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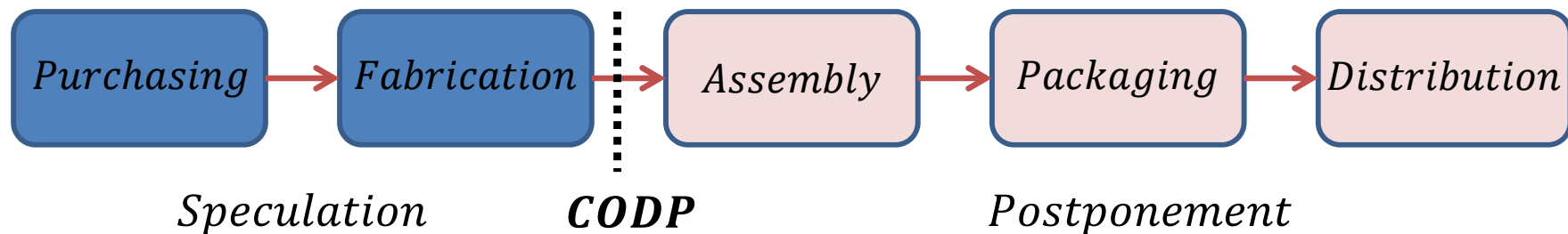


**DIGITALIZING SUPPLY CHAIN STRATEGY
WITH 3D PRINTING
6TH JULY 2016**

**accenture**

Preliminary Concepts

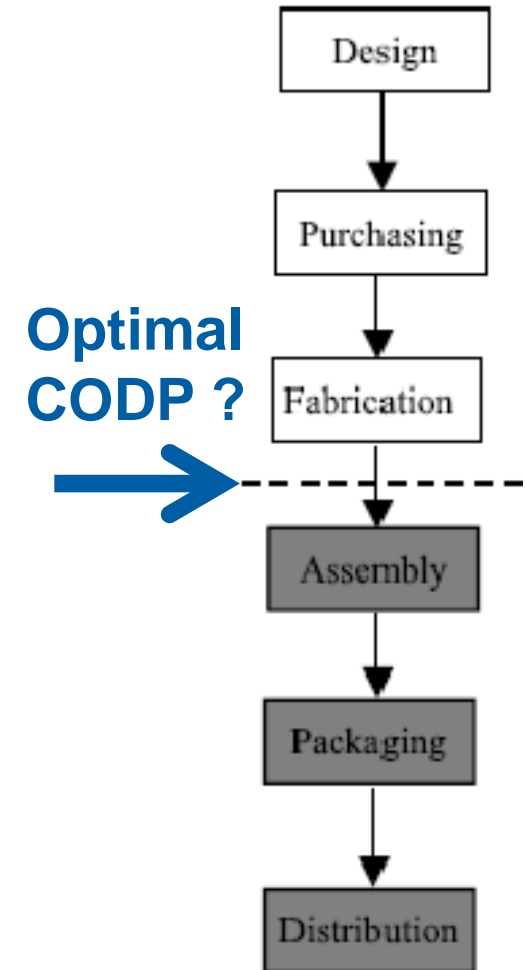
- A **supply chain** consists of all stages that are directly or indirectly involved in fulfilling a customer request.
- **Postponement** is an organizational concept whereby some of the activities in the supply chain are not performed until customer orders are received, as opposed to **speculation**.
- The **customer order decoupling point** (CODP) is the point which separates the forecast-driven production (speculation) from the order-driven production (postponement).



Objectives

“When should an enterprise implement certain strategic supply chain models that use 3D Printing?”

1. Perform an extensive **review of the existing bibliography** on supply chain strategies and manufacture with 3D printing.
2. Formulate a **mathematical optimization model** and obtain a computational implementation.
3. Use the mathematical model to **asses how to introduce 3D printing and postponement** for some test cases.



Contributions

We propose a new SP model that copes with some of the characteristics not considered in previous works. The main characteristics of this model are:

