Optimal Postponement in Supply Chain Network Design Under Uncertainty: An Application for Additive Manufacturing

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(PREPRINT)

ABSTRACT: This study presents a new two-stage stochastic programming decision model for assessing how to introduce some new manufacturing technology into any generic supply and distribution chain. It additionally determines the optimal degree of postponement, as represented by the so-called customer order decoupling point (CODP), while assuming uncertainty in demand for multiple products. To this end, we propose here the formulation of a generic supply chain through an oriented graph that represents all the deployable alternative technologies, which are defined through a set of operations that are characterized by lead times and cost parameters. Based on this graph, we develop a mixed integer two-stage stochastic program that finds the optimal manufacturing technology for meeting each market's demand, each operation's optimal production quantity, and each selected technology's optimal CODP. We also present and analyse a case study for introducing additive manufacturing technologies.

KEYWORDS: manufacturing; postponement; stochastic programming; supply chain network design; 3D printing; additive manufacturing

1. Introduction

According to Govindan et al. (2017), supply chain network design (SCND) forms part of the planning process in supply chain management, which itself determines the infrastructure and physical structure of a supply chain (SC). Due to changes in technology and consumer behaviours, as well as product life cycles and variety, companies are forced to redesign their production schemes in search of flexible supply chains and postponement strategies. Two opposing production strategies can be chosen for the strategic design of a supply chain: speculation or postponement. According to Bucklin (1965): "The principle of speculation holds that changes in form, and the movement of goods to forward inventories, should be made at the earliest possible time in the marketing flow". Regarding form and logistics postponement, Alderson (1957) established that

This work was developed under an Accenture Open Innovation University Grant I-01326 and was also partially supported by grant RTI2018-097580-B-I00 of the Ministry of Economy and Competitiveness of Spain.

To cite this paper: Daniel Ramón-Lumbierres, F.-Javier Heredia Cervera, Joaquim Minguella-Canela and Asier Muguruza-Blanco (2020) *Optimal postponement in supply chain network design under uncertainty: an application for additive manufacturing*. International Journal of Production Research, DOI: 10.1080/00207543.2020.1775908

these "postpone changes in form and identity to the latest possible point in the marketing flow; postpone change in inventory location to the latest possible point in time". Giesberts and Tang (1992) define the customer order decoupling point (CODP) as "(…) the point in the flood of goods of the supply chain where forecast-driven (pushed) production and customer order-driven (pulled) production are separated". According to Yang and Burns (2003), it is the point where the customer order penetrates and that distinguishes forecast and order-driven activities. Therefore, the CODP specifies the extent to which operations perform a speculative or postponed strategy. Furthermore, it sets the operation/facility at the point in the SC where finished or semi-finished production is stored before delivering the customer's orders. The optimal positioning of the CODP within the SC remains an open question in today's SCND research, and it constitutes one of the main contributions of this study (see Section 2). The practical motivation behind this research is to, first, ascertain when and where to apply postponement as a supply chain strategy and, second, demonstrate how additive manufacturing (3D printing) can be used to accelerate the deployment of postponement strategies. In order to conduct this study, we adopted the methodology of Two-Stage Stochastic Programming (TSSP): the degree of uncertainty is significant for selecting an appropriate postponement strategy, Yang, Burns and Backhouse (2004), and TSSP models are generally considered to be among the most effective at incorporating stochasticity into SCND problems, Govindan et al. (2017). Beyond that, we use TSSP in this work to introduce a completely new form of modelling for postponement, specifically to calculate the optimal positioning of multiple CODPs and other relevant decision variables in SCND. The capabilities of this TSSP model are then assessed as an analytical tool by using the model afterwards to introduce additive manufacturing into a real-case SCND problem for the toy industry. The main contributions of this study are:

1. A new and general two-stage stochastic programming model for addressing a general SCND problem with demand uncertainty. It determines the optimal selection of facilities and manufacturing technologies; production and distribution flows; the degree of form and logistics postponement. This is accomplished by optimally positioning the CODPs and the associated inventory level for the selected technologies/facilities.

2. A generalized understanding of CODPs, which allows for defining multiple CODPs within the optimal SC network of selected operations/facilities. Having multiple CODPs for each process also requires redefining the classical dichotomist categorization in which every operation is run as either speculation or postponement.

3. A detailed analysis of a real-case SCND problem in the toy industry. Here, the goal is to assess the use of 3D printing as a means for implementing postponement strategies.

The remainder of this paper is structured as follows. Section 2 provides a literature overview on supply chain network design problems and postponement strategies. Section 3 introduces the mathematical formulation of the optimization problem. Finally, Section 4 presents the results of the proposed model using the real-world case of a manufacturing company. Section 5 draws some conclusions, managerial insights and proposes further work for this project.

2. Literature Review

There is a vast literature on Two-Stage Stochastic Programming models (TSSP) for SCND problems. In order to orient this study with precision in the field of study, we follow a classification similar to that of Govindan et al. (2017). To this end, Table 1 shows some of the main characteristics of the most representative TSSP models for SCND, specifically in terms of both: the SC network structure in the associated facility location problem; and the SC management problem's characteristics.

		SC network			Characteristics of the SC management problem																
					A									B			C			D	
		Number of location layers	Multi-product	Intra-layer flows	Location costs	Transportation costs	Production costs	Procurement costs	Inventory costs	Shortage costs	Cap. costs of facilities	Processing costs	SC income	Technology sel. costs	Discarding costs	Transportation link	Recovery costs	Capacity penalty	Risk/Robustness	Responsiveness	**Postponement**
		nLL	MP	ILF	LC	TC	PC	PRC	IC	SC	CC	PC	SCI	TSC	DC	CTL	RC	CP	Ri	Re	**P**
Forward logistics	**This study**	**>3**	**V**	**V**	**V**	**V**	**V**	**V**	**V**	**V**	**V**	**V**	**V**	**V**	**V**	**V**				**V**	**V**
	Tong et al. (2013)	3			V	V	V	V			V			V		V					
	Govindan and Fattahi (2017)	2	V		V	V	V		V	V	V	V									
	Alonso-Ayuso et al. (2003)	1	V	V	V	V	V	V	V		V		V								
	Kazemzadeh and Hu (2013)	1			V	V	V				V	V	V					V			
	Klibi and Martel (2013)	1			V	V		V				V									
	Madadi et al. (2014)	1			V	V				V					V				V		
	Cardona-Valdés et al. (2014)	1			V	V														V	
	Weskamp et al. (2019)	3	V	V	V	V	V		V	V		V	V	V					V	V	V
	Biller et al. (2006)	1	V		V		V						V							V	V
Reverse logistics	Soleimani et al. (2014)	>3	V		V	V	V	V	V	V							V		V		
	Ayvaz et al. (2015)	3	V		V	V							V				V	V			
	Li and Hu (2014)	2			V	V				V	V	V	V					V			
	Ramezani et al. (2013)	2	V		V		V	V			V	V	V				V	V	V	V	
	Kaya et al. (2014)	2	V		V			V	V				V				V	V			
	Amin and Zhang (2013)	1	V		V	V	V										V				

Table 1: TSSP formulations for SCND problems.

We can make distinctions among those studies by considering, first, a forward logistic network in which it is impossible to recover products rejected by customers and, second, those models that allow for some recovery (reverse logistics). Facility location (FL) problems in supply chain management (SCM) consist of selecting different potential facilities in the same layer (i.e.: suppliers, plants, warehouses, and distribution, among others). Studies on SCND usually allow for deciding on locations in no more than 3 layers. One exception to this trend is Soleimani et al. (2014), who allow for locating a reverse logistic network in every layer. Our work allows for complete flexibility in the embedded FL problem, because location decisions may affect operations and facilities in every existing layer of the network: suppliers, manufacturing plants, warehouses, and distribution centres. Our SC network also allows for any number of products (which is not very usual in FL works) and product flows between the facilities of the same layer (see columns MP and ILF in Table 1). The A set of columns in Table 1 display the most common characteristics of SC management costs considered by SCND studies, such as transportation, production, inventory, stock-out, and others. Aside from those common features, the model presented in this paper includes some characteristics that are quite unusual in the area (columns B). Only the paper by Tong et al. (2013) considers the costs associated with the different manufacturing technologies available, but it is restricted to an integrated hydrocarbon biofuel and Petroleum refinery problem. Similarly, only Madadi et al. (2014) consider the discarding costs associated with the excess production. Moreover, none of the other works in Table 1 consider the cost of establishing a transportation link between two facilities, which is fundamental for connecting the two candidate SC operations in our model. In contrast, our model lacks the characteristics displayed in the C set of columns, which some other studies consider as recovery costs, penalties for unused capacity, and modelling risk/robustness.

