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# Integrating Uncertainty into a Supply Chain Network for Adaptive S&OP Process

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**Abstract.** Instability is the new normal for supply chain networks. In this context, the Adaptive Sales and Operations Planning (AS&OP) process proposed by the Demand-Driven Adaptive-Enterprise model aims to improve the way these supply chain networks manage volatile, uncertain, complex and ambiguous environments. However, the process, as originally defined, relies mainly on a deterministic maximum likelihood approach, thus limiting its scope. The present research work examines existing strategies for integrating uncertainty into the strategic planning and ultimately proposes an original Decision Support System that integrates uncertainty via interval data and scenario-based planning. An illustrative case study validates this proposal and discusses its limitations.

**Keywords:** Adaptive S&OP · Demand-Driven · Uncertainty · Supply chain Network

## 1 Introduction

Market globalization and intensifying competition are driving companies to maximize profitability while better managing uncertainties and contextual variations. In supply Chain networks (SCN), numerous approaches have been developed by practitioners and academics to meet these challenges: Just-in-Time, Theory of Constraints, Lean Management or Manufacturing Resources Planning for instance. The aim of all these approaches is to generate profits while optimizing the use of SCN resources. However, as [1] points out, most of these methods labour to deal effectively with today's growing uncertainties and variabilities. The DDAE method [9] transforms SCN into adaptive, reactive systems, focused on real demand. It is an innovative flow management system presented in [9, 10] which combines the advantages of a push-flow system and a pull-flow system in a single approach. DDAE is based on three management processes: the Demand Driven Requirement Planning (DDMRP) process addresses the operational level and generates replenishment orders according to product effective demand and to inventory sizing parameters (Average Demand Usage, decoupled Lead Time, lead time factor, variability factor, Peek limit, Minimum Order Quantity, demand adjustment factors); the Demand Driven Sales and Operations Planning (DDS&OP) addresses the

mid-term decisions and adapts dynamically the inventory sizing parameters and items categories according to improvement and forecast decisions. The Adaptive Sales and Operations Planning (AS&OP) process deals with the strategic point of view.

The AS&OP process [11] is an essential component of DDAE, evolving from the traditional S&OP (Sales and Operations Planning) process to make it more agile and responsive but also integrating DDAE specific decisions (physical, time and capacity buffers location in the manufacturing process).. The general principles of the AS&OP process are (i) alignment of objectives (ensures that operational decisions support the SCN's strategic objectives), (ii) integration of real-time data (use of real-time data to counterbalance forecast and respond to variations in demand), (iii) continuous and iterative cycle (continuous process enabling constant adjustments in line with market changes), (iv) cross-functional collaboration (requiring close collaboration between sales, operations, finance and marketing to ensure a coherent view of demand and supply), and (v) use of dynamic buffers (managing uncertainties and variabilities in demand by adjusting buffers according to current market conditions).

Although the objectives of the AS&OP process are relevant to improving the performance of SCN, it has been shown in [2] that it remains essentially conceptual and lacks the concrete tools required for practical implementation. Against this backdrop, recent research work has proposed a number of first steps in this direction. [3] in particular has developed an initial model for the aggregate evaluation of capability scenarios based on the decision-making strategies proposed by the players in the AS&OP process. Although this proposal provides an effective tool for the AS&OP process, it has certain limitations, notably its inability to consider the uncertainties to which SCNs are subject. Thus, the research question that this work proposes to address is: “how to integrate the uncertainty dimension within the AS&OP process and calculations?”. The paper is organized as follows. First, a brief review of the state of the art in approaches to integrating the notion of uncertainty into strategic planning processes is proposed. Second, our proposal for a decision support system is developed, before being validated and discussed via an illustrative case study.

## 2 Background

Recent literature on the Sales and Operations Planning (S&OP) process highlights the importance of integrating uncertainty to better manage the Volatility, Uncertainty Complexity and Ambiguity (VUCA) environment in which SCNs now operate [4–8]. The creators of the AS&OP approach [9–11] advocate several important practices: (i) using globally true data rather than precisely false data, representing demand in the form of intervals rather than as an absolute value, (ii) integrating the notion of risks and opportunities, often neglected by decision-makers, by using them as input to the process, and finally (iii) systematizing “what-if” planning (a set of several scenarios) rather than looking for a single more or less optimal option. Unfortunately, however, these recommendations are not accompanied by practical tools for their implementation, which is a major shortcoming of the DDAE approach [3]. Some authors have sought to include this notion of risk and uncertainty within the S&OP process, with elements relating to (i) the integration of uncertainty via operational research models [4–6, 12], or (ii) the use of

simulation to enable "what-if" scenario-based planning [7, 8]. It is these two elements that we will be looking at in more detail, using optimization and simulation approaches.