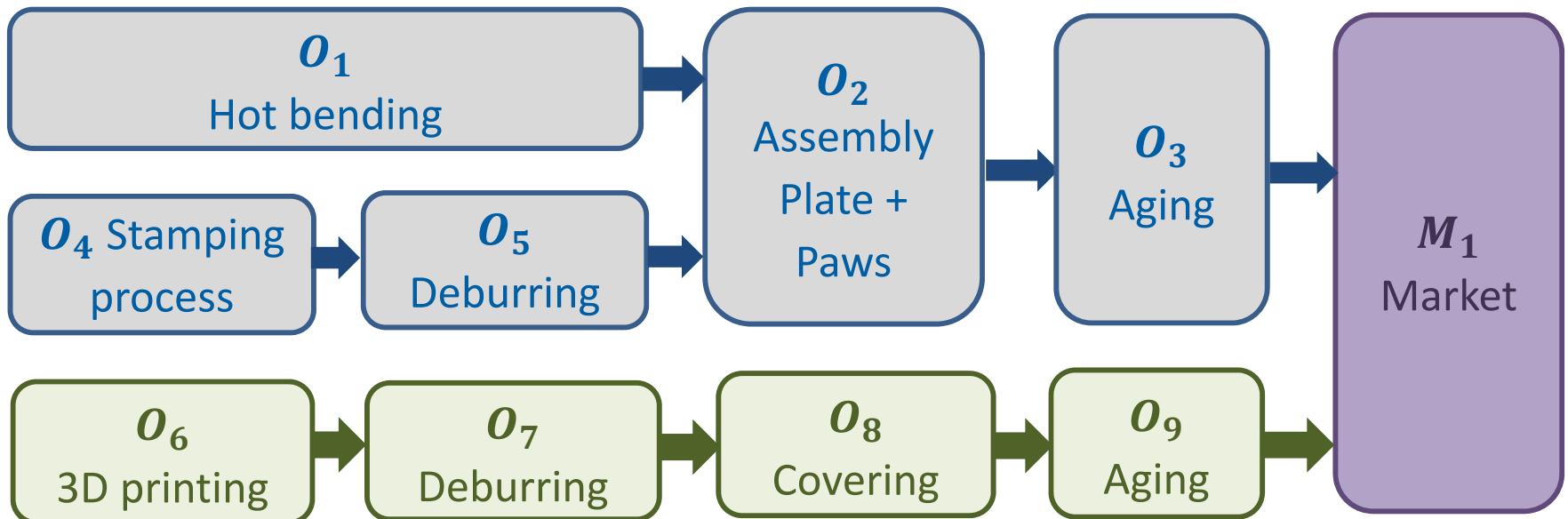
- A **two-stage stochastic program** can clearly describe both speculative (1st stage) and postponed (2nd stage) decisions.
- A speculation/postponement strategy deciding which operations shall be **decoupling points**.
- **Cost characterization** based on set-up of operations, production, holding and stock-out.
- We will consider **time periods** to introduce a **maximum delivery time**.
- **Demand uncertainty** discretized in a finite number of scenarios. We will also decompose possible **realizations of demand** by time periods.
- A **network configuration** of the supply chain allowing the model adapt form and place postponement problems.

Contents

1. Introduction
- 2. Problem definition**
 - Supply chain graph
 - Operations
 - Stochasticity
3. Problem formulation
4. Case studies
5. Conclusions and further research

Supply chain graph

- All the possible supply chain configurations are represented through an oriented graph that contains all the alternative manufacturing processes.

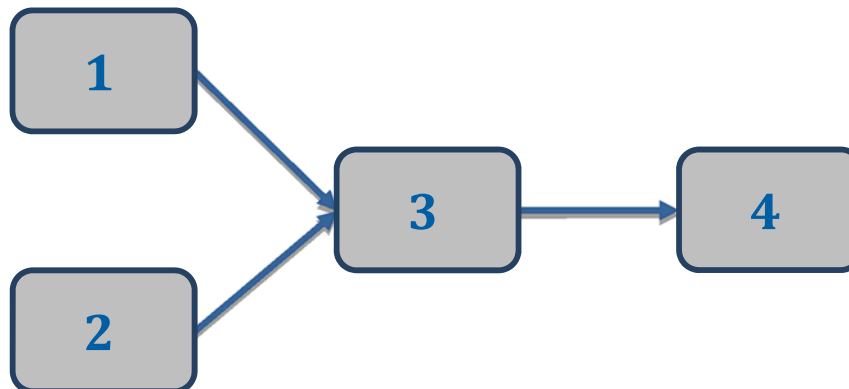


Process	Operations
P_1	$O_1, O_2, O_3, O_4, O_5 \rightarrow M_1$
P_2	$O_6, O_7, O_8, O_9 \rightarrow M_1$