Considering the relevance of postponement in this work, we discuss the relationship between a responsive supply chain (RSC) and postponement. According to Chopra and Meindl (2013) an RSC model should include the supply chain's ability to "respond to wide ranges of quantities demanded, meet short lead times, handle a large variety of products, build highly innovative products, [and] meet a high service level". For Gunasekaran et al. (2008), an RSC provides flexible solutions to changing market/customer requirements. Ivanov and Dolgui (2019) identifies postponement as one of the key factors of resilience in SC disruption risk management, an one of the gaps to be filled in current SC research, while Winkelhaus and Grosse (2019) mention postponement as one of the key facilitator in Logistics 4.0. Among the SCND works in Table 1 (apart from our study), only four of them include any responsiveness in the SC (see column Re). A classical strategy for RSC is to consider some of the objective function's terms that account for either minimizing customer service time, Cardona-Valdés et al. (2014), or maximizing customer service level in terms of suitable delivery time, Ramezani et al. (2013). Although postponement is recognized as one of the keys for RSC, it is quite unusual for TSSP models on SCND to explicitly introduce postponement in the mathematical formulation. In fact, and as far as we know, only Biller et al. (2006) and Weskamp et al. (2019) have proposed a TSSP model in which the degree of postponement is somehow optimized explicitly. Even if we broaden our review beyond the scope of TSSP methodology, we cannot find many studies that deal with qualitative mathematical models for postponement; and considerably less address postponement through the optimal positioning of the CODP – as our proposal does. Table 2 displays some of the most representative studies considering the optimal degree of SC postponement. The first five studies in Table 2 rely on deterministic optimization models that have normally distributed demands with known μ_j and σ_j for every product j. The first four references consider form postponement (i.e., delayed product differentiation), and find the optimal differentiation point n (i.e., the operation after which the products assume their unique characteristics) through either dynamic programming or by minimizing the single-variable cost function $C(n)$. Nevertheless, these four works assume that product differentiation remains forecast-driven and, therefore, takes place before customer demand materializes. Therefore, none of them includes CODP positioning. The work by Ernst and Kamrad (2000) finds the optimal product quantity for the two opposite strategies of complete speculation / complete postponement, doing so with a pre-set CODP in a very simple SC. Jabbarzadeh et al. (2019) propose a multi-objective robust optimization model for form, production, and logistic postponement, which is restricted to the second manufacturing layer of a four-layered SC (primary and secondary manufacturing; and central and regional distribution centres).

	Postponement degree				CODP positioning								
	Form	Price	Production	Logistics	Number	Preset	Optimized	# of products	General SC	Stochasticity	First-stage decision variables	Second-stage decision variables (postponed decisions)	Mathem. Modelling
Hsu and Wang (2004)	V							Any		Demand	Differentiation point.	None	Dynamic Prog.
Lee (1997)	V							2					Unconst. Minimization of total costs.
Ngniatedema (2015)	V							2					
Shao and Ji (2008)	V							Any		Demand, service time			
Ernst and Kamrad (2000)			V		1	V		2		Demand	Prod. Quantity.		
Jabbarzadeh et al. (2019)	V		V	V	Any	V		Any		Demand	Prod. Flows, holding and stock-out quant.		Robust optimization
Bish and Suwandechochai (2010)		V	V		1	V		2		Price	Plant capacity.	- Price - Prod. Quantity.	TSSP (pdf)
Biller et al. (2006)		V	V		1	V		Any		Demand	Flexible and dedicated plant capacity.		TSSP (scenarios)
Weskamp et al. (2019)	V		V	V	Any	V		Any	V	Demand	- Operations deployment. - Prod. Flows and inventory.	For every factory: - Prod. Flows. - Inventory. - Stock-out quant. - Sold production.	
This study	V		V	V	Any		V	Any	V	Demand	- Operations deployment. - Prod. flows and inventory. - **CODP positioning.**	For every facility: - Prod. flows. - Inventory. - Excess prod. - Stock-out quant. - Sold production.	

Table 2: Postponement formulations for SCND problems.

The works by Bish and Suwandechochai (2010) and Biller et al. (2006) introduce the idea of associating postponement decisions (price and production quantities) with the second-stage variables in a TSSP model. The approach in Bish and Suwandechochai (2010) theoretically analyses optimal postponement as the solution of a TSSP problem, using just two products while considering an inverse demand function $p_j = \alpha_j - d_j - \gamma_j d_{3-j}$, where p_j and d_j are the price and demand of product j respectively, γ_j a measure of product substitutability (see the reference), and α_j is the price intercept of product j, with α_j being continuous random variables with a known joint probability density function. Biller et al. (2006) propose a scenario-based multi-product TSSP for price and quantity postponement, using stochastic demand functions $d_j = \xi_j - \beta_j p_j$, with β_j being the known slope, and $\xi_j \geq 0$ the intercept, a random variable with mean μ_j and standard deviation σ_j. Recently, Weskamp et al. (2019) proposed a TSSP approach for SCND that is very similar to our proposal (see details in Table 2). Nevertheless, there are two major differences: first, they pre-set every facility for postponement operations, except for those in the first layer (factories); while any facility in any layer in our problem could operate in either postponement or speculation. Second, Weskamp et al. (2019) pre-set the CODPs to be positioned in every open factory, while our model finds which is the optimal positioning of CODPs at any operation in the SC (manufacturing, warehouses, distribution centres, and markets).

We can see that none of the reviewed formulations on postponement optimize the CODP positioning, meaning that the decision-maker must decide which of the SC operations and facilities are going to be operate in speculation (before receiving demand orders) and which will be delayed (postponed) until orders are placed. Wikner and Rudberg (2005) state that “the actual positioning of the CODP has not yet been thoroughly analysed in the literature”; and Boone et al. (2007) declare that the optimal positioning of CODPs is one of the new challenges for future postponement models. Our work fills this gap in the existing literature by providing a TSSP model for any general SNCD problem where form, production and logistics postponement can be optimized through optimal CODP positioning at every point in the SC.

3. Problem formulation

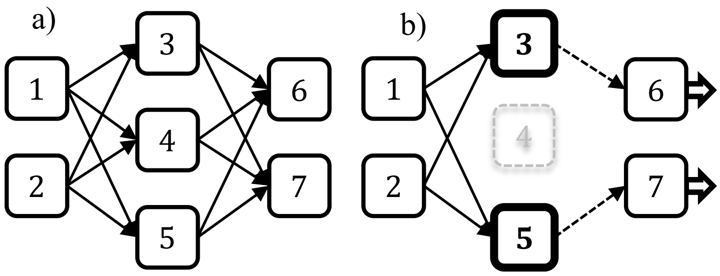
Let us consider a company that must choose the best available manufacturing process from a portfolio in order to satisfy the future demand of a given set of products. A process is defined as a set of sequential operations (purchasing, manufacturing, assembling, storage, distribution and selling), which transforms the raw materials into a finished product that is sold to some market. The Optimal Supply Chain Strategy ($OSCS$) model determines: (a) the best operations and processes to be deployed for satisfying the demand of several products over a time horizon; (b) the optimal production quantities for the speculation/postponement strategy of each deployed operation and process; and (c) the positioning of the deployed CODPs and their associated inventory levels. In this section, we define the two-stage stochastic mixed-integer linear programming model ($OSCS$) and develop the mathematical formulation for this problem. Model ($OSCS$) considers the following two-stage decision process:

- The first decision stage, the so-called *speculation stage*, involves selecting the operations to be deployed, positioning the CODPs, and deciding on the production flow from the initial operations for periodically replenishing the CODP inventory. This production is called *speculative production.*

- The second decision stage, the so-called *postponement stage*, is where customer orders are received and production is triggered from the CODP inventory up to the final operations. This production is called *postponed production.*

3.1. Topology

The ($OSCS$) model represents all the possible operations and processes in a supply chain through an oriented graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where the nodes $\mathcal{N}$ correspond to operations and the arcs $\mathcal{A}$ represent the precedence between operations. Graph a) in Figure 1 illustrates an instance based on a graph with 7 nodes (operations) $\mathcal{N} = \{1, \dots, 7\}$ and 12 arcs $\mathcal{A} = \{(1,3), (1,4), \dots, (5,7)\}$. This graph represents a packaging and distribution company that purchases manufactured products (node 1) and packages (node 2). The products can be packaged in three different packaging factories (nodes $3, 4$ and 5), and they must be delivered to two different customer centres (nodes 6 and 7).



$\mathcal{N}$	Operation
1	Manufacturing of raw product
2	Purchase of packages
3	Packaging at factory A
4	Packaging at factory B
5	Packaging at factory C
6	Customer centre at location 1
7	Customer centre at location 2

$\mathcal{N}^O = \{1,2\}$, $\mathcal{N}^D = \{6,7\}$
$\mathcal{N}^A = \{3,4,5\}$, $\mathcal{N}^B = \{1,2,6,7\}$

Figure 1: Example of a packaging process

Given graph $\mathcal{G}$, we define the subset of origin operations $\mathcal{N}^O \subseteq \mathcal{N}$ for the nodes with no ingoing arcs, allowing it to stand for the initial operation of a process. Analogously, we define the subset of final operations $\mathcal{N}^D \subseteq \mathcal{N}$ for the nodes with no outgoing arcs, each one standing for a market to be supplied. We will assume that every manufacturing process starts at some origin operations with complete availability of raw materials, and ends at some final operation where production is sold. All operations can have as many suppliers (ingoing arcs) as needed, and all suppliers can have as many operations (outgoing arcs) as needed. In terms of relationships with the suppliers, we distinguish two types of operations:

- Assembly operations $\mathcal{N}^A$ represent operations that take several parts from their suppliers and assemble them. Here, we assume each ingoing arc is the production flow of each part to assemble.

- Base operations $\mathcal{N}^B$ represent the remaining operations. Here, we assume all ingoing arcs to be different possible suppliers of the same product. All origin and final operations are considered base operations.

In Figure 1, $\mathcal{N}^A = \{3,4,5\}$ indicates that all the packaging factories behave as assembly operations, i.e. they need one unit of raw product (from node 1) and one unit of package (from node 2) for operating one unit of packaged production. The base operations are $\mathcal{N}^B = \{1,2,6,7\}$. To manage the assembly operations, we declare the subset of assembly arcs $\mathcal{A}^A = \{(i,j) | j \in \mathcal{N}^A\} \subseteq \mathcal{A}$ ($\mathcal{A}^A = \{(1,3),(1,4),(1,5),(2,3),(2,4),(2,5)\}$ in Figure 1). Graph b) in Figure 1 shows one possible setup. In this configuration, the selected operations are 1,2, 3, 5, 6 and 7, while operations 3 and 5 (in bold) correspond to two CODPs. The speculative production flows are $(1,3)$, $(1,5)$, $(2,3)$ and $(2,5)$, drawn with solid lines; while the postponed production flows are $(3,6)$ and $(5,7)$, drawn with dashed lines. The artificial final arrows indicate the sales of each respective, final operation. Henceforth, we will use $\mathcal{O}_j$ and $\mathcal{D}_j$ as, respectively, the origin operations and destination operations of operation j; that is, $\mathcal{O}_j = \{i \in \mathcal{N}: (i,j) \in \mathcal{A}\}$ and $\mathcal{D}_j = \{k \in \mathcal{N}: (j,k) \in \mathcal{A}\}$.

