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Abstract

A new challenge for industries is to manage efficiently sales and operations in an uncertain and global environment. The sales and operations planning (S&OP) aims to improve the trade-off between production costs and customer satisfaction. For products with long procurement lead times, new flexibility parameters can be used in the S&OP to improve the supply chain agility and to satisfy efficiently customer demands. In this paper, we consider several inventory policies integrated within a flexible S&OP model. The problem is formulated as a stochastic multi-objective optimization model solved by a simulation-optimization approach. Based on the case study of the automobile manufacturer, Renault, we present a numerical comparative study of the different strategies in terms of system performance. We also provide managerial insights that are particularly relevant to improve the S&OP and inventory management for companies that face uncertain demand, impatient customers and distant sourcing.

Keywords

sales and operations planning ; flexibility ; uncertain demand ; customer impatience ; distant sourcing ; inventory management ; MRP ; CONWIP ; simulation-optimization

1 Introduction

Supply chains become more complex and vulnerable with the globalization and changes in customer behavior. Simple pull or build-to-order strategies are not appropriate to handle high uncertainties with long procurement lead times, and build-to-stock systems are very costly in terms of inventories. Under the increasing economical pressure, companies strive to improve the trade-off between the conflicting objectives such as reducing production costs, inventories and satisfying customers within short delivery times and with personalized products.

Improving the flexibility and the reactivity of the supply chain is crucial for companies facing uncertain environment with strong logistics constraints. To achieve this, the sales and operations planning (S&OP) should be revisited. The S&OP represents the tactical production plan that links the company's strategy to daily operations (Olhager et al., 2001; Grimson and Pyke, 2007). This cross-functional and collaborative process is essential to efficiently balance the market demand with the production capacities (Oliva and Watson, 2011). The S&OP has a strong impact on the firm's performance and flexibility (Thomé et al., 2012, 2013). A new method to improve the supply chain flexibility through the S&OP is presented in Lim et al. (2014a). This method consists in defining upper limits, called flexibility constraints, on the positioning of customer demands in the production plan. For products with long procurement lead times, this new concept of flexible S&OP increases the stability of the production plan in a build-to-order environment.

In this paper, we couple the flexible S&OP model of Lim et al. (2014a) with several inventory strategies, based on the mechanisms of MRP, reorder point policies or constant work-in-process system. We also consider the policies currently applied in Renault, a global automobile manufacturer. The problem is formulated as a stochastic multi-objective optimization model and a simulation-optimization approach is used for the resolution.

The research objective of this paper is, first of all, to study the coupling of various inventory policies with a S&OP that uses flexibility constraints for controlling the arrival of demands. Here, we consider the most classical inventory management systems commonly used in industry. We compare the performances of these methods under a flexible S&OP. Initially applied to operational levels, the flexibility issues are nowadays extended to all planning activities. However, the impact of adding flexibility in the mid-term and long-term planning on the existing inventory management techniques has not been studied. To the best of our knowledge, this study is the first that compares quantitatively several inventory policies associated with a flexibility management for mid-term production planning. We present a large numerical study based on the industrial data of Renault. We show that some policies perform relatively well or bad, depending on system parameters. Based on these results, we also provide practical recommendations to help decision makers in choosing the best strategies for jointly managing flexibility and inventories. This research is relevant for both practitioners and researchers.

The paper is organized as follows. Section 2 summarizes the relevant literature related to our problem. Section 3 presents the problem and formulates the mathematical model. Section 4 explains the different policies studied in this article for managing flexibility and inventories. Section 5 describes the simulation-optimization method we used to compute the optimal policies and the experimental design. Section 6 presents the numerical study based on the Renault's case and provides some practical recommendations. Finally, Section 7 presents several research perspectives related to this work.

2 Literature review

In order to help readers to better understand and situate the problem and the solution approach, we briefly review four streams of literature relevant, to our study: sales and operations planning, supply chain flexibility, inventory control and simulation-optimization.

2.1 Sales and operations planning to match production capacities with market demand

The S&OP has received a growing attention during the last decade from both practitioners and researchers. Grimson and Pyke (2007) present a general framework for improving the integration of the different functions involved in the S&OP. Thomé et al. (2012) present a comprehensive literature review on the S&OP. The authors show that the research is highly dispersed. Recently, Thomé et al. (2013) conduct a survey on 725 manufacturers from 34 countries and highlight the significant impact of efficient S&OP on firm's performance.

Conflicts of interest are frequent during S&OP because of its cross-functional character (Rexhausen et al., 2012). Resolving these conflicts becomes more challenging with the increasing globalization. Indeed, on one hand, sales functions need more flexibility to meet customer requirements and earn new market shares. And on the other hand, the production functions ask for more visibility because of strong constraints on the supply chain and long procurement lead times (Lim et al., 2014a).

A better coordination and synchronisation between forecasts and production planning helps companies to handle uncertainties and improve the global firm performance (Nakano, 2009). Lim et al. (2014a) detail a new concept of flexibility management integrated in the S&OP. New sales constraints are defined to better coordinate forecasts and production planning for reducing the logistic costs while meeting customer requirements.

In this article, we extend the research of Lim et al. (2014a) by coupling the model of flexible S&OP with different inventory policies.

2.2 Improving the supply chain flexibility

The concept of flexibility in supply chain management is complex and multidimensional (Sanchez and Perez, 2005; Bernardes and Hanna, 2009). A flexible supply chain allows the company to better adapt and react to uncertainties and disturbances Svensson (2000); Christopher and Peck (2004).

Christopher and Holweg (2011) argue that most current supply chain management models emanate from a period of relative stability and they are not adequate for the current era with increasing turbulence. The authors show that demand variability causes stockouts, poor capacity utilization and increases buffers, and supply chain needs for more structural flexibility to reduce risk and vulnerabilities.

Based on a large survey and a structural equation model, Merschmann and Thonemann (2011) analyse the relations between uncertainties, supply chain flexibility and firm's performance. The authors show that flexible supply chains are more costly in stable environments but they largely outperform rigid supply chains facing uncertainties.

We refer the reader to Reichhart and Holweg (2007), Bernardes and Hanna (2009) and Stevenson and Spring (2009) for comprehensive literature reviews on the concept of supply chain flexibility.