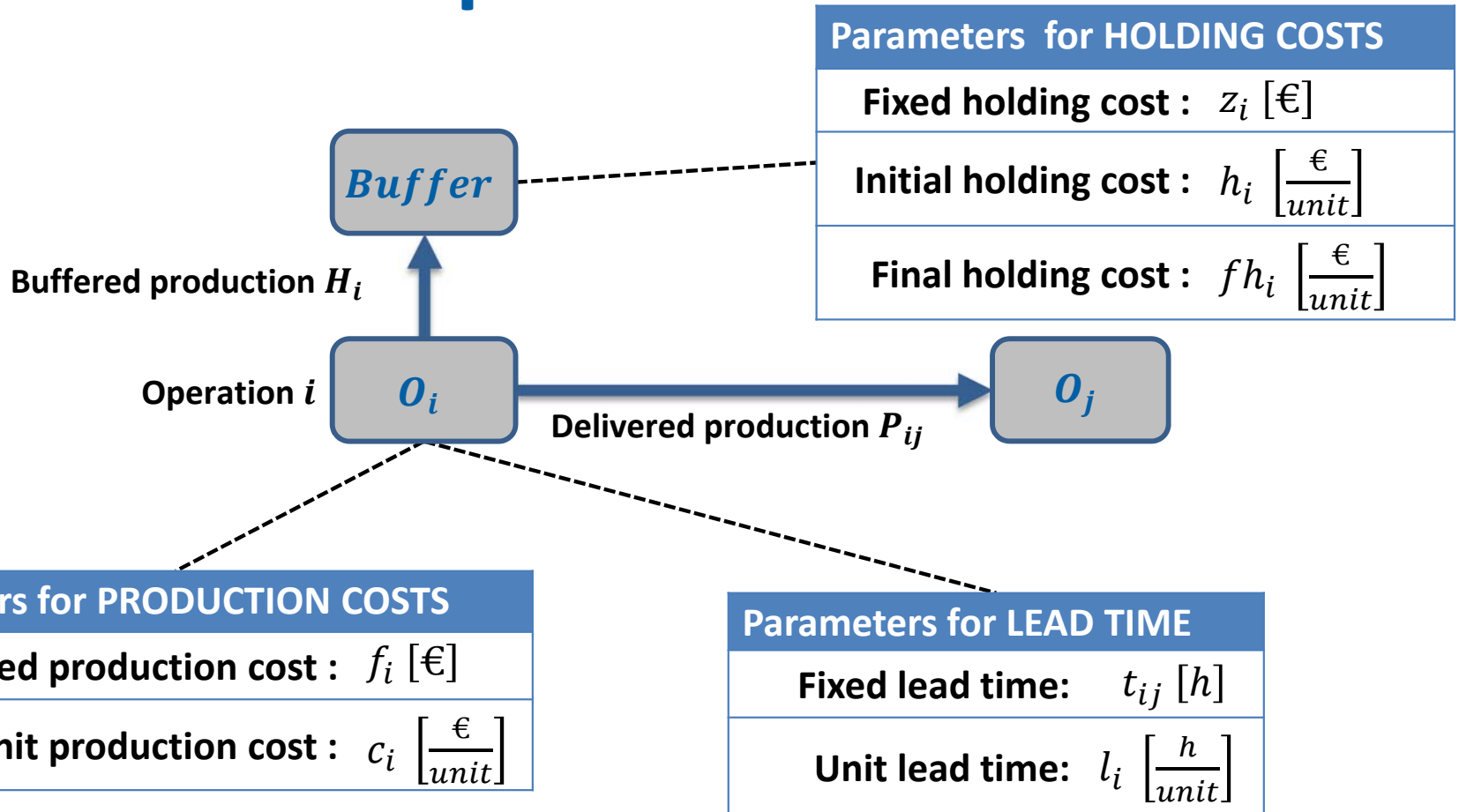
Types of nodes

We distinguish four types of nodes in the supply chain graph, in order to model different flows through the arcs of the graph:

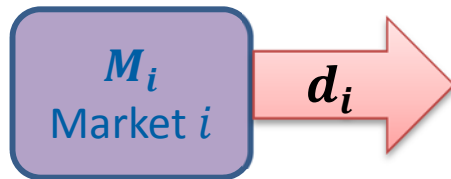
- **Initial nodes** are those where processes begin.
- **Assembly nodes** are those where their ingoing arcs move parts that will be assembled.
- **Production nodes** are those where any ingoing arc carries a given amount of the same product.
- **Market nodes** are those where processes end and production is sold.



Operations



Characterization of the market



Parameters for the MARKET

Demand: d_s^i [units]

