This property gives the CDV the same consistency as marketable products. The ACs making up a CDV can thus easily be identified from predicates.

To illustrate how this approach works, take the example of a vehicle that is configurable from the SASs specified in Chart 1 (Commercial Region, Motorization, Equipment level, Transmission, Driver Side, Wheel rim, Cooling System, Embedded Computer). To simplify matters, let's assume a stable commercial offering over the planning period and a production line dedicated to the assembly of the relevant vehicle model.

In the approach described in this section and inspired from the process currently used by several car manufacturers, the sales department expresses its demand in the form of forecasts for each AS for all the SASs. These forecasts are expressed as a percentage of total production per period. The sales forecast enrichment process can be described in four steps. The role of each step is illustrated through the previous example.

The first step in the enrichment process is construction of several Meta-SASs as shown below. It may be noted that in this arbitrary construction, SASs belonging to a Meta-SAS are interdependent and that the Meta-SASs, taken in pairs, are independent except where one of them is that formed from the SASs: Equipment Level, Commercial Region and Motorization. This particular Meta-SAS, called "principal" and highlighted in dark grey in Chart 1, constitutes a base from which sales forecasts will be enriched by combining their elements with those of the secondary Meta-SASs highlighted in light grey in Chart 1.

Chart 1 : Meta-SAS Definition



The second stage of the enrichment process consists in applying the optimization method referred to above (see beginning of the section) to each Meta-SAS in order to calculate coefficients for AS combinations. This yields marginal coefficients related to new synthetic ASs, called Meta-ASs, resulting from the combination of ASs. The coefficients thus obtained for the secondary Meta-ASs from different secondary Meta-SASs are considered as independent probabilities.

The third step also uses the above optimization method to calculate the coefficients associated with the combination of two Meta-ASs, one of which belongs to the principal Meta-SAS.

The fourth and final step of the enrichment process is to build, using the coefficients calculated in the third step, a number of CDVs that correspond to assembly line total production for the period. To this end, the coefficients calculated in the third step are transformed into conditional probabilities (probability of having a CDV with a Meta-AS belonging to a secondary Meta-SAS knowing that this CDV is characterized by a Meta-AS of the principal Meta-SAS). These conditional probabilities are used to generate a random integer number of different CDVs. The total number of generated CDVs must be equal to total assembly line production for the period. The independence of the secondary Meta-SASs serves to characterize independently a CDV for each one of them. The conditional probabilities are updated after each draw (draw without replacement) to reflect the changes in the properties of the population. The products generated and characterized for all SASs correspond to the MPS at level 0 of the BOM. The quantities generated for the MPS are considered as reliable over the non-frozen horizon. It is then possible to calculate AC requirements from these quantities through their predicates.

Because they match the physical features of CDVs, MPS defined at BOM level 0 are comfortable for upstream supply chain management purposes. Indeed, their use for medium-term planning is treated as a mere extension of the short-term schedule. By construction, the use of finished product level MPS guarantees consistent component requisitions in terms of technical and commercial constraints. While finished product level production scheduling is mandatory for the short-term, conducting this exercise beyond the frozen horizon produces the impression of having reliable information for the medium-term.

In practice, the quest for strict consistency through compliance with the technical and commercial constraints, by means of finished product level MPSs has substantial consequences on the performance of the upstream supply chain. The rules inherent in the enrichment process can generate serious disturbances that propagate along the upstream supply chain, generating a bullwhip effect (Childerhouse *et al*., 2008, Niranjan *et al*., 2011).

The detailed analysis of the enrichment process used by Renault, briefly summarized in this section, revealed the existence of this effect (Sali 2012). From AS planning BOM coefficients provided by the sales department, the solution selected by the automaker to generate MPSs at end-product level uses mathematical programming techniques to solve a series of cascading optimization problems for each period of the planning horizon. By propagating errors in each iteration, this solution ultimately produced unreliable forecasts leading to shortages and costly emergency supplies, or overstock that impacted cash flow.

5. CONCLUSION

In the context of mass customization, characterized by multiple combinatory restrictions of the ACs, organizations represent end products through combinations of alternative services that correspond to functional features understandable by both customers and sales departments.

One must rely on SASs to prepare MPSs beyond the frozen horizon since sales department forecasts are based on a functional product description. Switching from AS- to AC-based forecasts is however not straightforward when ACs are determined by several ASs. Two MPS formulation options are available and described in our paper: one, used by several carmakers, boils down to defining MPSs at level-0 of the BOM, the other is based on level-1. Both solutions present advantages and drawbacks, which calls for further analysis and research.

Whatever the preferred solution, both increasing diversity and longer lead times in the supply chain severely impact forecasting reliability beyond the frozen horizon. This induces unwarranted supply chain costs resulting from stockout and associated remedial measures. From a strategic standpoint one should focus on the root cause of both these approaches implemented in the hope of increasing margin often without proper evaluation of their potential impact on supply chain management cost.

In order to improve their planning process sustainably in a context of strong diversity, carmakers have strategic levers on product and upstream supply chain design at their disposal. Streamlining diversity to limit the cases of determination involving a multiplicity of steps requires standardization and modularization measures at the product design stage including ACs. To address technical unfeasibility of perfect modularity involving fully standardized interfaces, the supply chain design lever may be relied on to switch back to local procurement to cut lead times beyond the frozen horizon for the ACs determined by more than one AS.

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