In this research, we focus on the internal flexibility through the coordination of sales and supply chain functions in the S&OP. For products with long procurement lead times and uncertain demand, applying build-to-order strategies may be difficult in practice (Holweg et al., 2005) and satisfying customers may require very long delivery times or high logistic costs. Lim et al. (2014a) present a new model of flexible S&OP for impatient customers. The idea is to keep a build-to-order strategy but new constraints are defined to avoid high deviations between forecasts and real demands. In this article, we show how a flexible S&OP impacts the performances of different inventory policies.

2.3 Basic inventory policies

In this work, we consider different classes of policies to manage parts inventory: Material Requirements Planning, (s, S) policies, base-stock policies and CONWIP. There is a large amount of literature about these inventory policies. To the best of our knowledge, the quantitative study presented here is the first that compares their performances when they are integrated within a S&OP, and that analyses how the flexibility management impacts them.

The Material Requirements Planning system or MRP (Orlicky, 1975) determines the quantity and timing of parts replenishments based on the future production plan, the bill of materials and the procurement lead times. The basic mechanism of MRP performs very well in deterministic environments. However, the major drawback is that MRP does not take into account any uncertainty Vollmann et al. (1997). Therefore, in uncertain environments, some parameters should be adjusted (Dolgui and Prodhon, 2007). We refer the reader to the literature reviews of, among others, Guide Jr and Srivastava (2000), Koh et al. (2002), Dolgui and Prodhon (2007) for more information on MRP systems, and how to apply them under uncertainties.

Another well-known and often used class of policies is the (s, S)-policies (Arrow et al., 1951). They consist in replenishing the inventory position to the order-up-to-level S, if the inventory position is below the reorder point s. These reorder policies appear to be optimal in several stochastic inventory problems Presman and Sethi (2006). A special case of (s, S)-policies is the base-stock or $(S-1, S)$ policy which is often used for controlling inventories, especially for expensive and slow-moving items (Schultz, 1990). Although base-stock policies are not generally optimal (Hill, 1999; Feng et al., 2006), they are simpler to optimize than (s, S)-policies by using approximations (Roundy and Muckstadt, 2000). Because of their simple structure, (s, S)-policies and base-stock policies are widely applied in practice and have been largely studied by researchers. We refer the reader to the literature reviews of Silver et al. (2008); Xu et al. (2010).

We also consider a policy based on CONWIP (CONstant Work-In Process) systems (Spearman et al., 1990). This pull-oriented strategy consists in keeping the same total quantity of work-in-process in the whole production system. Hence, the CONWIP mechanism determines when to release raw parts at the input of the system in response to a customer demand at the output of the system (Tardif and Maaseidvaag, 2001). In this sense, CONWIP can be seen as a single-stage kanban system. CONWIP systems have attracted a lot of attention from practitioners and researchers (Framinan et al., 2003). Spearman and Zazanis (1992) discuss the superiority of CONWIP over classical push and pull systems.

There is an extensive literature that compares different inventory control strategies. For example, Jacobs and Whybark (1992) compare MRP systems (that relie on forecasts) with reorder policies (implicitly based on past demands). The authors show that the MRP outperforms reorder policies if the forecasts are relatively accurate. Yang (1998) presents a comparative study between kanban systems and reorder policies.

2.4 Solutions based on simulation-optimization

In this research, we aim to determine the optimal parameters for several inventory policies. To do so, we use a simulation-optimization approach.

The simulation is a powerful tool to incorporate uncertainties in large and complex systems Robinson (2004) but is inadequate for solving optimization problems (Glover et al., 1999). To remediate this, we use the simulation-optimization. This approach consists in using structured and efficient methods to determine optimal input parameter values to optimize an objective function which is measured by a simulation module (Carson and Maria, 1997; Swisher et al., 2000).

The simulation-optimisation combines the advantages of simulation (taking into account uncertainties, complex systems and hypotheses) and optimization (finding efficiently the best parameter values). This method receives a growing interest because it is efficient for solving complex and stochastic industrial problems (Lee et al., 2013).

In simulation-optimization problems, there exists various optimization methods such as random search (Andradóttir, 2006), metaheuristics (Ólafsson, 2006), gradient-based procedures (Fu, 2006) etc. Performances of these techniques depend on the context and the problem. There are several literature reviews about simulation-optimization and its application. We refer the reader to, among others, Fu (1994), Swisher et al. (2004), Fu et al. (2005).

3 Problem description

3.1 Flexible S&OP for managing components with distant sourcing

We are interested in a S&OP problem with uncertain demand and impatient customers. During the S&OP, the sales and supply chain functions aim to balance efficiently the production capacities with the market demand. Every week, the sales functions (marketing, sales department) provide demand forecasts. Based on these forecasts, the supply chain elaborates the production plan that fits at best the market demand.

The first weeks of the production plan are frozen (i.e. no changes are allowed) to ensure a minimum stability for the manufacturing plant. Some products or components require very long procurement lead times due to distant sourcing. Having a long frozen horizon in the production plan can also help to stabilize the procurement for such components. However, it is not possible to extend the frozen horizon's length because customers are impatient and cannot wait for long delivery times. Most of real demands are only known few weeks before production. Therefore, parts procurements are mainly based on forecasts that are not reliable. To avoid very high differences between customer demands and these forecasts, the sales and the supply chain departments create the so-called flexibility constraints. These constraints limit the positioning of customer demands in the production plan. A flexibility constraint determines the maximum quantity of orders that can be placed during a given period. For the rest of the paper, we only present a single-product model because we assume that the demands are independent for components with long procurement lead times.

The flexibility constraints represent the main original aspect of our S&OP model. These parameters are negotiated between supply chain and sales departments. Policies for managing flexibility are described in Section 4. With this flexible S&OP, the company is able to partially limit the demand variability and high deviations from forecasts. However, with flexibility constraints, customer orders can be delayed and there is a risk of lost sales because of the customer impatience that depends on the delay length.

Parts inventories are replenished every week (periodic-review inventory management). We consider various inventory strategies that are described in Section 4. Customer orders arrive every week and are positioned in the production plan according to sales constraints. Moreover, customer orders can be asked for a specific week or as soon as possible. If there is a stockout, missing parts are supplied on emergency, that incurring an additional cost. Hence, the accepted orders are always satisfied. We also assume there are no capacity restrictions for suppliers, transportation or inventories.