Set-up cost parameters, operations $i \in \mathcal{N}$		**Sales parameters, final operations $i \in \mathcal{N}^D$**	
f_i:	operation set-up cost (€)	p_i:	selling price ($€/unit$)
z_i:	CODP set-up cost (€)	o_i:	stock-out cost ($€/unit$)
Production parameters, arcs $(i,j) \in \mathcal{A}$		**CODP inventory parameters, base operations $i \in \mathcal{N}^B$**	
c_{ij}:	variable production cost ($€/unit$)	h_i^B:	holding inventory cost ($€/unit \cdot time\ period$)
e_{ij}:	fix production cost (€)	g_i^B:	discarding inventory cost ($€/unit$)
a_{ij}:	variable lead time ($h/unit$)	q_i^B:	inventory capacity ($units$)
b_{ij}:	fixed lead time (h)	**CODP inventory parameters, assembly arcs $(i,j) \in \mathcal{A}^A$**	
Bill of materials, assembly arcs $(i,j) \in \mathcal{A}^A$		h_{ij}^A:	holding inventory cost ($€/unit \cdot time\ period$)
r_{ij}:	number of units to assemble	g_{ij}^A:	discarding inventory cost ($€/unit$)
		q_{ij}^A:	inventory capacity ($units$)

Table 3: Parameters related to supply chain operations

The parameters used in the $(OSCS)$ model to characterize the supply chain are displayed in Table 3. Production parameters are indexed by arcs $(i,j) \in \mathcal{A}$, instead of operations $i \in \mathcal{N}$, because flexible operations $i \in \mathcal{N}$ may possibly yield either the same or different products to several subsequent operations $j \in \mathcal{D}_i$ (for instance, the same 3D printer can make different parts for several products; see case study in Section 4. Moreover, the inventory parameters of the assembly operations $j \in \mathcal{N}^A$ depend also on the piece $i \in \mathcal{O}_j$ to be assembled, because the different pieces might have different holding and discarding inventory costs, as well as for inventory capacities.

3.2. Decision stages and stochasticity

As mentioned previously, the first decision stage of the $(OSCS)$ model represents the speculation stage, which involves setting the operations to deploy and the positioning of the CODPs, as well as deciding on the CODP inventory levels and speculative production flow for replenishing the inventory before demand is known. The second decision stage represents the postponement stage, which is where the speculative CODP production stock is released, finished, and served once the demand value is known. We assume that the postponement stage spans a time horizon comprised of n^P periods of equal length l^P, and that during this stage there are going to be n^R periodical replenishments of the CODP inventories evenly distributed through the total time horizon. The stochastic parameters of this model are the demand along the time horizon in the final operations of every product. As usual in stochastic programming, demand $d = d_j, j \in \mathcal{N}^D$ is going to be represented in our model by a set of scenarios: $d_{js}, j \in \mathcal{N}^D, s \in \Omega$, with probability π_s and size $|\Omega| = \bar{s}$.

3.3. Variables and constraints

The model formulation is composed of three blocks: SC production flow, SC design, and lead time. The first block models the feasibility of the production flow along the deployed supply chain graph; the second block sets the design of the SC graph that determines the operations and the CODPs to be deployed; the third block guarantees maximum service time for postponed production.

3.3.1. SC production flow

SC production flow variables and equations guarantee that the sequence of selected operations and links defines feasible manufacturing processes from origin to final operations. The so-called *Production variables* are displayed in Table 4.

	Name	Domain	Definition
Speculation (first stage)	Speculative Production	$P_{ij}^0 \geq 0$	Speculative production at operation i delivered to operation j through arc $(i,j) \in \mathcal{A}$.
	Inventory (Base ops.)	$H_j^B \geq 0$	Speculative production stored in the CODP inventory for base operation $j \in \mathcal{N}^B$.
	Inventory (Assembly ops.)	$H_{ij}^A \geq 0$	Speculative production of piece $i \in \mathcal{O}_j$ stored in the CODP inventory for assembly operation $j \in \mathcal{N}^A$.
Postponed (second stage)	Postponed Production	$P_{ijs} \geq 0$	Postponed production at operation i delivered to operation j through arc $(i,j) \in \mathcal{A}$ in scenario $s \in \Omega$.
	Released Speculative Production (Assembly ops.)	$R_{ijs}^A \geq 0$	Speculative production of piece $i \in \mathcal{O}_j$ released from the CODP inventory for the assembly operation $j \in \mathcal{N}^A$ in scenario $s \in \Omega$.
	Released Speculative Production (Base ops.)	$R_{js}^B \geq 0$	Speculative production released from the CODP inventory for the base operation $j \in \mathcal{N}^B$ in scenario $s \in \Omega$.
	Excess Speculative Production (Assembly ops.)	$F_{ijs}^A \geq 0$	Excess of speculative production of piece $i \in \mathcal{O}_j$ stored at the end of the time horizon at the CODP inventory for the assembly operation $j \in \mathcal{N}^A$ in scenario $s \in \Omega$.
	Excess Speculative Production (Base ops.)	$F_{js}^B \geq 0$	Excess of speculative production stored at the end of the time horizon in the CODP inventory for the base operation $j \in \mathcal{N}^B$ in scenario $s \in \Omega$.
	Stock-Out	$B_{js} \geq 0$	Stock-out of final operation $j \in \mathcal{N}^D$ in scenario $s \in \Omega$.
	Sold Production	$V_{js} \geq 0$	Sold production at final operation $j \in \mathcal{N}^D$ in scenario $s \in \Omega$.

Table 4: Production variables

In the production flow equations (1)-(8) below, we model the production flow through the supply chain graph as a set of balance equations. They also consider the possibility of placing a CODP in a given operation that may receive some speculative production in advance of taking an order (first-stage production), and then releasing it once the demand is known (second-stage production). The production flow equations for assembly, base and final operations are, respectively:

$$P_{ij}^0 = H_{ij}^A + r_{ij} \sum_{k \in \mathcal{D}_j} P_{jk}^0 \qquad (i,j) \in \mathcal{A}^A \tag{1}$$

$$H_{ij}^A = R_{ijs}^A + F_{ijs}^A \qquad (i,j) \in \mathcal{A}^A, s \in \Omega \tag{2}$$

$$R_{ijs}^A + P_{ijs} = r_{ij} \sum_{k \in \mathcal{D}_j} P_{jks} \qquad (i,j) \in \mathcal{A}^A, s \in \Omega \tag{3}$$

$$\sum_{i \in \mathcal{O}_j} P_{ij}^0 = H_j^B + \sum_{k \in \mathcal{D}_j} P_{jk}^0 \qquad j \in \mathcal{N}^B \setminus \mathcal{N}^O \qquad (4)$$

$$H_j^B = R_{js}^B + F_{js}^B \qquad j \in \mathcal{N}^B, s \in \Omega \qquad (5)$$

$$R_{js}^B + \sum_{i \in \mathcal{O}_j} P_{ijs} = \sum_{k \in \mathcal{D}_j} P_{jks} \qquad j \in \mathcal{N}^B \setminus \mathcal{N}^D, s \in \Omega \qquad (6)$$

$$R_{js}^B + \sum_{i \in \mathcal{O}_j} P_{ijs} = V_{js} \qquad j \in \mathcal{N}^D, s \in \Omega \qquad (7)$$

$$d_{js} = B_{js} + V_{js} \qquad j \in \mathcal{N}^D, s \in \Omega \qquad (8)$$

Figure 2 illustrates the meaning of equations (1)-(6), where solid arcs are the production flow in speculation, dotted arcs are production flow in postponement. Equation (1) describes the speculative flow equation of any assembly operation j: the ingoing production P_{ij}^0 of each piece can be either stored in a CODP or processed and delivered to further operations. If some quantity H_{ij}^A is stored, the operation becomes a CODP, as modelled by equation (2) with the capacity to release this production R_{ijs}^A during the second stage and a remaining excess production F_{ijs}^A. Equation (3) takes the released production R_{ijs}^A together with the postponed ingoing production P_{ijs} and transforms it into assembled production for delivery to further operations. Every assembly operation (1)-(3) assumes that r_{ij} units of part $i \in \mathcal{O}_j$ are used to assemble a unit of product j. Equations (4)-(6) are analogous to equations (1)-(3) for base operations, which are unlike the assembly case in that each ingoing arc is assumed to carry the same type of product. Production ultimately reaches the final operations in equation (7) , where delivery occurs to fulfil demand d_s in scenario $s \in \Omega$. The model allows for both an excess and a shortage of production through variables $F^{A,B}$ and B, respectively. While the excess production $F^{A,B}$ is considered in equations (2) and (5), the numbers of sales and stock-out production are modelled in equation (8). We do not consider backorders; therefore unsatisfied demand is lost.