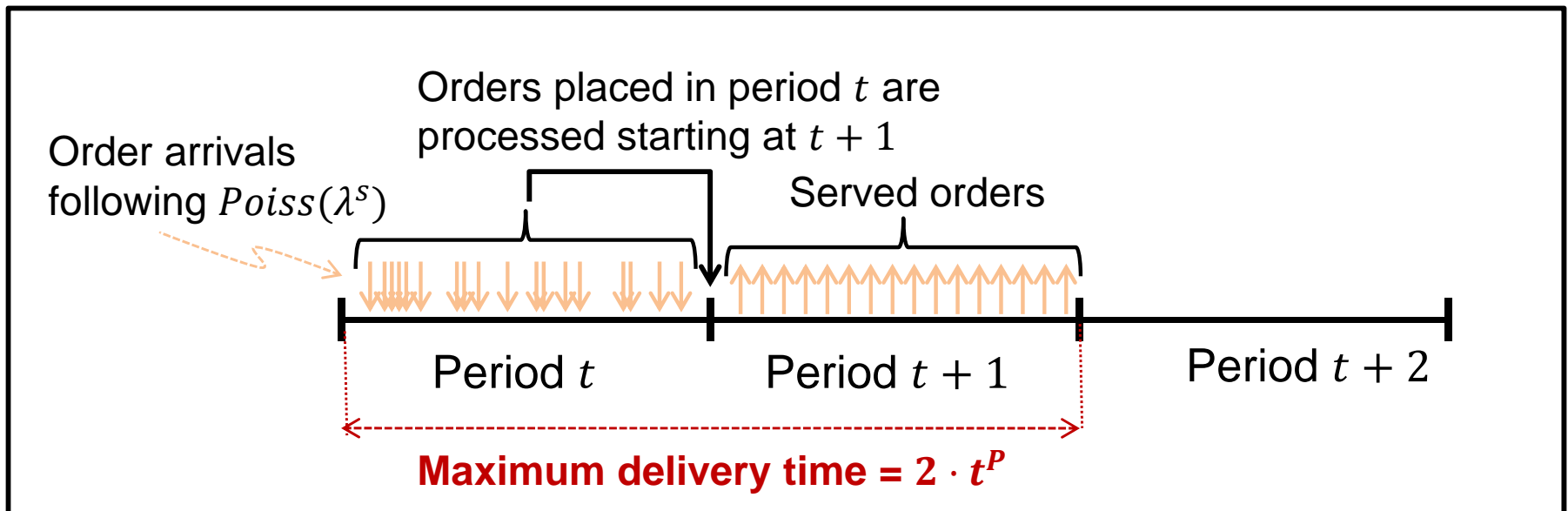
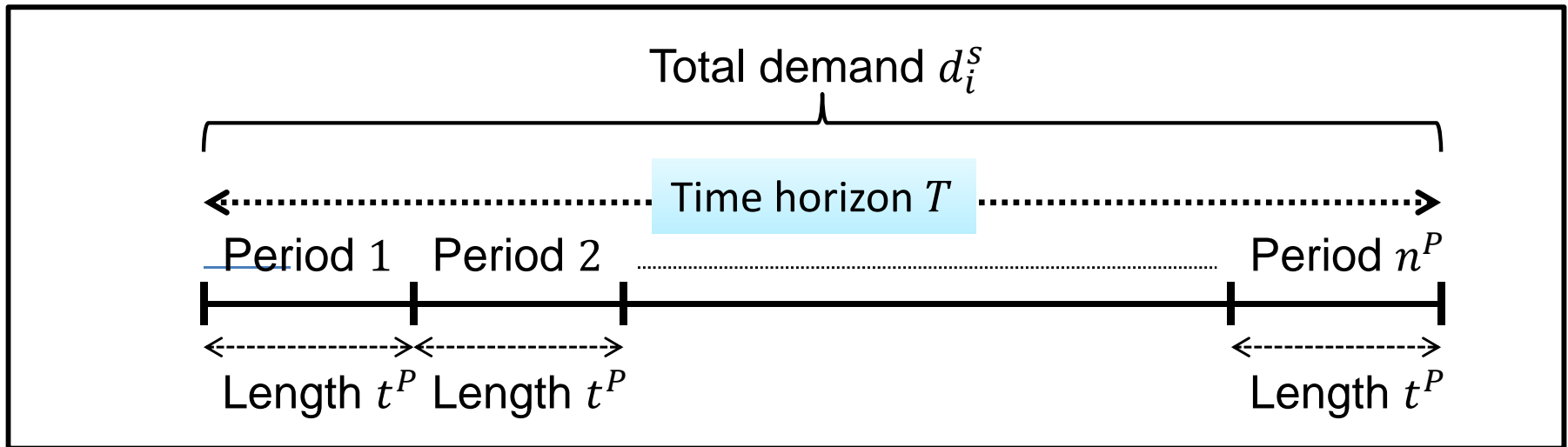
Unit selling price: $p_i \left[\frac{\text{€}}{\text{units}} \right]$

Unit stock-out cost: $o_i \left[\frac{\text{€}}{\text{unit}} \right]$

The treatment of the demand uncertainty is based on the following assumptions:

- i. The demand **along a given time horizon T** is represented by a set of known scenarios $d_s^i, s = 1, \dots, s_{set}$ with probability ω^s following a Normal distribution $N(\mu, \sigma)$.
- ii. The time horizon is divided in **n^P time periods of the same length t^P** ($T = n^P \cdot t^P$); and the total demand d_s^i of each scenario is **evenly distributed** over the n^P periods.
- iii. Within each period, **the number of orders placed by the customers follows a Poisson distribution $Poiss(\lambda_s^i = d_s^i/n^P)$** , that are discretized through the generation of a set of realizations $d_{sq}^{Pi}, q = 1, \dots, q_{set}$ with known conditional frequency π_{sq} .