The S&OP is a cross-functional process that involves business and operations functions with conflicting objectives. Therefore, the overall system performance is measured by several indicators: the logistic costs (inventory and emergency supply), the percentage of delayed orders, the percentage of lost sales and the average delay of a customer order. Fixed costs are neglected. The sales department defines limits on the percentage of delayed orders, lost sales and the average delay to meet the customer requirements. Given these limit values, the objective of the supply chain departments is to satisfy customer demands while reducing the logistic costs.

3.2 Notations and system dynamics

The notations used in this article are summarized in Table 1. We give the following clarification for the notations. The quantity $m_{j-i}D_j$ represents the quantity of customer orders received during the week i and asked for the week j. The total demand received by the system (not necessarily satisfied) is computed according to $D_{\text{tot}} = \sum_{i<j} m_{j-i} D_j$. A sales constraint d_t^{max} represents the maximum quantity of demands that the production system can accept for the week t. If a constraint is saturated ($d_t^f = d_t^{max}$), then new orders asked for this week are delayed to the next week, with a risk of lost sales. If an order is delayed by k weeks, then the probability of losing this order equals p_k. The decision variables (x_t, d_t^{max}) depend on the policy used for managing inventories and flexibility (see Section 4).

Notation	Description
Input parameters	
H	Number of periods
L	Procurement lead time (normal transportation)
F	Frozen horizon length with $F < L$
c_h	Holding cost per unit per week
c_e	Emergency supply extra cost per unit
s_0	Initial stock level
D_t	Random variable of real demand for week t
D_{tot}	Total demand received by the system
F_t	Random variable of demand forecast for week t
m_k	Demand arrival rate, k weeks before real demand, with $1 \leq k \leq H$
p_k	Probability to lose the order if it is delayed by k weeks
ξ_b	limit value for the percentage of delayed orders
ξ_l	limit value for the percentage of lost sales
ξ_w	limit value for the average delay
Decision variables	
x_t	Quantity of parts ordered in week $t - L$ and that will arrive in week t
d_t^{max}	Sales constraint for week t
System variables	
s_t	Net inventory level of parts at the end of week t, $0 \leq t \leq H$
$\hat{s}_t$	Expected inventory level of parts at the end of week t
y_t	Quantity of parts ordered in week t and that will arrive in week t by emergency supply
d_t^f	Quantity of forecasted orders placed in week t in the production plan
d_t^r	Quantity of real orders placed in week t in the production plan
b_t	Quantity of delayed orders in week t
l_t	Quantity of lost sales in week t
w	Average delay of a customer order which has been postponed
LC	Average logistic cost per week (inventory and emergency supply)

Table 1: Input parameters and system variables

Figure 1 represents the system dynamics with the balanced flows of supplies, demands and inventories at the end of week t. There are three noticeable horizons: the frozen horizon during which the production plan is fixed, the flexible horizon during which the production plan is partially controlled by flexibility constraints and the free horizon during which there is no constraint for customer orders.

3.3 Mathematical model formulation

We formulate the problem as a multi-objective optimization problem with ϵ-constraints (see Haimes et al., 1971; Chankong and Haimes, 1983, for more information on ϵ-constraints). The advantage of this approach is that it can deal with non-normalized and non-comparable objective functions. With an ϵ-constraint approach, there is one single objective function and all other criteria to optimize are expressed as additional constraints.

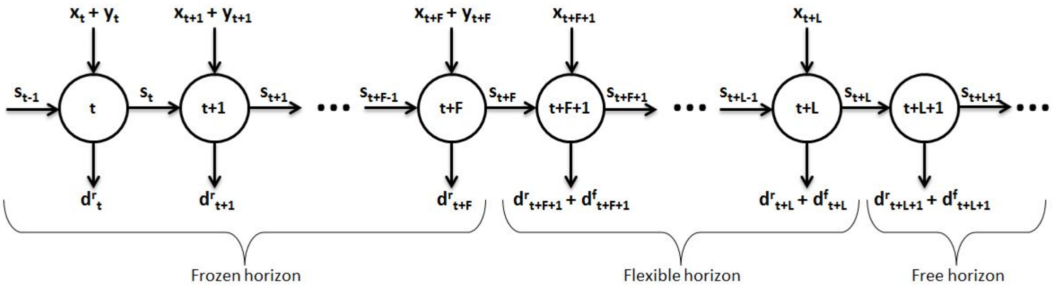

Figure 1: System dynamics: flows of supplies, demands and inventories at the end of week t

$$\min \quad LC = \frac{1}{H}\sum_{k=0}^{H}(c_h s_k + c_e y_k) \tag{1}$$

$$\text{subject to:} \quad \sum_{k=0}^{H}\frac{b_k}{D_{\text{tot}}} \le \xi_b \tag{2}$$

$$\sum_{k=0}^{H}\frac{l_k}{D_{\text{tot}}} \le \xi_l \tag{3}$$

$$w \le \xi_w \tag{4}$$

$$d_t^f + d_t^r \le d_t^{max} \qquad \forall t \in \{0,\dots,H\} \tag{5}$$

$$s_t = s_{t-1} + x_t + y_t - d_t^r \qquad \forall t \in \{1,\dots,H\} \tag{6}$$

$$y_t = \max\{0\ ;\ d_t^r - (s_t + x_t)\} \qquad \forall t \in \{0,\dots,H\} \tag{7}$$

$$\sum_{k=F}^{H} m_k = 1 \tag{8}$$

$$x_t \ge 0 \qquad \forall t \in \{0,\dots,H\} \tag{9}$$

$$d_t^{max} \ge 0 \qquad \forall t \in \{0,\dots,H\} \tag{10}$$

The objective function (1) is to minimize the average holding and emergency supply costs. Constraints (2), (3) and (4) are the ϵ-constraints related to, respectively, the percentage of delayed orders, the percentage of lost sales and the average delay. Constraint (5) represents the sales constraints that limit the positioning of customer demands in the production plan. Constraint (6) is the flow balance equation. Constraint (7) represents the emergency supplies used for missing parts. Constraint (8) represents the frozen horizon of F weeks (customer demands are known at the latest F weeks before production). Constraints (9) and (10) define the validity domain of decision variables.