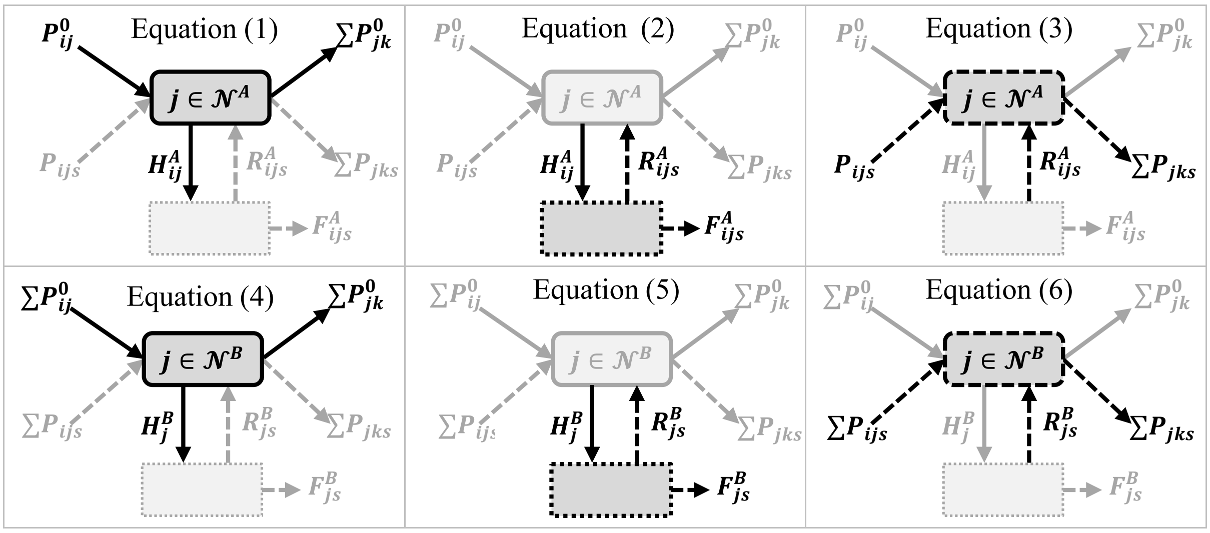


Figure 2: Production flow through assembly and base operations, equations (1)-(6).

3.3.2. *SC design*

Table 5 shows the so-called *design variables*. This set of binary variables determines the design of the SC; that is, which operations are going to be deployed and which of these deployed operations are going to be a CODP.

	Name	Domain	Definition
Speculation (first stage)	Operation Deployment	$Y_j \in \{0,1\}$	$Y_j = 1 \leftrightarrow$ operation j is deployed for $j \in \mathcal{N}$.
	CODP positioning	$Z_j \in \{0,1\}$	$Z_j = 1 \leftrightarrow$ a CODP is deployed for operation $j \in \mathcal{N}$.
	Speculative production indicator	$X^0_{ij} \in \{0,1\}$	$X^0_{ij} = 1 \leftrightarrow$ operation i operates and delivers production to operation j in speculation for $(i,j) \in \mathcal{A}$.
Postponed (second stage)	Postponement production Indicator	$X_{ijs} \in \{0,1\}$	$X_{ijs} = 1 \leftrightarrow$ operation i operates and delivers production to operation j in postponement for $(i,j) \in \mathcal{A}$.

Table 5: Design variables

The relationships between the production and design variables are established in the following constraints, where parameter $\bar{P}$ is any upper bound on the total production flow:

$$P_{ij}^0 \leq \bar{P} \cdot X_{ij}^0 \qquad (i,j) \in \mathcal{A} \qquad (9)$$

$$P_{ijs} \leq \bar{P}\, X_{ijs} \qquad (i,j) \in \mathcal{A}, s \in \Omega \qquad (10)$$

$$X_{ij}^0 \leq Y_i \qquad (i,j) \in \mathcal{A} \qquad (11)$$

$$X_{ijs} \leq Y_i \qquad (i,j) \in \mathcal{A}, s \in \Omega \qquad (12)$$

$$V_{js} \leq d_{js} Y_j \qquad j \in \mathcal{N}^D, s \in \Omega \qquad (13)$$

$$\frac{1}{n^R} H_j^B + \frac{n^R - 1}{n^R} F_{js}^B \leq q_j^B\, Z_j \qquad j \in \mathcal{N}^B, s \in \Omega \qquad (14)$$

$$\frac{1}{n^R} H_{ij}^A + \frac{n^R - 1}{n^R} F_{ijs}^A \leq q_{ij}^A\, Z_j \qquad (i,j) \in \mathcal{A}^A, s \in \Omega \qquad (15)$$

Equations (9)-(10) couple the speculative and postponed production variables P_{ij}^0 and P_{ijs} to its production indicators X_{ij}^0 and X_{ijs}, respectively; while equations (11)-(13) link, respectively, the speculative and postponement production indicators X_{ij}^0 and X_{ijs} and the sales variable V_{is} to the associated set-up variable Y_i. Equation (14) guarantees that if a base operation $j \in \mathcal{N}^B$ is a CODP, the inventory capacity q_j^B of every base operation can accommodate the maximum level of the inventory through the time horizon; that is, the fresh speculative production batch at the last replenishment H_j^B / n^R plus the excess of speculative production per replenishment F_j^B / n^R that is accumulated during the previous $n^R - 1$ replenishements. Equation (15) imposes the same condition on assembly operations.

3.3.3. Lead time

At the postponement stage, postponed production per period departing from CODPs must arrive at the final operations before a maximum allowed service time l^S. Additionally, operations i with positive lead times ($a_{ij} > 0$ and/or $b_{ij} > 0$, for $j \in \mathcal{D}_i$) must be finished in a single time period of length l^P. The lead time equations guaranteeing these assumptions are:

$$L_{js} \geq L_{is} + b_{ij} + \frac{a_{ij}}{n^P} P_{ijs} - M_{ij}\left(1 - X_{ijs}\right) \qquad (i,j) \in \mathcal{A}, s \in \Omega \qquad (16)$$

$$\sum_{j \in \mathcal{D}_i} \frac{a_{ij}}{n^P} \left(P_{ij}^0 + P_{ijs}\right) \leq l^P \qquad i \in \mathcal{N}, s \in \Omega \qquad (17)$$

$$0 \leq L_{is} \leq l^S \qquad i \in \mathcal{N}^D, s \in \Omega \qquad (18)$$

where the auxiliary variable $L_{js} \geq 0$ measures the lead time from the CODPs to operation $j \in \mathcal{N}$ in demand scenario $s \in \Omega$. Equation (16) connects the lead time between operations i and j whenever some production per period is processed and delivered in postponement, with $M_{ij} = l^S + b_{ij} + \frac{a_{ij}}{n^P} \bar{P}$ being an upper bound of the lead time.

Equation (17) computes the time that an operation takes to process the total production per period, postponed P_{ijs}/n^p plus speculative P_{ij}^0/n^P. Finally, equation (18) guarantees that the actual lead time of the final operations will not be greater than the maximum allowed service time l^S.

3.4. Expectation of the total profit and final model

The goal of this model is to maximize the total expected profit of the supply chain deployment and operations, expressed in equation (19). The first-stage costs A-F include the cost of the speculative production and design decisions, while the second-stage costs G-L correspond to the costs associated with postponement. The expressions for the holding costs E-F of the inventory variables $H^{A,B}$ and for K-L of the excess production variables $F^{A,B}$ results from the policy n^R, which evenly distributes identical replenishments along a total time horizon of n^P time periods. At the beginning of every replenishment cycle of length n^P/n^R time periods, a fresh production batch $H^{A,B}/n^R$ enters the CODP's inventory, leaving an amount of $F^{A,B}/n^R$ in excess production stored at the end of that same replenishment cycle.

$$\begin{aligned} TotalProfit = & -\overbrace{\sum_{i\in\mathcal{N}} f_i Y_i}^{\text{A: Operations setup cost}} - \overbrace{\sum_{i\in\mathcal{N}} z_i Z_i}^{\text{B: CODP setup cost}} - \overbrace{n^R \sum_{(i,j)\in\mathcal{A}} e_{ij} X_{ij}^0}^{\text{C: Fixed cost, speculative production.}} \\ & - \overbrace{\sum_{(i,j)\in\mathcal{A}} c_{ij} P_{ij}^0}^{\text{D: Variable cost, speculative production.}} - \overbrace{\sum_{(i,j)\in\mathcal{A}^A} \frac{n^P}{2n^R} h_{ij}^A H_{ij}^A}^{\text{E: Holding cost, assembly inventory}} - \overbrace{\sum_{j\in\mathcal{N}^B} \frac{n^P}{2n^R} h_j^B H_j^B}^{\text{F: Holding cost, base inventory}} \\ & + \sum_{s\in\Omega} \pi_s \left(\overbrace{\sum_{i\in\mathcal{N}^D} p_i V_{is}}^{\text{G: Sales incomes}} - \overbrace{\sum_{i\in\mathcal{N}^D} o_i B_{is}}^{\text{H: Stock-out cost}} - \overbrace{n^P \sum_{(i,j)\in\mathcal{A}} e_{ij} X_{ijs}}^{\text{I: Fixed cost, postponed production}} - \overbrace{\sum_{(i,j)\in\mathcal{A}} c_{ij} P_{ijs}}^{\text{J: Variable cost, postponed production}} \right. \\ & \left. - \overbrace{\sum_{(i,j)\in\mathcal{A}^A} \left(\frac{n^P}{2} h_{ij}^A + g_{ij}^A\right) F_{ijs}^A}^{\text{K: Holding+Discarding cost assembly excess prod.}} - \overbrace{\sum_{j\in\mathcal{N}^B} \left(\frac{n^P}{2} h_j^B + g_j^B\right) F_{js}^B}^{\text{L: Holding+Discarding cost base excess prod.}} \right) \end{aligned} \tag{19}$$

In summary, the extended form of model $(OSCS)$ that has been developed so far is the mixed integer linear programming problem represented by:

$$(OCSC)\begin{cases} \text{max} & TotalProfit & (19) \\ \text{s.t.:} & & \\ & SC\ production\ Flow & (1)-(8) \\ & SC\ design & (9)-(15) \\ & Lead\ time & (16)-(18) \\ & Variables\ domain & \text{Table 4} - \text{Table 5} \end{cases}$$

Model $(OSCS)$ was implemented using the mathematical programming language AMPL (AMPL, 2016) with the optimizer CPLEX 12.8 (CPLEX, 2018), running on a Dell POWEREDGE R630 (2 x Xeon E5-2697 v4 (2,3 GHz,18C/36T,45 MB cache) server using 256GB RAM). All the computational runs referred to in this study from this point forward were obtained with a relative MILP gap of 1% while using 8 threads for the root node processing and up to 32 threads for a parallel branch and cut. All execution times are wall clock time.