Demand uncertainty characterization



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1. Introduction
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- 3. Problem formulation**
 - Strategy
 - Process Flow
 - Time
 - Objective Function
4. Case studies
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Strategy

Strategy refers to decisions on:

1. Which operations are going to be selected to take part in the deployment of the supply chain.
2. If the selected operations are going to fall under speculation or postponement.

Strategic Variables

$W^j \in \{0,1\}$	$1 \Leftrightarrow$ operation j selected
$Z^j \in \{0,1\}$	$1 \Leftrightarrow$ operation j is a CODP
$X^{ij} \in \{0,1\}$	$1 \Leftrightarrow$ arc (i, j) active
$Y^{ij} \in \{0,1\}$	$1 \Leftrightarrow$ arc (i, j) active and postponed

Process Flow

Flow refers to those elements of the model that guarantee the coherency of the manufacturing strategy, i.e. that the sequence of active operations and links defines a **feasible manufacturing process** (path) from initial to market nodes.

Flow Variables

$P_0^{ij} \in \mathbb{Z}_0^+$	Speculative (deterministic) flow of arc (i, j)
$P_{sq}^{ij} \in \mathbb{Z}_0^+$	Postponed (stochastic) flow of arc (i, j) in realization (s, q)
$H^j \in \mathbb{Z}_0^+$	Production stored at $j \in N$ in speculation
$R_{sq}^j \in \mathbb{Z}_0^+$	Production released at $j \in N$ in realization (s, q) for scenario s
$S_{sq}^j \in \mathbb{Z}_0^+$	Sales in market $j \in M$ and realization (s, q)
$O_{sq}^j \in \mathbb{Z}_0^+$	Stock-out in market $j \in M$ and realization (s, q)
$F_s^j \in \mathbb{R}_0^+$	Production finally stored at $j \in N$ in scenario s

Process Flow Equations

There are four families of flow constraints modeling the production, buffering, distribution and selling activities of each type of operation.

The **Production Flow Equations** are a generalization of the network flow equations, assuming a **two-stage formulation** and the possibility of **buffering some amount of production** before demand is realized.

$$\sum_{i \in D(j)} P_0^{ij} = H^j + \sum_{k \in O(j)} P_0^{jk}$$

$$R_{sq}^j + \sum_{i \in D(j)} P_{sq}^{ij} = \sum_{k \in O(j)} P_{sq}^{jk}$$

$$H^j - \sum_{q \in Q_s} \pi_{sq} \cdot R_{sq}^j = F_s^j$$

Time equations

Time equations model the **lead time** the postponed production takes to arrive at markets since demand orders are placed.

- We allow the system to take some **extra time** to deliver postponed production whenever **this time can be recovered** in other realizations of same scenario.

Time Variables

$T_{sq}^j \in \mathbb{R}_0^+$	Postponement lead time until $j \in N$ in realization (s, q) .
$U_{sq}^j \in \mathbb{R}_0^+$	Idle time in market $j \in M$ in realization (s, q) .
$V_{sq}^j \in \mathbb{R}_0^+$	Saturation time in market $j \in M$ in realization (s, q) .

Objective Function

From among all feasible solutions, we are interested in finding those that **maximize the total expected profit** of running the supply chain.

<i>Total Profit:</i>		
1st stage	Operation set-up costs	$-\sum f_j \cdot W^j$
	Decoupling Point set-up costs	$-\sum z_j \cdot Z^j$
	Speculative production costs	$-n^P \sum c_j \cdot P_0^{ij}$
	Initial holding costs	$-n^P \sum h_j \cdot H^j$
2nd stage	Postponed production costs	$\mathbb{E}_{sq}(-n^P \sum c_j \cdot P_{sq}^{ij})$
	Sales benefits	$\mathbb{E}_{sq}(n^P \sum p \cdot S_{sq}^j)$
	Stock-out costs	$\mathbb{E}_{sq}(-n^P \sum o \cdot O_{sq}^j)$
	Final holding costs	$\mathbb{E}_s(-n^P \sum fh_j \cdot F_s^j)$

Final Model (*OSCS*)

$$\begin{array}{l}
 \text{(OSCS)} \left\{ \begin{array}{l}
 \max \quad \textit{TotalProfit} \\
 \textit{s. t. :} \\
 \textit{Strategic Constraints} \\
 \textit{Process Flow Equations} \\
 \textit{Time Equations} \\
 \textit{Variable Domains}
 \end{array}
 \right.
 \end{array}$$

Binary 1st stage:	$2 \cdot L + 2 \cdot N - M $
Integer 1st stage:	$ L + I + N - A + D(A) $
Integer 2nd stage:	$(L + N - A + D(A) + 2 \cdot M) \cdot s_{set} \cdot q_{set}$
Continuous 2nd stage:	$(N - A + D(A)) \cdot s_{set} + (N + 2 \cdot M) \cdot s_{set} \cdot q_{set}$