4 Policies for managing inventories and flexibility

In this section, we first present the policies to compute the procurement quantities. Then, we present the policies to compute the flexibility constraints that are defined during the S&OP and limit the positioning of demands in the production plan. Flexibility policies aim to partially control the arrival of customer orders and they directly impact the sales performance.

4.1 Inventory policies

Before computing the procurement quantities, we need to know the expected inventory level until the week when the ordered parts are received. This quantity $\hat{s}_{t+L-1}$ is computed according to Equation (11). This formula can easily be adapted to compute the expected inventory level until the end of the frozen horizon $\hat{s}_{t+F-1}$ (known with certainty).

$$\hat{s}_{t+L-1} = s_0 + \sum_{k=0}^{t+L-1} \Big((x_k + y_k) - \Big(d_k^r + d_k^f \Big) \Big) \qquad \forall t \in \{0, \dots, H-L+1\} \tag{11}$$

We consider various inventory strategies for managing parts procurements. First, we consider the basic MRP policy with a traditionnal safety stock. This policy consists in replenishing inventories based on the expected demand while keeping a safety stock of S_{MRP} parts. The procurement quantity is computed according to Equation (12).

$$\text{MRP policy :} \qquad x_{t+L} = \max \Big\{ 0 \ ; \ d_{t+L}^r + d_{t+L}^f + S_{MRP} - \hat{s}_{t+L-1} \Big\} \qquad \forall t \in \{0, \dots, H-L\} \tag{12}$$

We also consider the class of (s, S)-policies. A (s, S)-policy consists in ordering parts to reach the order-up-to level S if the expected inventory level drops below the reorder point s. The procurement quantity is formulated in Equation (13).

$$(s, S) \text{ policy :} \qquad x_{t+L} = \begin{cases} S - \hat{s}_{t+L-1} & \text{if} \quad \hat{s}_{t+L-1} \leq s \\ 0 & \text{if} \quad \hat{s}_{t+L-1} > s \end{cases} \qquad \forall t \in \{0, \dots, H-L\} \tag{13}$$

A special case of (s, S)-policies is the class of base-stock policies or $(S-1, S)$-policies. Base-stock policies are easier to compute and to implement in practice. Moreover, in certain conditions, they perform as well as (s, S). A base-stock policy consists in replenishing inventories every week to reach the base-stock level of S parts. The procurement quantity is formulated in Equation (14).

$$\text{BS policy :} \qquad x_{t+L} = \begin{cases} S - \hat{s}_{t+L-1} & \text{if} \quad \hat{s}_{t+L-1} < S \\ 0 & \text{if} \quad \hat{s}_{t+L-1} \geq S \end{cases} \qquad \forall t \in \{0, \dots, H-L\} \tag{14}$$

We also consider the CONWIP strategy. This policy consists in keeping a constant quantity of parts C in the pipeline of the normal transportation mode, as illustrated in Figure 2. The procurement quantity is computed according to Equation (15).

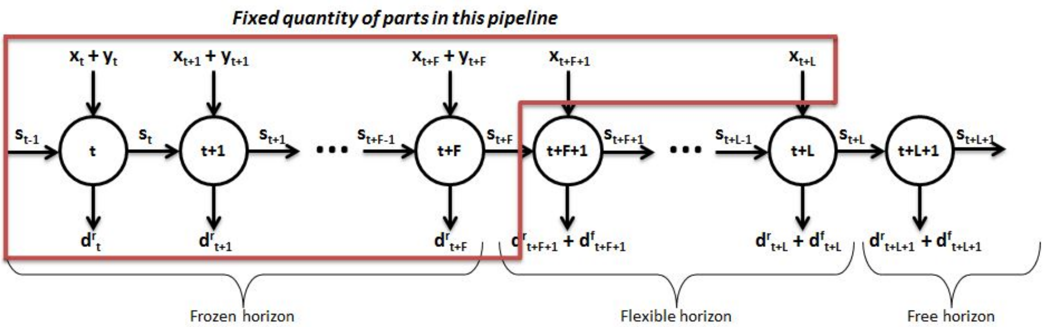

Figure 2: CONWIP policy

$$\text{CONWIP policy :} \qquad x_{t+L} = C - \left(\hat{s}_{t+F} + \sum_{k=t+F+1}^{t+L-1} x_k \right) \qquad \forall t \in \{0, \ldots, H-L\} \tag{15}$$

This equation can also be reformulated as follows, by replacing $\hat{s}_{t+F}$ with Equation (11) and with $s_0 = 0$. This formulation shows that the procurement quantity is independent of the future forecasted demands, and is only based on the parts previously ordered and the real demand.

$$\text{CONWIP policy :} \qquad x_{t+L} = C - \left(\sum_{k=0}^{t+L-1} x_k + \sum_{k=0}^{t+F} y_k - \sum_{k=0}^{t+F} d_k^r \right) \qquad \forall t \in \{0, \ldots, H-L\} \tag{16}$$

Finally, we consider the static policy Π_{static} and the linear policy Π_{linear} (introduced in Lim et al. (2014b) and are currently applied in the automobile manufacturer Renault for managing parts with long procurement lead times). The Π_{static} policy consists in using a safety stock expressed in percentage of the future demand, according to a parameter π^s called the safety stock margin. The procurement quantity is computed according to Equation (17).

$$\text{Static policy, } \Pi_{static} : \qquad x_{t+L} = \max \left\{ 0; d_{t+L}^r + d_{t+L}^f + \pi^s \sum_{k=t+F+1}^{t+L} \left(d_k^r + d_k^f \right) - \hat{s}_{t+L-1} \right\} \tag{17}$$

The Π_{linear} policy generalizes the static policies. It also consists in using a safety stock expressed in percentage of the future demand, but with different percentages depending on the magnitude of the forecast. Indeed, low forecasts generate low safety stocks and are more likely to underestimate the real demand (conversely with high forecasts, see Lim et al., 2014b, for more details). For linear policies, we need to compute the average historical demand, measured by the moving average over the last M weeks. To compare the forecast with the historical demand, every week t, we compute η_t, the ratio of the future expected demand over the moving average (Equation (18)).

$$\eta_t = \frac{d_{t+L}^r + d_{t+L}^f}{\sum\limits_{k=t-M+1}^{t} \frac{d_k^f}{M}} \qquad \forall t \in \{M, \ldots, H\} \tag{18}$$

Then, a linear policy is defined by two variables, expressed as percentages, named π_{abs}^s (absolute value for the safety stock) and π_{rel}^s (relative coefficient for the safety stock). The procurement quantity is computed according to Equation (19).