3.5. Scalability

The dimension of model $(OSCS)$ in terms of the structure of the SC is:

- # of binary variables: $2 \cdot |\mathcal{N}| + |\mathcal{A}| + |\Omega| \cdot |\mathcal{A}|$
- # of cont. variables: $|\mathcal{A}| + |\mathcal{N}^B| + |\mathcal{A}^A| +$
  $|\Omega| \cdot (|\mathcal{N}| + 2|\mathcal{N}^B| + 2|\mathcal{N}^D| + |\mathcal{A}| + 2|\mathcal{A}^A|)$
- # of constraints: $|\mathcal{N}^B| - |\mathcal{N}^O| + 2|\mathcal{A}| + |\mathcal{A}^A| +$
  $|\Omega| \cdot (|\mathcal{N}| + 3|\mathcal{N}^B| + 3|\mathcal{N}^D| + 3|\mathcal{A}| + 3|\mathcal{A}^A|)$

We tested a set of randomly generated instances of model $(OSCS)$ in order to analyse the scalability of the problem, namely: how the size of the SC affects the complexity of the optimization problem in terms of its execution time. These instances represent an SCND problem with 3 layers (suppliers, manufacturers and retailers), $k = 3{,}6{,}12{,}18$, and there are 24 base operations per layer. In addition, there are forward arcs between every operation in layers 1 and 2 and layers 2 and 3. Every instance has $|\Omega| = 100$ scenarios, $n^P = 180$ time periods of length $l^P = 24\ h$, $n^R = 24$ replenishments, and the maximum service time is $l^S = 24\ h$. Table 6 displays the size and execution times of every instance in the 3-layer SC problem. The size of the $(OSCS)$ and the execution time remain nearly linear w.r.t. the numbers of operations per layer k for every instance, except for the last one, where the execution time explodes to nearly 30 hours. Nevertheless, taking into account that we are solving a mid- to long-term planning problem with a time horizon that comprise the whole life-cycle of a product (seasons to years), this model's applicability does not seem to be compromised by the execution time – which is below 2.5 hours for instances with no more than 18 operations per layer and reaches even 30 hours for larger instances.

k	$\lvert\mathcal{N}\rvert$	$\lvert\mathcal{A}\rvert$	# binary variables	# continuous variables	# of constraints	Execution time
3	9	18	1,836	5,127	12,360	76 s
6	18	72	7,308	13,890	39,228	532 s
12	36	288	29,160	42,324	136,488	2,806 s
18	54	648	65,556	85,302	291,780	8,414 s
24	72	1,152	116,496	142,824	505,104	108,762 s

Table 6: Sizes and execution times of 3-layer SC instances.

4. Case study: Introducing additive manufacturing technology into the toy industry

Let us consider the SCND problem of a toy company that supplies collections of figurines from several soccer teams. Figure 3 (a) represents the current manufacturing process that assembles two modules for each figurine: a common body and some differentiated parts (head and extremities).

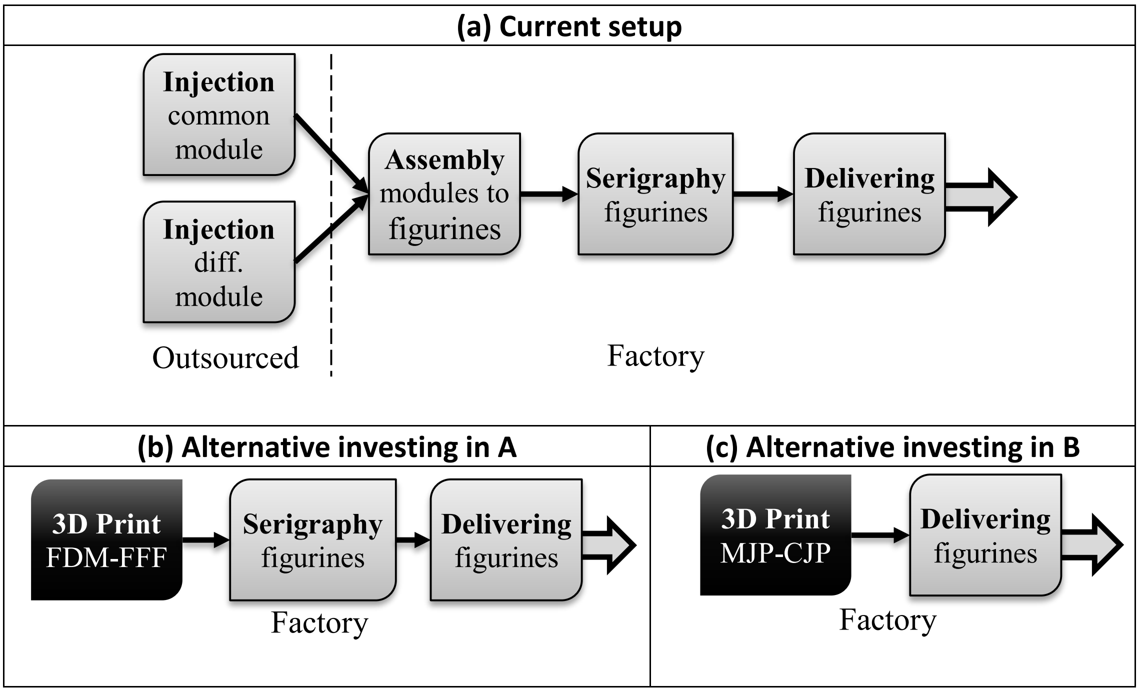
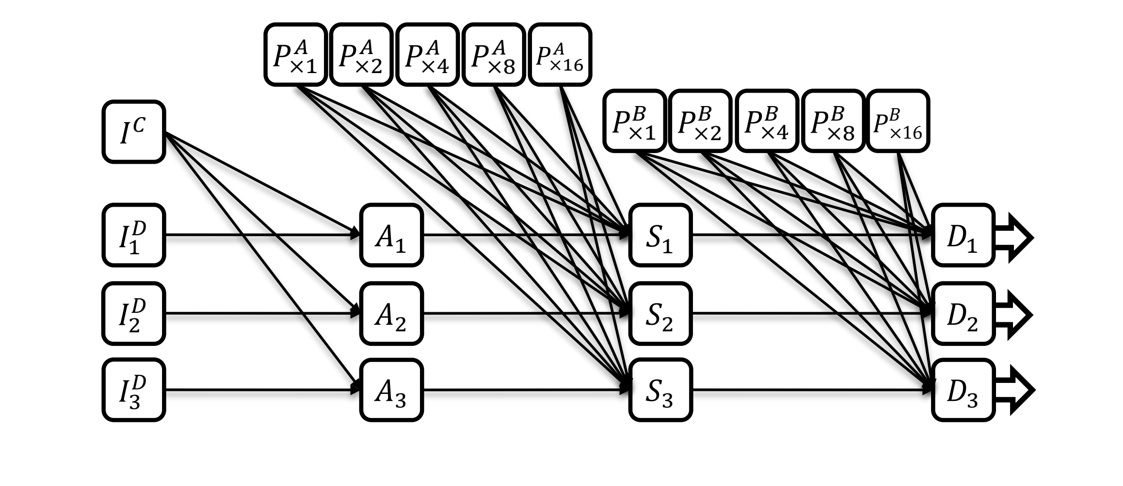


Figure 3: Current and alternative setups: toy industry

The fabrication of the modules is outsourced while the assembly, serigraphy and distribution operations are performed using the company's own resources. Model $(OSCS)$ is used in this study to assess the convenience of additive manufacturing introduced into the current SC configuration by means of two different kinds of 3D Printers: printer A is a single colour 3D printer FDM-FFF (Fused Deposition Modelling – Fused Filament Fabrication AM printer); printer B is a multi-colour 3D printer MJP-CJP (Multi Jet Printing – Colour Jet Printing AM printer), see ASTM (2005), Balletti et al. (2017) and Lee et al. (2017). Figure 3 displays the portfolio of available technologies: the current injection setup (Figure 3 (a)); and the two available alternatives based on additive printing. Alternative A uses FDM-FFF printers to substitute the injection and assembly operations (Figure 3 (b)), while alternative B uses MJP-CJP printers to replace the injection, assembly and serigraphy operations (Figure 3 (c)). An additional investment decision concerns the number of printers to deploy in cases where any AM technologies are being used. In this case study, we consider a 3-figurine collection.

The supply chain graph associated with the test case is shown in Figure 4. Operations I_p^D, A_p, S_p and D_p, $p = 1, \ldots, 3$ correspond to a set of operations that are different for every item p. This is in contrast to operations I^C, $P_{\times n}^A$ and $P_{\times n}^B$, which are common to all items. In addition, we use $P_{\times n}^A$ and $P_{\times n}^B$ to describe parallel operations comprising, respectively, n AM printers of type A and B. In this case study, we consider an investment of up to 31 AM machines of each type (up to 1 + 2 + 4 + 8 + 16 machines of types A and B among $P_{\times 1}^A$, $P_{\times 2}^A$, $P_{\times 4}^A$, $P_{\times 8}^A$ and $P_{\times 16}^A$, and $P_{\times 1}^B$, $P_{\times 2}^B$, $P_{\times 4}^B$, $P_{\times 8}^B$ and $P_{\times 16}^B$).