Equality constraints:	$(D + I + D(A) + M) \cdot (1 + s_{set}) + (D + 2 \cdot I + D(A) + 3 \cdot M) \cdot s_{set} \cdot q_{set}$
Inequality constraints:	$4 \cdot L + 2 \cdot N + O(I) + D(M) + 2 \cdot L \cdot s_{set} \cdot q_{set} + 2 \cdot \kappa$

being $s_{set} = |\Omega|$, $q_{set} = |Q_s|$, and κ the number of pair of arcs connected, as defined before, i.e.:

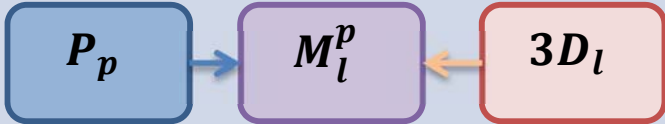
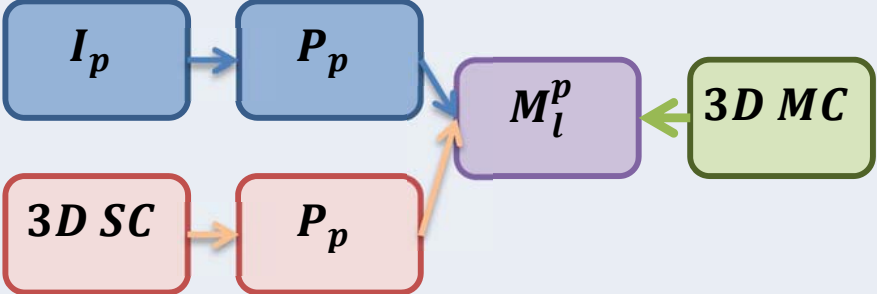
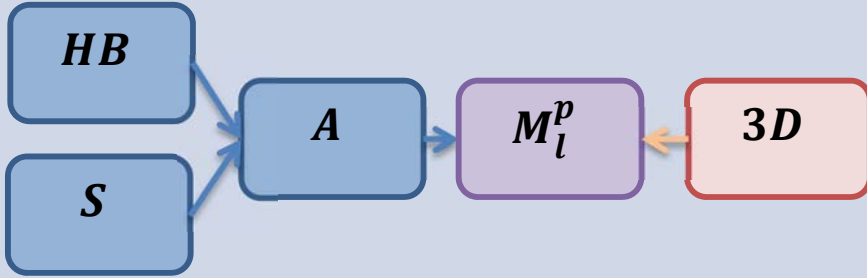
$$\kappa = |\{(i, j) \times (k, l) \in L \times L : j = k\}|$$



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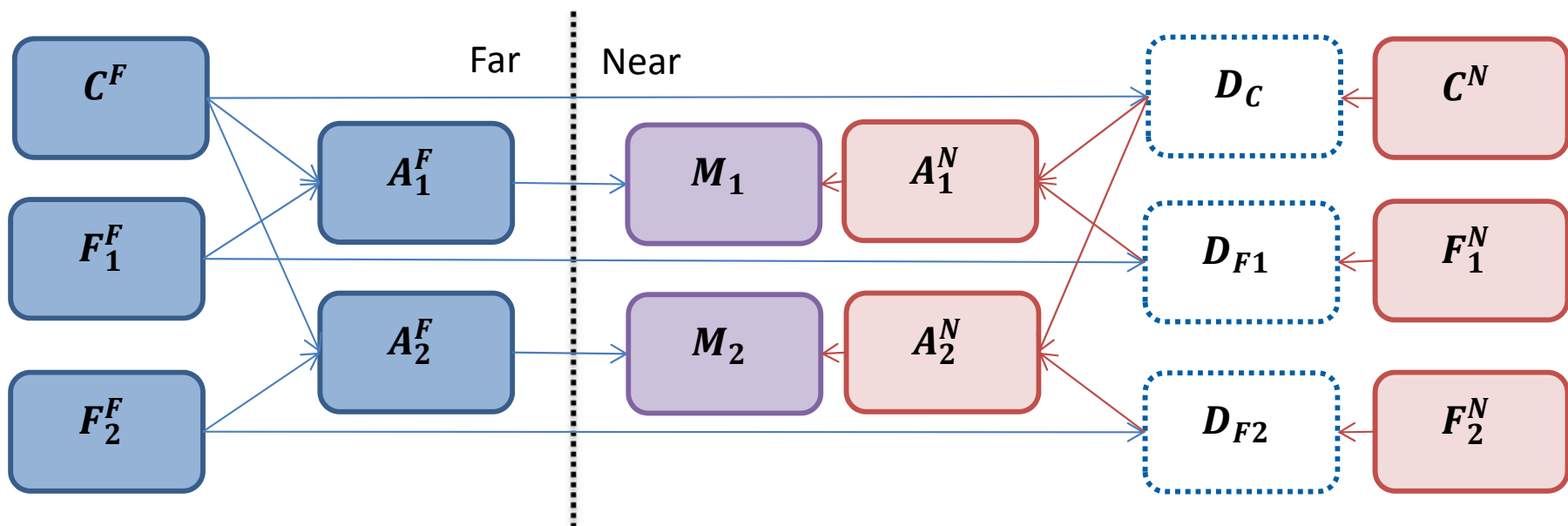
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- 4. Case studies**
 - Applications in different areas
 - Application for multiple products
5. Conclusions and further research