Linear policy, Π_{linear} :

$$x_{t+L} = \max \left\{ 0; d_{t+L}^r + d_{t+L}^f + \max\left\{0 \; ; \; \pi_{abs}^s - \pi_{rel}^s \eta_t \right\} \sum_{k=t+F+1}^{t+L} \left(d_k^r + d_k^f \right) - \hat{s}_{t+L-1} \right\} \tag{19}$$

4.2 Flexibility policies

To manage flexibility with the sales constraints in the S&OP, we consider two classes of policies. The first one consists in giving a constant rate of flexibility expressed as a percentage π^f for the whole horizon (static flexibility policy). The sales constraint d_t^{max} for week t is computed based on the expected demand

and the flexibility rate according to Equation (20).

$$d_t^{max} = \left(1 + \pi^f\right)\left(d_t^r + d_t^f\right) \qquad \forall t \in \{0, \ldots, H\} \tag{20}$$

With a high flexibility rate π^f, the production system can accept many demands, even if forecasts underestimated the real demand. Conversely, with a low flexibility rate, the number of real demands has to be close to the forecasts, otherwise orders are delayed with a risk of lost sales.

The second method consists in using different flexibility rates depending on the magnitude of the forecast, like for linear inventory policies. Therefore, a linear policy is defined by two variables, expressed as percentages, named π^f_{abs} (absolute value for the flexibility rate) and π^f_{rel} (relative coefficient for the flexibility rate). The sales constraint for linear flexibility policy is computed according to Equation (21).

$$d_t^{max} = \left(1 + \max\left\{0\ ;\ \pi^f_{abs} - \pi^f_{rel}\eta_t\right\}\right)\left(d_t^r + d_t^f\right) \qquad \forall t \in \{0, \ldots, H\} \tag{21}$$

In theory, the flexibility rates (and also the safety stock margins) can be continuous. However, in this article, we make the choice of discretizing the flexibility rates with an accuracy of 10^{-2}. A more accurate discretization is always possible and it is also possible to refine the discretization by using successive optimizations with higher accuracy on variables.

In total, we consider 8 different policies for managing stocks and flexibility (by pairing 2 methods for flexibility and 4 methods for inventory), plus the 2 policies used in Renault (static and linear policies). Notations are summarized in Table 2.

Policy notation	Inventory policy	Type of flexibility
Π_{static}	Static stock margin	Static
Π_{linear}	Linear stock margin	Linear
MRP-Sta	MRP	Static
(s, S)-Sta	(s, S)	Static
BS-Sta	BS	Static
CONWIP-Sta	CONWIP	Static
MRP-Lin	MRP	Linear
(s, S)-Lin	(s, S)	Linear
BS-Lin	BS	Linear
CONWIP-Lin	CONWIP	Linear

Table 2: List of policies for managing sales flexibility and parts inventory

5 Resolution by simulation-optimization and experimental design

5.1 Simulation-optimization

Because the system is complex and stochastic (uncertain demand, forecasts, stochastic customer impatience), we use a simulation-approach to analyse the system. We create, in Java programming language, a module that reproduces accurately the system dynamics (arrival of demands, positioning in the production plan, postponement of orders, lost sales, inventory management, emergency supplies etc.) and evaluates the system variables.

To obtain the optimal policy values, we couple the simulation module with an optimization procedure, also implemented in Java. The aim of this optimization module is to search efficiently the policy parameters that minimizes the objective function measured by the simulation module. Several methods and heuristics exist to optimize the system parameters. In this article, we use a random local search method to explore the solution state-space. This method appears to be a good trade-off between time and cost performance (Lim et al., 2014b). But it does not guarantee the global optimality of the solution because there is no information about the properties of the objective function.

To perform a local search, the algorithm needs to compare the quality of different solutions. To do so, we define the quantity γ (Equation (22)) that represents an overall indicator of the saturation of ϵ-constraints for the multi-objective optimization problem. Indeed, $\gamma = 0$ means that all ϵ-constraints are satisfied and $\gamma > 0$ means that at least one ϵ-constraint is not satisfied.

$$\gamma = \max\left\{0\ ;\ \frac{\sum_{k=0}^{H} b_k}{D_{\text{tot}}} - \xi_b\right\} + \max\left\{0\ ;\ \frac{\sum_{k=0}^{H} l_k}{D_{\text{tot}}} - \xi_l\right\} + \max\left\{0\ ;\ w - \xi_w\right\} \tag{22}$$

Then, the optimization algorithm considers that a solution A is better than a solution B if Statement (23) is verified. The statement on the left ensures that if A and B are feasible solutions, then the algorithm chooses the one with the lowest logistic cost. The statement on the right ensures that if at least one solution is not feasible, then the algorithm moves to the solution with the lowest value of γ.

$$\begin{cases} LC(A) \leq LC(B) \\ \gamma(A) = \gamma(B) = 0 \end{cases} \quad \text{or} \quad \begin{cases} \gamma(B) > 0 \\ \gamma(A) \leq \gamma(B) \end{cases} \tag{23}$$

The state-space of solutions explored by the optimization algorithm can largely vary depending on the policy used and the problem instance. For example, for the Π_{static} policy, there are two parameters expressed as percentage to optimize whereas for the (s, S)-Lin, there are two parameters expressed as percentage and two parameters expressed as stock levels. For the optimization procedure, we use the following settings for exploring the state-space (Table 3). Note that it could be possible to speed up the optimization procedure by improving or refining these settings.

Type of policy	Parameters	Starting values	Search step
MRP	S_{MRP}	0	5
CONWIP	C	1500	25
(s, S)	(s, S)	(0,0)	(5,5)
BS	S	0	5
Π_{static}	π^s, π^f	0, 0	1%, 1%
Π_{linear}	$(\pi^s_{abs}, \pi^s_{rel})$, $(\pi^f_{abs}, \pi^f_{rel})$	(0,0), (0,0)	(1%,1%), (1%,1%)

Table 3: Optimization settings for exploring the state-space of solutions

Figure 3 illustrates the simulation-optimization framework with the different input and output parameters.