The optimization approaches [4–6] to modeling uncertainty include several methodologies: (i) Stochastic models: use of random variables to model specific uncertainties [5, 13], (ii) Robust models: consideration of worst-case scenarios to ensure acceptable performance under various conditions [14];(iii) Fuzzy models: use of fuzzy logic to manage uncertainty linked to imprecise or incomplete data [5, 15]. These models provide a better grasp of uncertainty in strategic planning, although their integration into SCN is often costly and complex [16, 17].

Simulation is also often used to analyze uncertain situations and predict the consequences of different decisions [18–21]. In particular, what-if planning is recommended for dealing with strategic uncertainty by simulating different possible scenarios and assessing their respective impacts. This approach enables SCNs to remain flexible and resilient in the face of unforeseen changes. It is often recommended to support scenario-based planning at the strategic level [22–24].

The integration of risk and opportunity assessment into the AS&OP process is also crucial to informed decision-making. This approach is supported by the literature, which shows that the S&OP process is ideal for managing an entire SCN, thanks to its hierarchical positioning and the cross-functional nature of the players involved. However, there is a lack of risk assessment methods within the S&OP process, which is an obstacle for manufacturers to overcome [7, 25–27].

The recommendations made by the designers of the AS&OP approach [11] are consistent with the findings of established practices in the academic world. However, the concrete implementation of these recommendations requires specific tools and methodologies adapted to effectively integrate uncertainty into the AS&OP process.

This summary of the literature highlights the importance of integrating uncertainty into the AS&OP process to improve strategic planning and decision-making in an uncertain and changing environment. The recommendations made by the approach's creators for integrating uncertainty into the AS&OP are in line with the research findings, but the concrete modalities of application have yet to be specified.

### **3 A New AS&OP Methodology**

In line with the recommendations of [11] on the AS&OP process, the proposed decision support system includes 5 steps: (i) collection of strategic data, (ii) establishment of the strategy based on these data, (iii) analysis of the various scenarios via an ad hoc evaluation model (calculation engine), (iv) elaboration of a strategic reconciliation to prepare the decisions to be validated by management, and (v) management review to validate the decisions and archive the assumptions for future iterations.

In [2] and [3], a calculation engine estimates the performances due to strategic decisions and DDMRP parameters, on the basis of an aggregated model. Our goal is to enhance the aforementioned calculation engine to take into account uncertainties. This implies evolutions in the business process on the one hand, and in the calculation algorithms on the other. Therefore, if the proposed methodology can be considered as generic to any Sales and Operations process, the resulting process is specific to a DDAE approach because of the aggregated model specificities and the calculation tool.

### 3.1 AS&OP Business Process Evolution

In this study, we define an opportunity as a decision to be studied that could have a beneficial effect on SCN performance. In contrast, a risk is an event that can have an impact on SCN performance, resulting from an abrupt change or the occurrence of unforeseen events. According to [29], the main risks and opportunities to be considered at AS&OP level are classified into different decision variables, such as capacity adjustment, partner network composition strategy (e.g. Make or Buy), industrial process technology choices, organizational performance improvement (e.g. cycle time reduction) or production management (e.g. changes in management laws and/or associated parameters).

Opportunities and data are subject to uncertainties. To incorporate uncertainty, we follow a data interval approach, transforming deterministic data into intervals of values that are all equiprobable for each period of the time horizon under consideration. These intervals are guided by the knowledge on opportunities that influence the level or nature of the decision variables in our AS&OP model. These decisions, which are diverse due to the horizontal integration of AS&OP services, must therefore be translated into variables specific to our model for use in our decision-support tool. The “establish a strategy” stage therefore now includes the identification of risks, opportunities and technical data, as well as the preparation of data for the Decision Support System in a scenario-based planning logic (Fig. 1).