Application in Different Areas

Application	Graph	Postponement 3D Printing
Automotive spare parts		Postponement limited by lead time of $3D_l$.
Toy		Postponement at demand peaks in stable products, assuming all production at unstable products.
Craft retail		NO

Application for Multiple Products

- Assume we have a family of **two products** with the same *Core* and differentiated features, *Feat1* and *Feat2*.
- These three parts can be manufactured and assembled in **two geographical places** and with different strategies.



C : Core manufacturing

F : Features manufacturing

A : Assembly operations

M : Market operations

D : Artificial distribution nodes

Application for Multiple Products

We have generated a sample of 12 scenarios with 5 period realizations each. We will study two cases corresponding different relationships between products:

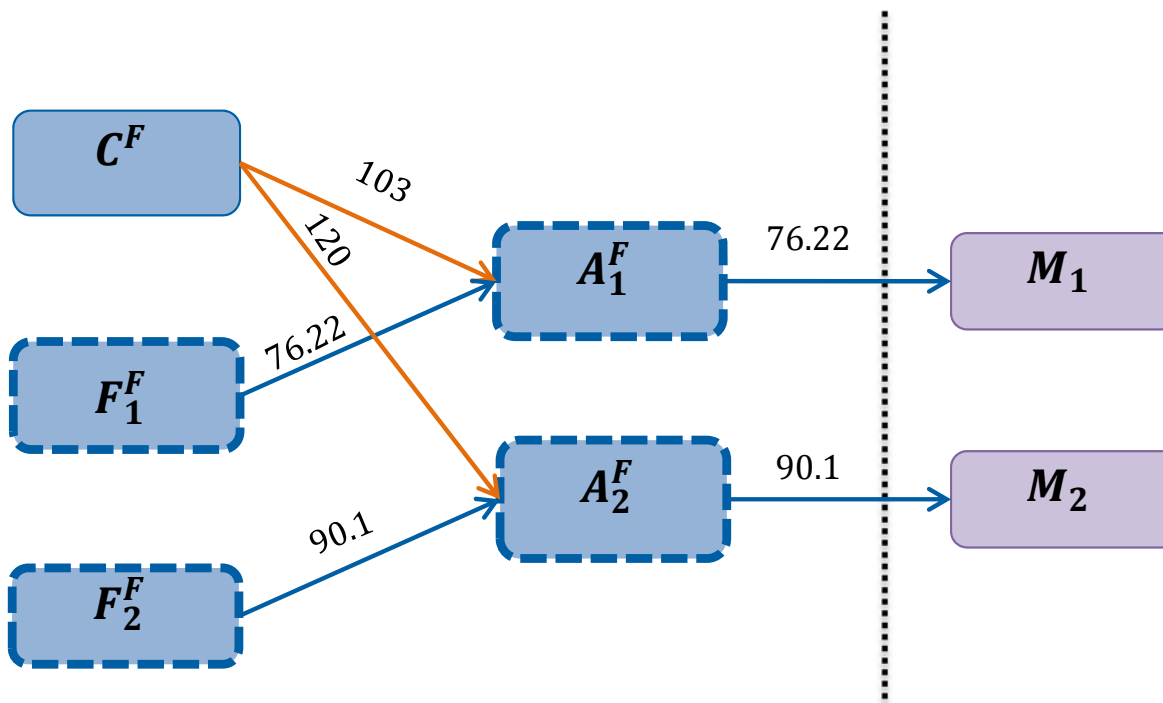
- The first case studies a pair of **complementary products**, i.e. products whose demand has positive correlation.
- The second case studies a pair of **substitutable products**, i.e. products whose demand has negative correlation.

This instance has 64 binary variables (1st stage), 2503 nonnegative integer variables (43 of 1st stage, 2460 of 2nd stage), 1368 nonnegative continuous variables (2nd stage), 1987 equality constraints and 2308 inequality constraints. The next cases have been resolved while allowing a relative MIP gap of 0.01.

Application for Multiple Products

Case 1: Complementary Products

Both products follow a gaussian distribution with respective parameters $\mu_1 = 9,000$, $\sigma_1 = 5,000$ and $\mu_2 = 11,000$, $\sigma_2 = 5,000$, and a correlation of $\rho_{12} = 0.5$.