5.2 Experimental design

We consider the following values for the system parameters (Table 4) based on the case study of Renault. Note that we use uniform distributions to model the demand and the forecast errors, since they model

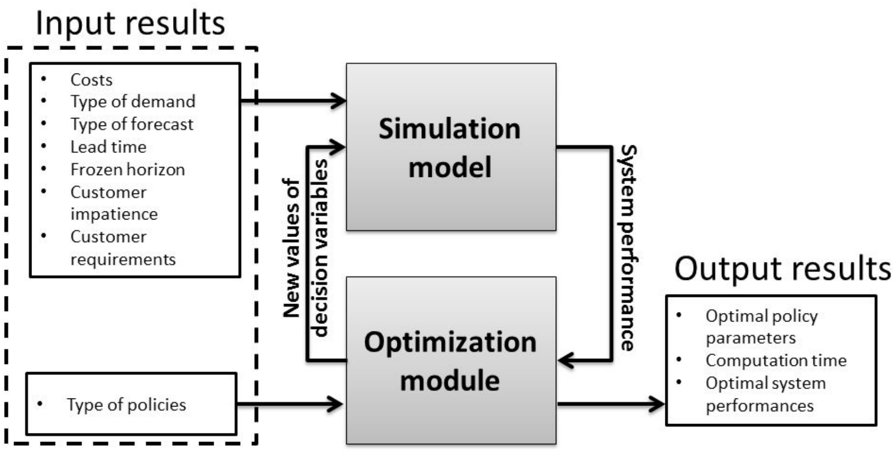

Figure 3: Simulation-optimization module with input and output parameters

appropriately the industrial data at hand. For the demand arrival rates m_k and the customer impatience p_k, we use the settings of Table 5 and 6. In total, the test bed of our numerical study consists of 135 different instances.

Parameter	Notations	Values
Simulation length	H	2000 weeks
Number of replications	R	50 replications
Warm-up period	W	15 weeks
Normal lead time	L	10 weeks
Frozen horizon	F	4 weeks
Initial stock	s_0	0
Moving average parameter	M	6
Holding unit cost	c_h	1
Emergency unit cost	c_e	5; 10; 20; 30; 50
Demand variability	(D_{min}, D_{max})	Low (200, 400); Medium (100, 500); High (50, 550);
Forecast accuracy	$F_t - D_t$	Low (±60%); Medium (100, 500); High (50, 550);

Table 4: Test bed settings

6 Numerical study based on the case study of Renault

In this section, we first compare the different policies performance in terms of computation time and average logistic cost. Then, we present some results on the optimal stock parameters. Several managerial insights derived from these results are given in the last subsection.

k	m_k
$k < F$	0
$k = F$	0.40
$k = F + 1$	0.30
$k = F + 2$	0.15
$k = F + 3$	0.10
$k = F + 4$	0.05
$k > F + 4$	0

Table 5: Demand arrival rates settings

k	p_k
0	0
1	0.05
2	0.10
3	0.20
4	0.30
5	0.50
6	0.70
7	0.90
$k > 7$	1.00

Table 6: Customer impatience settings

6.1 Comparison of policies performance

Table 7 presents the time performance of the different policies, with the average computation time for the 135 instances. Min and max values are related to the slowest and the fastest instance.

Policies	Time (sec.)	Min	Max
Π_{static}	201.99	75.43	424.65
Π_{linear}	1115.31	613.24	2504.63
MRP-Sta	394.59	151.12	932.21
(s, S)-Sta	652.29	192.63	1771.35
BS-Sta	215.18	73.34	601.76
CONWIP-Sta	357.66	100.12	898.28
MRP-Lin	999.67	362.78	1621.56
(s, S)-Lin	5147.59	2436.66	9920.51
BS-Lin	572.47	232.71	1217.86
CONWIP-Lin	870.21	385.59	1759.65

Table 7: Average computation time for the 135 instances

Results show that the computation time varies largely from one policy to another. The (s, S)-Lin policy clearly has the slowest computation time and requires on average 1.4 hours to optimize one instance. This result is due to the large size of the state-space to explore. Indeed, (s, S)-Lin is defined by four parameters, of which two are related to stock levels which can be very high. The MRP-Lin policy also requires four parameters but all of them are expressed as percentages and the state-space of solutions is smaller than (s, S)-Lin. It could be possible to reduce the computation time for these policies by using different initial solutions or search step values in the optimization algorithm.

As expected, policies using linear flexibility are more time consuming than policies with static flexibility because they need two decision variables (absolute and relative coefficients) to compute sales constraints (instead of one for static policies). The fastest policy is Π_{static} (with about 3 minutes to optimize one instance). Base-stock policies are also very fast to optimize with also about 3 minutes on average (9 minutes if coupled with linear flexibility).

Table 8 presents the average logistic cost for the 135 instances. As in Table 7, min and max values are related to the best and the worst instance.

Policies	Logistic cost	Min	Max
Π_{static}	518.35	267.01	1046.04
Π_{linear}	497.40	265.34	1011.09
MRP-Sta	468.56	266.31	787.02
(s, S)-Sta	581.41	303.36	894.34
BS-Sta	581.90	304.62	898.88
CONWIP-Sta	477.11	158.03	867.99
MRP-Lin	459.77	265.43	786.00
(s, S)-Lin	568.13	303.28	923.52
BS-Lin	568.03	302.92	892.10
CONWIP-Lin	470.78	156.94	844.60

Table 8: Logistic cost performance for the 135 instances

Cost performances are very variable depending on the policies. First, we note that, for any given stock policy, coupling with a linear flexibility is better in terms of cost performance. This result is not surprising since linear policies generalize the static ones. Moreover, two inventory strategies appear to perform very well. First, MRP policies provide the best overall cost performance when they are coupled with linear flexibility. Second, CONWIP policies also lead to relatively close cost (about 2.4% cost increase for CONWIP-lin compared to MRP-lin). In the opposite, order-up-to level strategies ((s, S) and BS policies) perform badly, even if they are coupled with linear flexibility. They do not even outperform static policies (about 10% cost increase for BS-lin compared to Π_{static}). An interesting result is that the (s, S) and the BS policies lead to almost the same cost performances. We will explain this result by analyzing the structure of optimal policies in the next subsection.