Operations			
Current setup		**Alternative A**	
$\boldsymbol{I^C}$	Injection operation of common module	$\boldsymbol{P^A_{\times n}}$	AM operation with n printers type A
$\boldsymbol{I^D_p}$	Injection operation of module $p = 1,2,3$		
$\boldsymbol{A_p}$	Assembly operation of item $p = 1,2,3$	**Alternative B**	
$\boldsymbol{S_p}$	Serigraphy operation of item $p = 1,2,3$	$\boldsymbol{P^B_{\times n}}$	AM operation with n printers type B
$\boldsymbol{D_p}$	Delivery operation of item $p = 1,2,3$		

Figure 4: Graph of toy industry

Production costs and lead times				
$\mathcal{A}$	c_{ij} (€/u)	a_{ij} (h/u)	b_{ij} (h)	e_{ij} (€)
$I^C \to A_p$	0.1	0	120	5
$I_p^D \to A_p$	0.1	0	120	5
$A_p \to S_p$	0.2	0.05	2	10
$S_p \to D_p$	0.05	0.02	4	20
$P_{\times 1}^A \to S_p$	0.5	0.3	0	0
$P_{\times 2}^A \to S_p$	0.5	0.15	0	0
$P_{\times 4}^A \to S_p$	0.5	0.075	0	0
$P_{\times 8}^A \to S_p$	0.5	0.0375	0	0
$P_{\times 16}^A \to S_p$	0.5	0.01875	0	0
$P_{\times 1}^B \to D_p$	0.7	0.5	0	0
$P_{\times 2}^B \to D_p$	0.7	0.25	0	0
$P_{\times 4}^B \to D_p$	0.7	0.125	0	0
$P_{\times 8}^B \to D_p$	0.7	0.0625	0	0
$P_{\times 16}^B \to D_p$	0.7	0.04375	0	0

	CODP inventory parameters, base operations		
$\mathcal{N}^B$	q_i^B (u)	h_i^B (€/$u \cdot t$)	g_i^B (€/u)
I^C	60,000	0.0005	0.1
I_p^D	60,000	0.0005	0.1
S_p	60,000	0.005	1
D_p	40,000	0.007	1.4
$P_{\times n}^A$	90,000	0.00005	0.01
$P_{\times n}^B$	90,000	0.00005	0.01

	Bill of materials
$\mathcal{A}^A$	r_{ij}
$I^C \to A_p$	1
$I_p^D \to A_p$	1

Setup costs		
$\mathcal{N}$	z_i (€)	f_i (€)
I^C	5,000	1,000
I_p^D	5,000	1,000
A_p	7,000	2,000
S_p	10,000	1,000
D_p	15,000	1,000
$P_{\times 1}^A$	100	4,000
$P_{\times 2}^A$	100	8,000
$P_{\times 4}^A$	100	16,000
$P_{\times 8}^A$	100	32,000
$P_{\times 16}^A$	100	64,000
$P_{\times 1}^B$	100	60,000
$P_{\times 2}^B$	100	120,000
$P_{\times 4}^B$	100	240,000
$P_{\times 8}^B$	100	480,000
$P_{\times 16}^B$	100	960,000

	CODP inventory parameters, assembly operations		
$\mathcal{A}^A$	q_{ij}^A (u)	h_j^A (€/$u \cdot t$)	g_j^A (€/u)
$I^C \to A_p$	60,000	0.002	0.4
$I_p^D \to A_p$	60,000	0.002	0.4

Sales & Stock-out		
$\mathcal{N}^D$	p_i (€/u)	o_i (€/u)
D_p	5	1

Table 7: Toy industry dataset.

Table 7 summarizes the supply chain parameters of the operations and arcs of the supply chain graph. Note that the parameters of operations $P_{\times 2}^A$, $P_{\times 4}^A$, $P_{\times 8}^A$ and $P_{\times 16}^A$ are based on the parameters of $P_{\times 1}^A$, with the fixed setup cost being $f_{(\times n)}^A = n \cdot f_{P_{\times 1}^A}$, and the unit lead time $a_{P_{\times n}^A} = a_{P_{\times 1}^A}/n$. We study a time horizon of six months discretized into $n^P = 180$ time periods of $l^P = 24$ hours, with a maximum service time of $l^S = 12\ h$ and $n^R = 24$ replenishments. We assume that the joint demand of all figurines follows a multivariate Gaussian distribution with mean μ, standard deviation σ, and correlation matrix ρ

$$\mu = \begin{pmatrix} 90{,}000 \\ 54{,}000 \\ 27{,}000 \end{pmatrix} \quad \sigma = \begin{pmatrix} 63{,}000 \\ 37{,}800 \\ 18{,}900 \end{pmatrix} \quad \rho = \begin{pmatrix} 1 & 0.3 & -0.1 \\ 0.3 & 1 & 0.1 \\ -0.1 & 0.1 & 1 \end{pmatrix}.$$

We have randomly generated 100 scenarios of $d_s \sim \mathcal{G}(\mu, \sigma, \rho)$, each containing the number of customer orders for each final operation, i.e., $d_s = (d_{js}), j \in \mathcal{N}^D$ and the same probability of $\pi_s = 0.01$.

4.1. Case study solution

The instance of model $(OSCS)$ associated with this case study of 100 scenarios contains: 4,288 binary variables (88 for the first stage and 42 for every scenario at the second stage); $12{,}368$ continuous variables (68 for the first stage and 123 for every scenario in the second stage); and 23,696 linear constraints (96 for the first stage and 236 for every scenario in the second stage). The execution wall-clock time for the case study was 29 seconds. The optimal solution gains an expected total benefit of $443{,}064$ € and executes the processes illustrated in Figure 5. The operations (nodes) in Figure 5 with dimmed dashed lines are discarded, while the operations with thin solid lines are executed. Among the latter, the operations with thick solid lines are CODPs. Regarding production flows (arcs), the solid arrows show the speculative production flows that provide the inventories for the four CODPs, while the dashed arrows denote postponement production flows from the CODPs to the markets. The salient features of this solution are:

- Regarding the selection of the best technologies, the optimal solution is a hybrid policy for figurines 1 and 2 combining the current supply chain setup (injection, assembly and serigraphy) with a AM facility using 16 printers of type A to fulfil the demand. However, the optimal policy for figurine 3 is to use exclusively AM printers of type A. Moreover, AM printers of type B are fully discarded.

- Regarding the choice between speculation/postponement strategies, the model $(OSCS)$ also finds that the optimal degree of postponement for every process is a non-trivial combination of speculative and postponed production, specifically by optimally positioning four different CODPs: the delivery operations D_1 and D_2 for, respectively, figurines 1 and 2; the serigraphy operation S_1 for figurine 1; and the facility with 16 AM printers, $P^A_{\times 16}$.

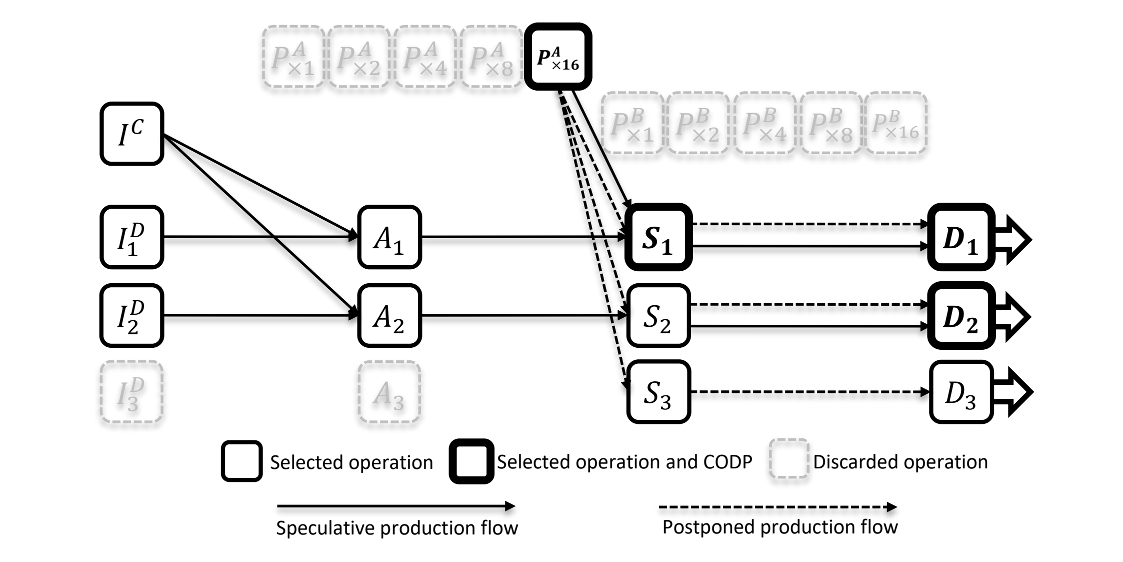
Figure 5 shows that the optimal speculative production policy for furnishing the four CODP inventories includes three speculative processes based on injection (SP2, 3 and 4) and two based on AM (SP1 and 5):

- The CODP inventory for S_1 is provided simultaneously by the speculative production of AM process SP1 and the injection process SP2 ($11{,}790\ u.$ and $46{,}400\ u.$, respectively).

- The CODP inventories for D_1 and D_2 are replenished completely by injection processes SP3 and SP4 ($40{,}000$ units each).

- Finally, SP5 denotes that the CODP inventory for the AM facility $P^A_{\times 16}$ stores raw material that can produce $81{,}450$ units for feeding the serigraphy operations $S_{1,2,3}$ in postponement, once the demand is known.