**Fig. 1.** Proposed evolution of the “Establish a strategy” step

Beyond this identification, the decision-maker now needs to be asked about the scenarios he/she wishes to evaluate. To this end, we propose to integrate a new “scenario generation” step into the AS&OP process, to support the implementation of an evaluation based on a scenario-based planning logic. Depending on the nature of the decisions, risks or opportunities to be tested in our decision support system, two situations may arise: (i) a change in the structure of the operational planning model (DDMRP) is required, implying a new parameterization of the aggregate model (e.g., the addition of an extra buffer), (ii) a change in the value of one or more decision variables is sufficient, requiring no re-parameterization of the model, but simply its use to project the impact of these values. In this new step, we will use the risk and opportunity data from the “establish a strategy” step to automate scenario generation. Each scenario will then be evaluated so

that the AS&OP team can make objective decisions. The following section presents the calculation elements proposed for this purpose.

### 3.2 AS&OP Calculation Principles

The notations used in this study are explained in Table 1. We propose to design scenario generation using a decision tree as shown in Fig. 2. The segmentation criteria are divided into four categories: Sales and financial strategy, Operations strategy, uncertainties, and risks/opportunities. Figure 3 shows that our scenario generator uses four blocks (i, j, k, m). Starting from a nominal scenario (Sc\_o) with fixed values for each variable, each block combines the elements to be tested to create a set of scenarios (Sc\_ijkm), representing different alternative values depending on the elements activated.

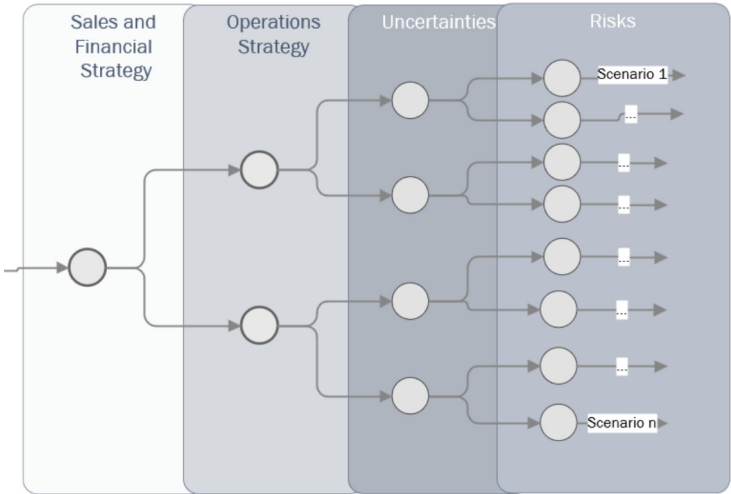


Fig. 2. General principle of scenario generation

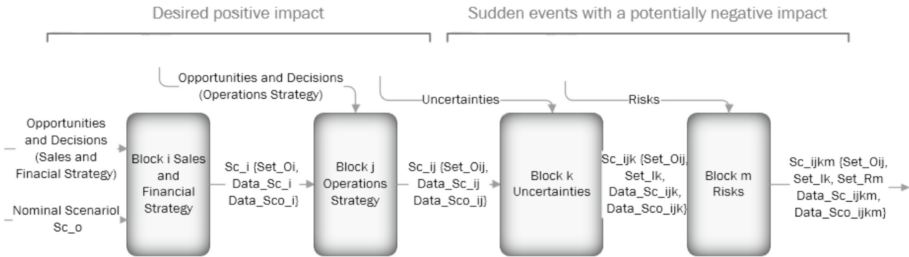


Fig. 3. Detailed scenario generation logic

Blocks i (sales and Financial strategy) and j (Operations strategy) create scenarios by combining opportunities of decisions translated into decision variables from the aggregate DDMRP model proposed by [3].

For block k and m, we propose to add risks and uncertainty along two dimensions: demand and capacity. These elements are relevant for decision-makers in the S&OP process, as shown in [9, 10] and [11]. We generate risks by considering a fixed high impact on the value per period, and apply uncertainty as intervals on the resulting value. Thus scenarios are randomly drawn from the range of values of the both demand (Forecast\_sales\_fam) and capacity (Capa\_WC) variables. For each scenario, we therefore take a random fixed value in the interval of the Capa\_WC and Forecast\_sales\_fam variables for each period. A business criterion, such as intervals on the cumulative sales and capacity forecasts, is added to select relevant scenarios.