$CODP$	H_j	$\mathbb{E}_{sq}(R_{sq}^j)$	$\mathbb{E}_s(F_s^j)$
F_1^F	103 u/p	76.22 u/p	26.78 u/p
F_2^F	120 u/p	90.1 u/p	29.9 u/p
A_1^F	103 u/p	76.22 u/p	26.78 u/p
A_2^F	120 u/p	90.1 u/p	29.9 u/p
M	$\mathbb{E}_{sq}(d_{sq}^{Pj})$	$\mathbb{E}_{sq}(S_{sq}^j)$	$\mathbb{E}_{sq}(O_{sq}^j)$
M_1	89.88 u/p	76.22 u/p	13.66 u/p
M_2	100.53 u/p	90.1 u/p	10.42 u/p

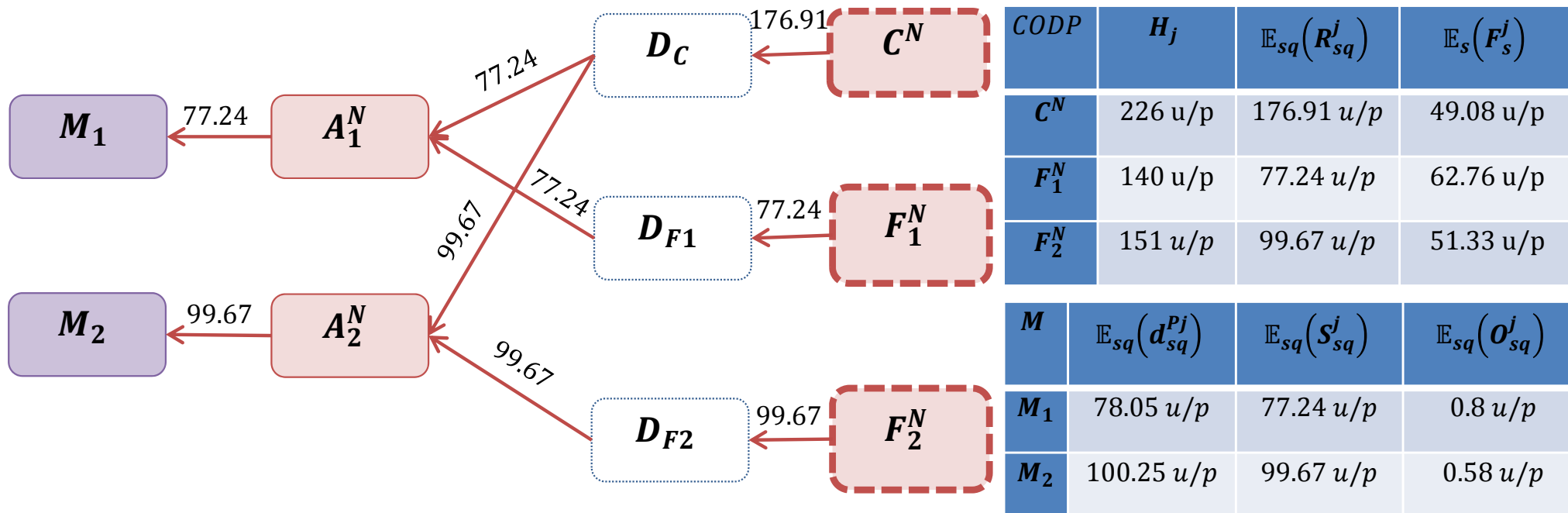
C: Core manufacturing **F:** Features manufacturing
M: Market operations

A: Assembly operations

Application for Multiple Products

Case 2: Substitutable Products

Both products follow a gaussian distribution with respective parameters $\mu_1 = 9,000$, $\sigma_1 = 5,000$ and $\mu_2 = 11,000$, $\sigma_2 = 5,000$, and a correlation of $\rho_{12} = -0.5$.



C: Core manufacturing **F:** Features manufacturing **A:** Assembly operations
M: Market operations **D:** Artificial distribution nodes



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Conclusions

The main conclusions drawn from this project are:

- **Stochastic programming is an appropriate tool** for modeling strategic supply chain decisions on speculation/postponement with stochastic demand.
- The methodology to assess **the introduction of 3D printing technologies can be generalized** to determine the best one among a portfolio of alternative options.
- The application of (*OSCS*) to the set of test cases reveals that
 - a) **Postponement strategies are preferable when products are more sensitive to inventory** than manufacturing costs.
 - b) **3D printing is often preferable for manufacturing in postponement**, but a single machine may not manufacture all quantity in a period.
 - c) **High degrees of uncertainty in demand** also facilitate the introduction of **postponement**.



Gràcies per la seva atenció!
Thanks for your attention!

Koniec