- The optimal production policy in postponement includes six postponed processes that push production from the four CODPs to the markets for the three figurines, after demand is known:



Speculative Processes (SP) and total production		Postponed Processes (PP) and total expected production	
SP1: $P^A_{\times 16} - \boldsymbol{S_1}$	11,790 u.	PP1: $\boldsymbol{P^A_{\times 16}} - S_1 - D_1$	2,982 u.
SP2: $\left.\begin{matrix} I^C \\ I^D_1 \end{matrix}\right\} - A_1 - \boldsymbol{S_1}$	46,400 u.	PP2: $\boldsymbol{S_1} - D_1$	35,121 u.
SP3: $\left.\begin{matrix} I^C \\ I^D_1 \end{matrix}\right\} - A_1 - S_1 - \boldsymbol{D_1}$	40,000 u.	PP3: $\boldsymbol{D_1}$	34,647 u.
SP4: $\left.\begin{matrix} I^C \\ I^D_2 \end{matrix}\right\} - A_2 - S_2 - \boldsymbol{D_2}$	40,000 u.	PP4: $\boldsymbol{P^A_{\times 16}} - S_2 - D_2$	15,758 u.
SP5: $\boldsymbol{P^A_{\times 16}}$	81,450 u.	PP5: $\boldsymbol{D_2}$	33,510 u.
		PP6: $\boldsymbol{P^A_{\times 16}} - S_3 - D_3$	26,485 u.

Figure 5: Optimal solution for toy industry.

- Demand for figurine 1 is supplied from production flows starting at the CODP inventories for $P^A_{\times 16}$, S_1, D_1 by means of three different processes: PP1, PP2 and PP3.

- Demand for figurine 2 is supplied from the postponed production starting at the CODP inventory of the AM facility $P^A_{\times 16}$ and from the finished figurines released from the CODP inventory at the delivering facility D_2 by means of processes PP4 and PP5.

- Finally, the complete demand for figurine 3 is fulfilled with the postponed production of PP6, which begins at AM facility $P^A_{\times 16}$.

Note also that some arcs, such as $S_1 \rightarrow D_1$, $P^A_{\times 16} \rightarrow S_1$ and $S_2 \rightarrow D_2$, handle production both in speculation and postponement.

Figure 6 provides us with deeper managerial insight into the optimal operation of the SC by helping us analyse the relationship between the demand level and the optimal postponed production strategy. The horizontal axis of the graph for each figurine corresponds to the scenarios, sorted by increasing value of the demand. For every scenario, the black line represents the demand, and the vertical bars in different shades of grey correspond to the production quantities for the postponed processes PP1 to PP6, as indicated in the figure.

The three graphs in Figure 6 identify the optimal supply policy rules for the three products, depending on the demand level:

- For Figurine 1, PP1 remains always active and will provide up to $40{,}000\ u.$; if demand exceeds $40{,}000\ u.$, production begins in the serigraphy operation through PP2; if demand is above $91{,}190\ u.$, AM printing also begins through PP3. Any demand level greater than $105{,}318\ u.$ is beyond the capacity of the SC and is lost, generating an expected stock-out of $15{,}946$ units (17% of the expected demand).

- For figurine 2, PP5 is always active and releases the finished figurines stored at delivering facility D_2; while PP4 must begin whenever the demand exceeds $40{,}000\ u.$ in order to provide additional figurines by means of AM printing. Orders cannot be serviced if the demand is greater than $77{,}161$ units, generating an expected stock-out of $3{,}986$ units (7% of the expected demand).

- For figurine 3, process PP6 will supply solely the demand by means of production at the AM facility, up to $37{,}161\ u.$ Orders above that threshold are lost, generating an expected stock-out of $1{,}668$ units (6% of the expected demand).

4.2. Sensitivity analyses

In this section, we study the optimal solution's sensitivity to changes in the costs associated with the CODP inventories: stock-out costs o_i, holding inventory costs $h^{A,B}$, and discarding inventory costs $g^{A,B}$. To this end, we have compared the balance between the total production of the injection and printing processes for a series of runs where the initial values of the parameters o_i, $h^{A,B}$ and $g^{A,B}$ in Table 7 have been multiplied by a factor of $2, 4, 6$ and 8. According to Figure 7 it appears that the increase in stock-out cost has no significant effect on the SC's optimal design and operation. Indeed, Figure 7 a) shows that the total production of the injection process remains constant at $130{,}157$ units while total printed production increases slightly from $52{,}470$ to $58{,}230$ units. What is more, the optimal solution maintains the same supply chain design as in Figure 5 for all multiplying factors, with the exception of the AM facility, which increases the number of AM machines from 16 to 25. In contrast, Figure 7 b) and c) show that the increase in holding and discarding inventory costs induces a clear reduction in total production by substituting injection production with AM printing, a technology that may help reduce inventory levels by increasing production in postponement. The results in Figure 7 a) show that the solution is almost insensitive to the stock-out costs o_i; that is, the stock-out level is not significantly reduced when stock-out cost increases. To better understand this, we have limited the stock-out level with additional constraints in model $(OSCS)$ by imposing an upper-bound to the allowed stock-out, up to a certain fraction α of the demand of each scenario. The solution with $\alpha = 40\%$ results in a negative total profit (losses) of $-57{,}052$ € due to the cost of deploying 14 AM printers of type A plus 10 AM printers of type B, which are needed to reduce the stock-out level. Similarly, in order for the stock-out to not be greater than a fraction $\alpha = 50\%$ of the demand, it is necessary to increase the number of AM printing facilities from the original 16 AM printers of type A to 20, plus 4 additional AM printers of type B. With the associated increase in production costs, the total profit is $245{,}686$ €, which is 45% less than that of the original solution. Therefore, in order to reduce the stock-out, additional AM devices must be deployed. The reduction in stock-out occurs at the expense of the considerable losses arising from the high setup and production costs of the AM printers.

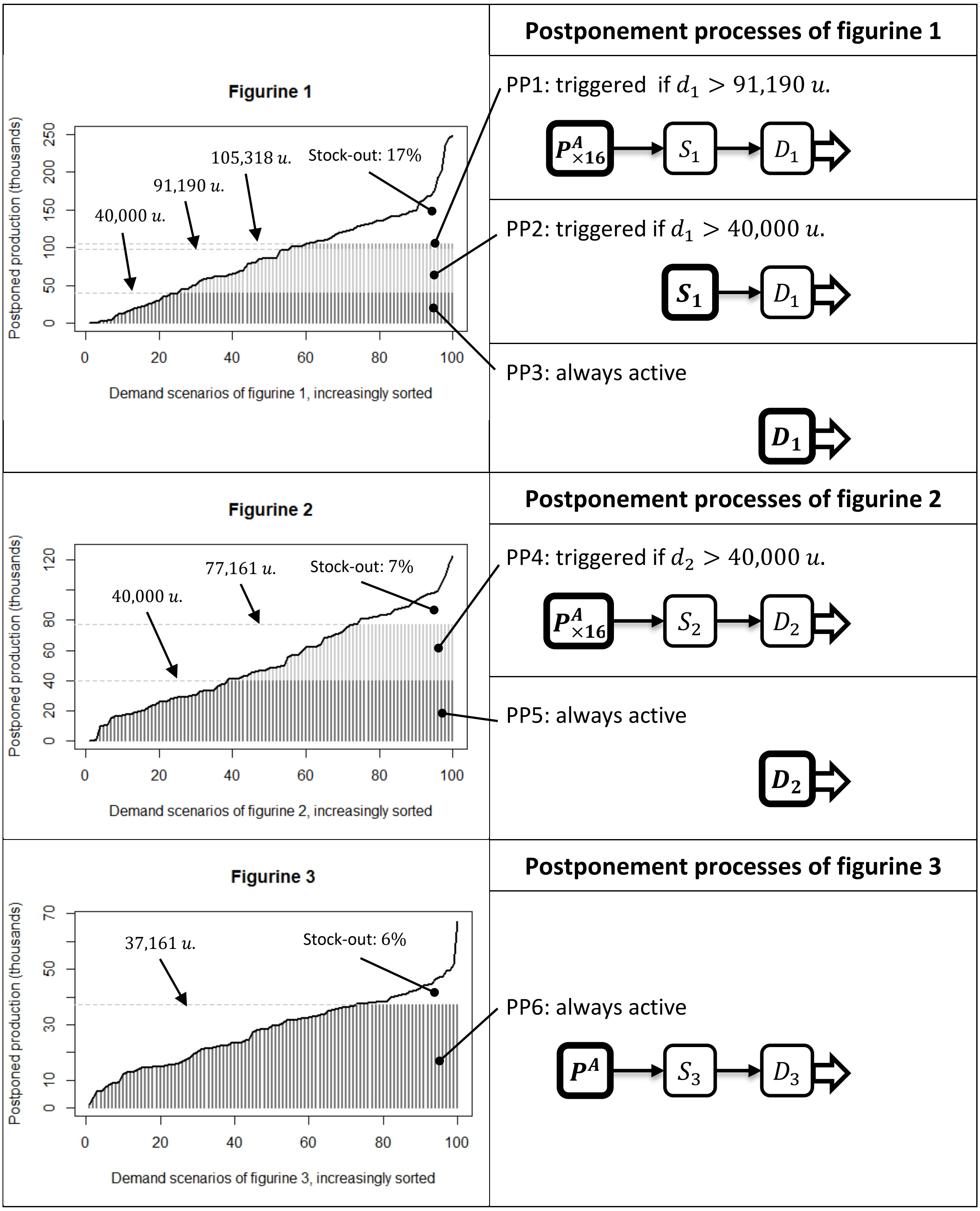


Figure 6: second stage processes by scenario.