All this logic has been implemented in a platform developed in Python, allowing us to automate scenario generation and store the information for each scenario Sc\_ijkm: {Set\_Oij, Set\_Ik, Set\_Rm, Data\_Sc\_ijkm, Data\_Sco\_ijkm, Data\_Kpi\_ijkm}. For each scenario, the DDMRP aggregate model derived from the work of [3] is used to project behavior and evaluate performance indicators. For each Sc\_ijkm scenario, an evaluation of the KPIs is stored in Data\_kpi\_ijkm. Finally, we propose the use of Business Intelligence tools to visualize the results, enabling SCN decision-makers to interpret the data in a flexible and personalized way.

**Table 1.** Notations used

Block considered	Notation	Explication
Block i Sales and Finance Strategy and Block j Operations Strategy	$Sc_o$	nominal scenery
	$Set_{Oi}$ and $Set_{Oij}$	reference to all opportunities activated by scenario i and then by scenario j
	$Data_{Sc_i}$ and $Data_{Sc_{ij}}$	all variables affected by a change in value due to the taking into account of an Oi/Oj opportunity
	$Data_{Sco_i}$ et $Data_{Sco_{ij}}$	Remaining data of the nominal scenario unaffected by step i (or by step j)
	$SC_i$ et $SC_{ij}$	Output scenario for block i/block j
Block k Uncertainties	$Capa_{WC}$ $[cc_{mini}; cc_{max}]_p$	$cc_{mini}$ and $cc_{max}$ represent the minimum and maximum values of the capacity interval considered for the load center WC for the period p considered

(continued)

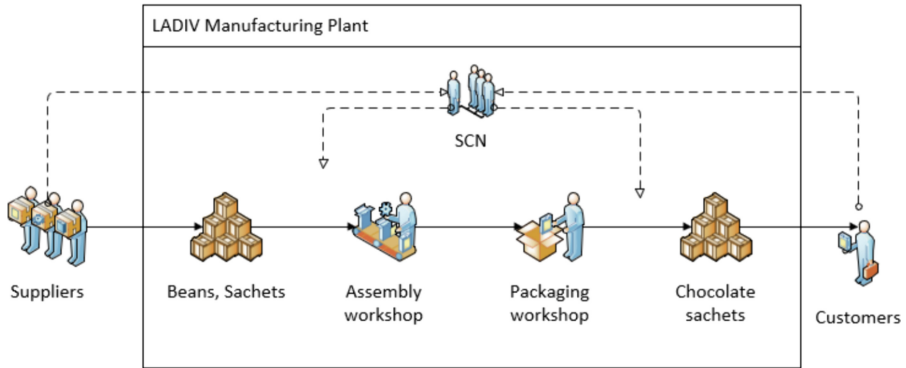
**Table 1.** (continued)

Block considered	Notation	Explication
	<i>Forecast_sales_fam[pv_mini, pv_max]_p</i>	<i>pv_mini</i> and <i>pv_max</i> represent the minimum and maximum values of the sales forecast interval for the family under consideration for the period <i>p</i>
	<i>Set_Ik</i>	represents references to the uncertainties considered
	<i>Data_Sc_ijk</i>	the set of variables with a fixed (deterministic) value derived from the data scan
	<i>Data_Sco_ijk</i>	Remaining data of the nominal scenario unaffected by step <i>k</i>
	<i>SC_ijk</i>	SC_ijk scenario at block <i>k</i> output
Block m Risks and Opportunities	<i>Risk_capacity[work center, * ou +, vr_cap]_p</i>	indicates that the capacity known in <i>Data_Sc_ijk</i> for the <i>Sc_ijk</i> will be modified by an operator (* or +) and the <i>vr_cap</i> value over the period <i>p</i>
	<i>Risk_sale[family, * ou +, vr_sale]_p</i>	which indicates that the sales forecast known in <i>Data_Sc_ijk</i> for <i>Sc_ijk</i> will be modified by an operator (* or +) and the value <i>vr_sale</i>
	<i>Data_Sc_ijkm</i>	values of variables modified by risks
	<i>Set_Rm</i>	reference to activated risks
	<i>Data_Sco_ikjm</i>	Remaining data of the nominal scenario unaffected by step <i>l</i>
	<i>SC_ijkm</i>	<i>m</i> block output scenario