Table 9 gives the detailed ranking depending on time performance and cost performance. It also presents the relative difference in percentage, compared to the fastest and the most efficient policy.

Time performance			*Cost performance*		
Rank	Policy	vs. best	Rank	Policy	vs. best
1	Π_{static}	0%	1	MRP-Lin	0%
2	BS-Sta	6.5%	2	MRP-Sta	1.9%
3	CONWIP-Sta	77.1%	3	CONWIP-Lin	2.4%
4	MRP-Sta	95.4%	4	CONWIP-Sta	3.8%
5	BS-Lin	183.4%	5	Π_{linear}	8.2%
6	(s, S)-Sta	222.9%	6	Π_{static}	12.7%
7	CONWIP-Lin	330.8%	7	BS-Lin	23.5%
8	MRP-Lin	394.9%	8	(s, S)-Lin	23.6%
9	Π_{linear}	452.2%	9	(s, S)-Sta	26.5%
10	(s, S)-Lin	2448.4%	10	BS-Sta	26.6%

Table 9: Ranking of policies

We note that the cost performance of the policies depends on the system parameters. In the following figures, for clarity, we only consider policies with linear flexibility but we obtain similar results for static flexibility.

Figure 4 presents the cost performance as a function of the demand variability. CONWIP appears to be the best strategy when the demand variability is low and it leads to very bad cost performance if this variability is high. This strategy is the most sensitive to the demand variability. In the opposite, MRP is not very sensitive to demand variability and leads to the best cost performance when this variability is high. BS and (s, S) policies are also very sensitive to the demand variability but they lead to poor performances for all situations.

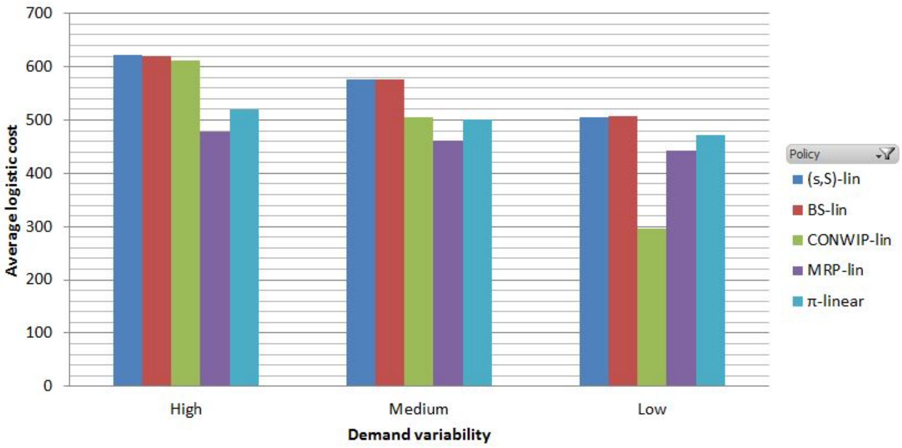

Figure 4: Cost performance vs. demand variability (policies with linear flexibility)

Figure 5 presents the cost performance as a function of the forecast accuracy. Like for the demand variability, the behaviors of CONWIP and MRP are opposite. On one hand, CONWIP performs very well when the forecasts are bad and, hence, is not sensitive to the forecast accuracy. On the other hand, MRP performs very well when the forecasts are accurate and is very sensitive to the forecast accuracy. This result is not surprising because, as explained in Section 4, parts procurements are not computed based on forecasts for CONWIP policies. In the opposite, MRP strategy is based on the future production plan which is mainly composed of forecasted demand for parts with distant sourcing. As for the demand variability, BS and (s, S) policies lead to poor performances in all situations.

Figure 6 shows the impact of sales objectives to satisfy customer requirements (in terms of delayed orders) on the cost performance. Π_{linear} is the most sensitive policy to the sales requirements. For high customer requirements (here, to obtain a low percentage of delayed orders), the cost performance Π_{linear} is very bad and close to the cost performance of BS and (s, S). In the opposite, for low customer requirements, Π_{linear} is the second best policy with a cost performance very close to the MRP.

Figure 7 presents the cost performance of the different policies depending on the emergency cost. As expected, increasing the emergency cost reduces the cost performance of all policies. In case of low emergency costs, the best strategy is CONWIP and for high emergency costs, MRP appears to perform better.

To explain this result, we detail the holding and emergency cost of MRP-lin, CONWIP-lin and Π_{linear} in Figure 8 and Table 10. These detailed results show that CONWIP favours emergency supplies compared to MRP which favours the use of inventories. Indeed, the emergency cost represents 26% of the total logistic costs for CONWIP versus 17% for MRP. Π_{linear} presents a more balanced ratio between emergency supplies and holding costs. However, Π_{linear} requires almost as much inventory as MRP, and

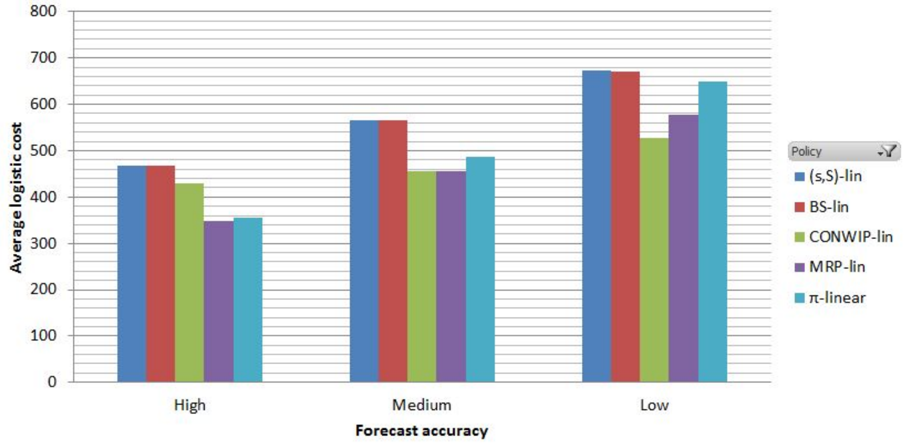

Figure 5: Cost performance vs. forecast accuracy (policies with linear flexibility)