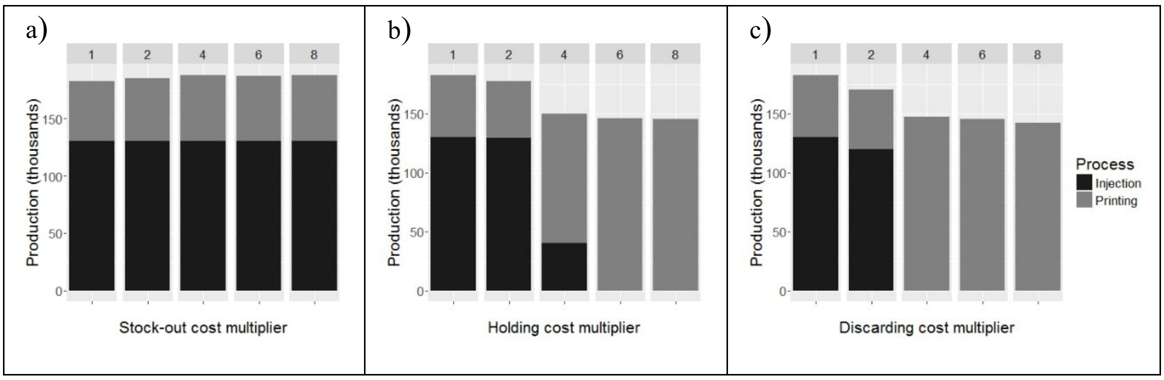
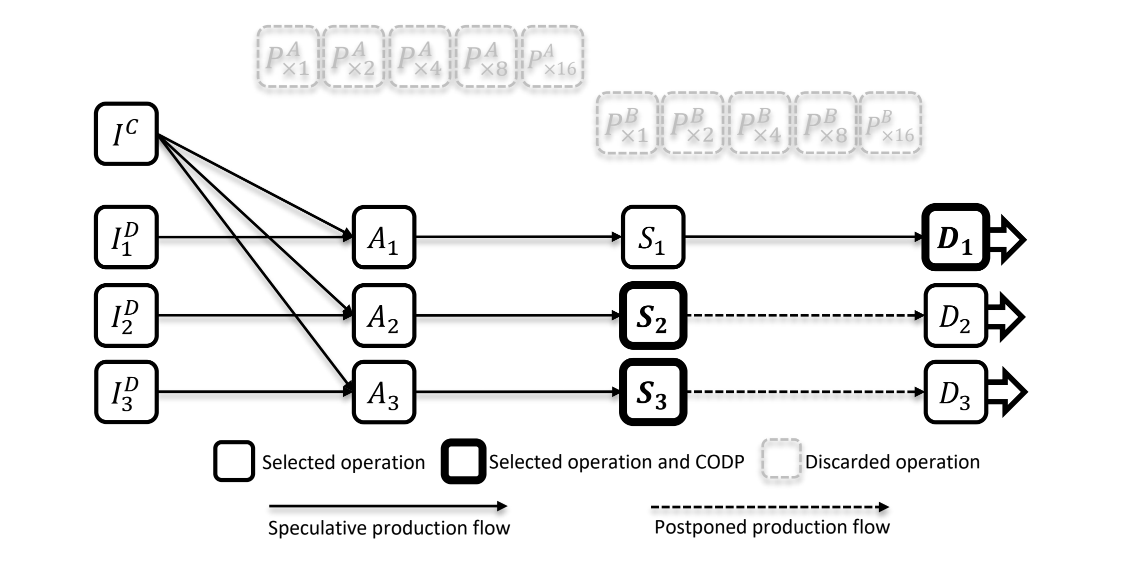


Figure 7: Production processes in terms of inventory costs

4.3. The Value of the Stochastic Solution

In order to evaluate the advantage of explicitly considering stochasticity in our model, we find the value of the stochastic solution VSS. First we find the expected value EV, which is the objective function at the optimal solution of the $(OSCS)$ problem under a single scenario defined with the expected values of all the stochastic parameters. The actual profit of the EV solution is the so-called expectation of the expected value EEV. It corresponds to the expected profit of model $(OSCS)$ when the values of the first stage variables are set to the values of the optimal solution for problem EV and the second stage variables are optimized. In our case $EEV = 383{,}355$ €. Finally, the so-called value of the stochastic solution VSS is defined as the difference between the solution of the stochastic $(OSCS)$ problem (known as the recourse problem RP, $RP = 443{,}064$ €) and the value of EEV. This turns out to be $VSS = RP - EEV = 59{,}709$ €, which is 13% of the value for the original solution. As is well known, this figure represents the increase in the total profit using the stochastic programming formulation with respect to the deterministic formulation. Figure 8 illustrates the optimal design and the supply chain flows for speculation and postponement in the EEV solution. In comparing Figure 5 with Figure 8, we can see that the solution of the respective stochastic and deterministic formulations, RP and EEV, are completely different. In the deterministic solution, the associated supply chain discards the AM printing facilities and deploys a single CODP by figurine: the delivery operation of figurine 1, and the serigraphy operations of figurines 2 and 3. Indeed, the solution of the EEV shows that much more stock-out is generated than in the RP solution: as the EV takes into account the expected demand, the EV optimal design does not foresee EEV scenarios with higher demand, as even some of the most extreme scenarios are infeasible. This made it necessary to relax some capacity constraints in order to solve the EEV problem.



Speculative Processes (SP) and total production		Postponed Processes (PP) and total expected production	
SP1: $\left.\begin{matrix}I^C\\ I_1^D\end{matrix}\right\} - A_1 - S_1 - \boldsymbol{D_1}$	90,000 $u.$	PP1: $\boldsymbol{D_1}$	65,886 $u.$
SP2: $\left.\begin{matrix}I^C\\ I_2^D\end{matrix}\right\} - A_2 - \boldsymbol{S_2}$	53,982 $u.$	PP2: $\boldsymbol{S_2} - D_2$	40,805 $u.$
SP3: $\left.\begin{matrix}I^C\\ I_3^D\end{matrix}\right\} - A_3 - \boldsymbol{S_3}$	27,000 $u.$	PP3: $\boldsymbol{S_3} - D_3$	22,143 $u.$

Figure 8: Supply chain design associated with the EEV solution.

5. Conclusions

This work proposes a new TSSP model $(OSCS)$ for supply network design problems. In addition to it including the most relevant characteristics of the SCND models published so far, it can choose the optimal speculation/postponement strategy. Indeed, the main novelty of model $(OSCS)$ is its capability to find not only the optimal operations/facilities for deployment and the production flow but also the optimal number and positioning of the CODPs for the selected operations and the associated inventory levels. Our work provides a new approach to treating the classical speculation/postponement categorization of SCND problems. In this classical approach: (i) there is a single CODP for every manufacturing process; (ii) its positioning is pre-set; and (iii) every operation in the process is run either in speculation or in postponement. In contrast, model $(OSCS)$: (i) can find the optimal positioning of the CODP and therefore solve one of the current major challenges to SCND postponement models, according to several authors; (ii) generalizes the classical SC concept of CODP and allows for several CODPs within the optimal SCND; and (iii) it permits both speculative and postponed production in the same operation. All the contributions of the model $(OSCS)$ to the SCND postponement model are illustrated and discussed in a detailed analysis of the optimal solution to a real problem in the toy industry, for which the model $(OSCS)$ was used to analyse the implemented alternative of additive manufacturing technologies. The case study for the toy industry is an example of how the model (OSCS) can contribute to real life applications to production systems and logistics. This is particularly true when the aim is to analyse the design of a responsive SC that takes advantage of new flexible manufacturing technologies, such as AM printing. In this case, we show that additive manufacturing is a valid technology for complementing and improving the efficiency of classical injection processes, but not for completely substituting it. Besides the case study presented in this research, the model

(OSCS) has proved to be useful analysing the introduction of AM printing in other industries, such as for spare car parts or retail crafts companies.

5.1. Managerial insights

The analyses of the case study using the model $(OSCS)$ unveils the degree of complexity that can be achieved with the optimal SCND using postponement, and they allow decision makers to gain several useful insights:

- When deciding to substitute an old technology with a new one (in this case, AM printing injection), the choice is not as simple as completely removing the old technology in favour of the new one or completely rejecting the new technology. Instead, as our case study shows, the optimal solution generally involves a complex combination of several technologies that is specific to every product. Therefore, managers must be aware that simple decisions can lead to inefficient SC designs.

- The same can be observed in the dichotomy between speculation/postponement. Our numerical results show that optimal policies for SC design may imply a sophisticated positioning of several CODPs throughout the same manufacturing process, and that this positioning is specific to every single product. Therefore, practitioners must avoid simple decisions involving complete speculation of postponement strategies, because such extreme strategies will lead to suboptimal designs that are rife with managerial inefficiencies.

- Depending on the deployment and operations costs, it could be preferable to incur relatively high stock-outs (as high as 17% of the total expected demand for some products in our test case) than to invest in increasing production capacities – although this may not be obvious from directly comparing the income/cost that is involved.

- Our computational sensitivity analysis clearly shows that high holding and discarding inventory costs promote the penetration of fast response technologies (such as AM printing) at the expense of less responsive manufacturing processes (such as injection). This increases the importance of postponement over speculative production.

- Finally, stochastic formulation is a must for SCND problems: our VSS analysis proved that the expected total profit of the stochastic formulation does increase by 13% over the deterministic formulation. Even worse, the solution to the deterministic formulation is biased towards sub-optimal speculative-dominant strategies, rejecting new technologies such as AM printing even though that technology is actually central to the optimal postponement strategies in SC design.

5.2. Further developments

We identify three major fields for future improvements to our work. Regarding the characteristics of the SCND model, there are some features that could be included in the current model, such as perishability, some risk-aversion measures, and closed-loop chains. Concerning the modelling of the stochasticity, the next natural step would be to extend the two-stage stochastic programming problem to a multistage stochastic programming problem with as many stages as time periods n^P in the formulation. Finally, with regard to optimization and the abovementioned issues associated with the model's scalability, decomposition techniques could be applied for dealing with large-scale instances, see Li and Grossmann, (2018) and Alonso-Ayuso et al. (2003).

Acknowledgments

This work was developed under an Accenture Open Innovation University Grant I-01326 and was also partially supported by grant RTI2018-097580-B-I00 of the Ministry of Economy and Competitiveness of Spain.

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