## 4 Experiments and Discussions

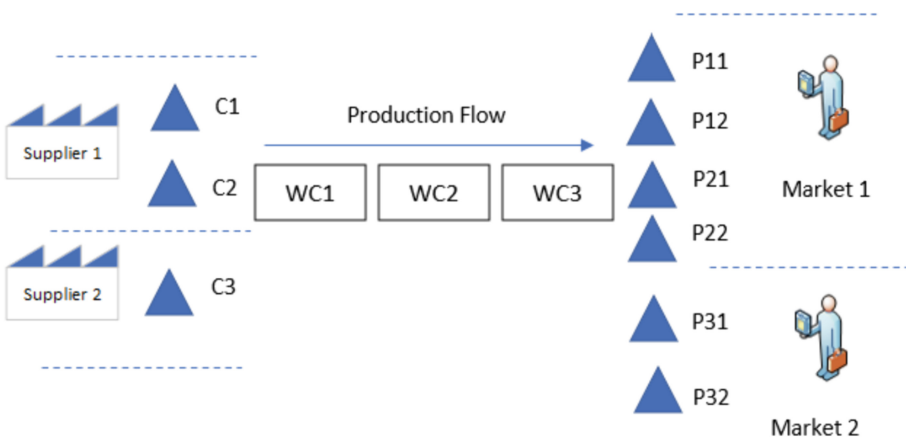
In this section, we will use the case study of a chocolate SCN centered on the LADIV manufacturing plant who produces chocolates (Fig. 4).

The LADIV SCN operates in two different markets (Market 1 and Market 2). The SCN has a portfolio of 6 products divided into 3 product families. The production flow is of the “flow manufacturing” type, passing through three load centers, WC1 and WC2, which constitute the assembly workshop, and load center WC3, which constitutes the packaging workshop. Two suppliers (Supplier 1 and Supplier 2) deliver the purchased components, i.e. cocoa beans and bags. Three components are purchased (C1, C2 and

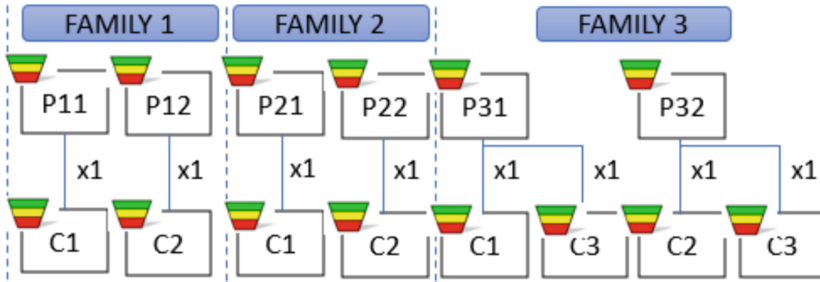


**Fig. 4.** The LADIV SCN

C3). Figure 5 illustrates the situation from a flow point of view. Figure 6 shows the product Bill Of Materials (BOMs).



**Fig. 5.** Flow model of the LADIV chocolate SCN



**Fig. 6.** Product BOMs for the LADIV chocolate SCN

The following tables summarize data from a commercial and financial point of view, production-related data and supplier-related data, respectively (Tables 2, 3, 4).

**Table 2.** Sales and Finance data of nominal scenario

Commercial Family	Family Product	Sales Volume	Seasonality	Market	Sales Price	Contribution Margin	Variability
F1	P11	High Volume	No	Market 1	Low	Very Low	Low
	P12	High Volume	No	Market 1	Low	Low	Low
F2	P21	Low Volume	Yes	Market 1	Low	Medium	Medium
	P22	Low Volume	Yes	Market 1	Low	Medium	Medium
F3	P31	Sporadic	No	Market 2	High	High	High
	P32	Sporadic	No	Market 2	High	High	High

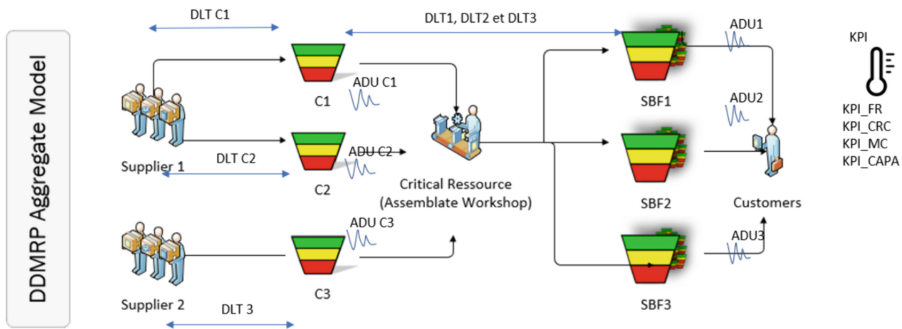
**Table 3.** Production data of nominal scenario

Workcenter	Capacity (in min per day)	Critical Ressource	Day (in jours)	Week (in days)
WC1	600	No	8	5
WC2	480	Yes	8	5
WC3	600	No	8	5

**Table 4.** Supplier data in nominal scenario

Supplier	Component	Variability	Purchase price
Supplier 1	C1	Low	Low
	C2	Low	Low
Supplier 2	C3	High	High

Let assume that the LADIV SCN has implemented a complete DDMRP model for all its items (Fig. 7). This model is then aggregated according to the logic described in [3].



**Fig. 7.** DDMRP aggregated model of the LADIV SCN

The main features of this model are summarized in Tables 5 and 6.

**Table 5.** Aggregate characteristics of Family 1, 2 and 3 Stock Buffers

Portfolio	Features of the aggregated DDMRP model ( <i>buffer de stock</i> )	
	(decoupled Lead Time) DLT	Delay Factor (DF)
Family or Component		
F1	60	0,4
F2	20	0,3
F3	20	0,2
C1	5	0,7
C2	5	0,7
C3	30	0,3

We start from a nominal sales scenario, with sales forecasts aggregated by family over a 24-month horizon (stable global market with market seasonal effected). We add

**Table 6.** Family 1, 2 and 3 macro-routing (BORi) on WC2 critical resource

Macro-routing (BORi)	
Family	WC2 (en min/p)
F1	0,77
F2	1,24
F3	2,25

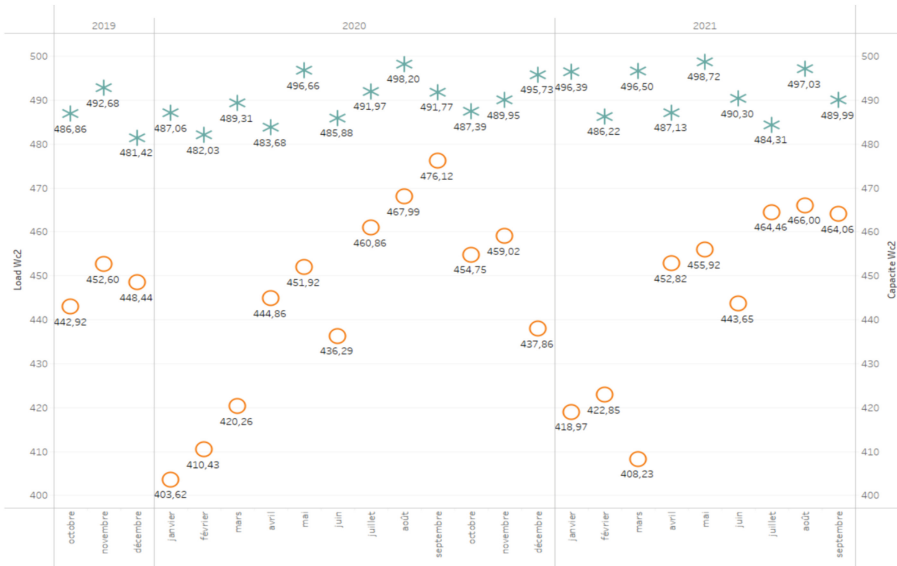
the following data: (i) a market opportunity for family 1 with a sales increase of 20% from next month onwards, (ii) uncertainties on sales forecasts and critical center capacity respectively, which are given as an interval over the entire horizon, and (iii) a risk of a 20% drop in critical center capacity. For this experiment, the total number of scenarios generated for the uncertainty block was set at 500, resulting in a combinatorial set of 2,000 scenarios to be evaluated. In around ten minutes, our system generated and evaluated these scenarios using the following performance indicators: working capital (KPI FR), contribution margin (KPI MC), load of Critical Ressource (KPI CRC) and unused capacity (KPI CAPA). The analysis of unused capacity (KPI CAPA) reveals some interesting points. For example, a single scenario may appear to be under control from a capacity point of view, but analysis of all the scenarios, with and without the sales increase opportunity, shows significant variations. This underlines the importance of considering all scenarios for a more complete assessment. The main elements of our experiment plan are summarized in Table 7.

**Table 7.** Summary of simulation elements

Uncertainties	Uncertainty interval per month around the nominal situation on sales forecasts ( $\pm 20\%$ ) and critical center capacity [+0;-10%] respectively. 500 forecast and capacity scenarios are generated considering a uniform distribution in the monthly intervals
Risk	a risk (Appears or not appears) of a 20% drop in critical center capacity
Opportunity	a market opportunity (accept Yes or No) for family 1 with a sales increase of 20% from next month onwards
KPI	working capital (KPI FR), contribution margin (KPI MC), load of Critical Ressource (KPI CRC) and unused capacity (KPI CAPA)
Decisions	preventive maintenance to avoid a drop in capacity (Yes or No), partial outsourcing of sales (yes or No), or maximizing sales on high-margin families (generic strategy when facing backorders)

Figure 8 shows the dynamic evolution of the KPI CRC, load (orange) versus capacity available (green) on a single scenario generated on the sole basis of uncertainties (no risk or opportunity activated). Figure 9 shows the comparison of the unused capacity for all scenarios, considering the case with and without the opportunity of a 20% increase

in sales for family 1, combined with the risk of capacity drop. The nominal scenario may lead decision makers to believe that the situation is under control from a capacity point of view, since according to Fig. 9, the capacity limit is never exceeded. However, just by integrating the uncertainty on sales and capacity (without risk or opportunity considered), Fig. 9 shows scenarios with limited capacity margin, posing a possible problem in June/July and August 2020. Moreover, if the market opportunity of more than 20% on family 1 is included, a majority of the scenarios generate overloads over almost the entire strategic horizon. Finally, a drop in capacity leads also to an overload situation in all scenarios.



**Fig. 8.** Dynamic evolution of load (orange) versus capacity (green) for 1 scenario

In such a situation, the AS&OP team must simulate several possible decisions, such as preventive maintenance to avoid a drop in capacity, partial outsourcing of sales, or maximizing sales on high-margin families. Each decision is translated into data for a new set of scenarios. For example, by outsourcing family 2 products, can we compensate for a 20% reduction in capacity? If so, how much sales should be outsourced, and is this profitable? Assuming a production constraint limiting outsourcing to 70% of sales volume per day. We intuitively set a reduced sales profile of 50–70% of periods via the Demand Adjust Factor (DAF) parameter and run the simulation again to test this decision (Fig. 10)

It is also crucial to assess the financial benefits of decisions, such as the impact of subcontracting on the contribution margin. For example, if subcontracting reduces the margin from €20 to €10 per part, its effect needs to be assessed. Financial indicators such as Working Capital (KPI FR) and Contribution Margin (KPI MC) are essential for this analysis. The simulator enables us to display these indicators to assess the impact of decisions, illustrating the evolution of the contribution margin as a function of capacity



variables and uncertainties. Thanks to an aggregated model of the DDAE model, it is explored with a quick computation time in our DDAE case study.

However, the study also highlights several limitations. One of the main challenges encountered during the experiment was the computational capacity required to generate and evaluate a large number of scenarios. With a total of 2,000 scenarios to process, it was possible to accomplish the computation in a matter of minutes. Extending the approach to larger supply chain network with a multitude of decision opportunities would require to decompose the decision tree for reducing the combinatoriality of scenarios. This challenge lies also in the realistic modeling of risks and opportunities. It is vital that the variables are as accurate and representative as possible of operational reality and capture the real nature of variabilities which may not be represented with intervals. Future research should explore robust versus agile not resilient strategies and consider the uncertainty on parameters of the DDAE model such as decoupled lead time or variability factors. The need to control the combinatoriality of the scenarios generated and the multitude of variables to be considered can make this a daunting task, requiring ongoing training and adequate technical support.

Although customizable dashboards offer a fairly clear visualization of scenario results, their interpretation requires significant expertise on the part of users. Decision-makers need to be trained not only in the use of visualization tools, but also in the analysis of the data generated by the scenario-based planning approach. Formalizing a Multicriteria Decision Analysis (MCDA) or the perspective of various decision makers on the decision tree could be of great support.

Finally, if the proposed methodology seems generic, extensions of the aggregated model are required to consider also S&OP and the MRP2 approach.

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