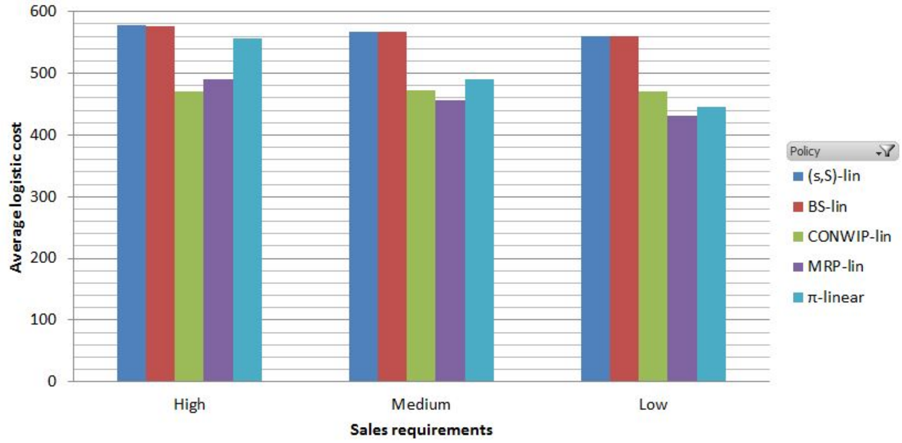

Figure 6: Cost performance vs. sales requirements (policies with linear flexibility)

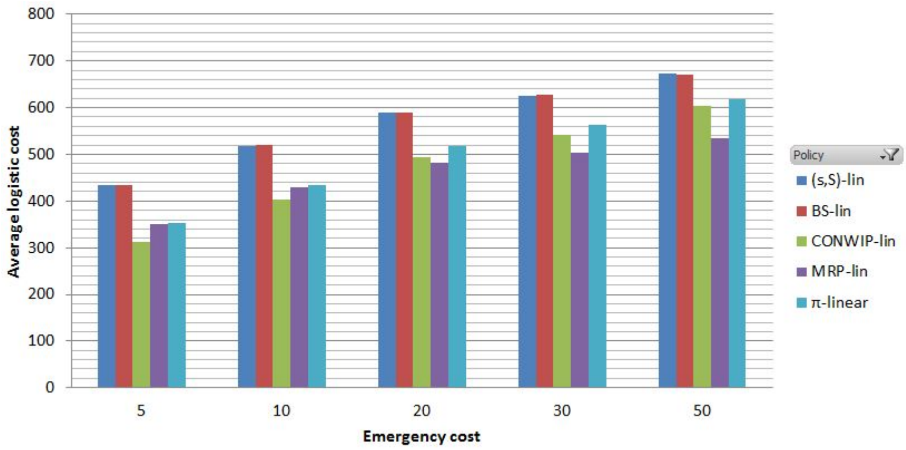

Figure 7: Cost performance vs. emergency cost (policies with linear flexibility)

almost as many emergency supplies as CONWIP. Therefore, Π_{linear} leads to worse cost performance than MRP and CONWIP on average.

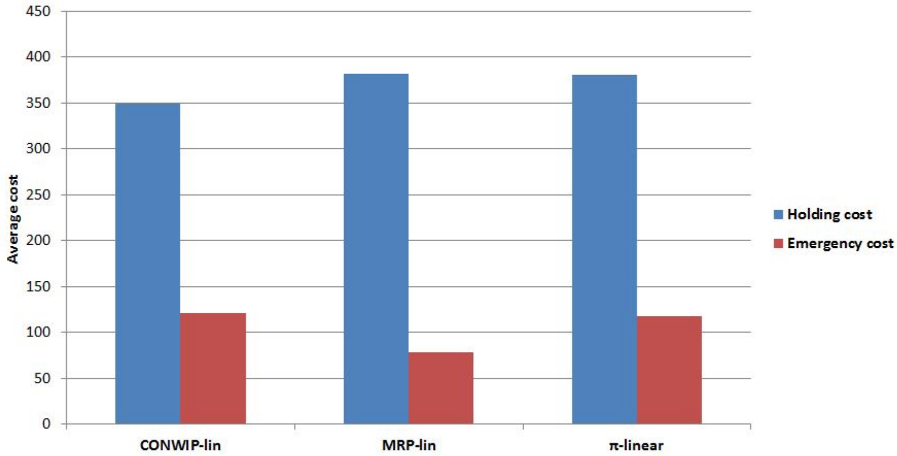

Figure 8: Holding and emergency cost of MRP-lin, CONWIP-lin and Π_{linear}

Policy	*Average cost*		*Percentage*	
	Holding	Emergency	Holding	Emergency
CONWIP-Lin	349.23	121.55	74.2%	25.8%
MRP-Lin	381.95	77.82	83.1%	16.9%
Π_{linear}	380.21	117.19	76.4%	23.6%

Table 10: Holding and emergency cost of MRP-lin, CONWIP-lin and Π_{linear}

To summarize, we make the following comments derived from the numerical study.

- Inventory strategies should be coupled with linear flexibility for better cost performances but this requires more computation time (for a cost reduction about 1% to 3%, the computation time increases by a factor of 2 to 8).
- Π_{static} is the fastest policy with only 202 seconds on average for the optimization of one instance.
- Π_{linear} is a very slow policy (1115 seconds) but leads to good cost performance (only outperformed by CONWIP and MRP).
- MRP is a relatively fast policy (outperformed by Π_{static}, CONWIP, MRP) and leads to the best cost performance (slightly better than CONWIP).
- CONWIP is a very fast policy (only outperformed by Π_{static} and BS) and leads to very good cost performance (only outperformed by MRP).
- (s, S) performs very badly on both computation time and cost performances.
- BS performs as good as (s, S) for the cost but it is very fast to optimize (almost as fast as Π_{static}).
- MRP is the best strategy for situations with high emergency cost or high demand variability or accurate forecast.
- CONWIP is the best strategy for situations with low emergency cost or low demand variability or in the absence of accurate demand forecasts.

6.2 Optimal stock levels

In this subsection, we present some insights on the optimal stock levels for different inventory policies. As detailed before, numerical results show that the cost performance of BS and (s, S) are almost equal. Figure 9 shows the optimal stock parameters for these policies, as a function of the emergency cost. We note that the optimal (s, S) policies are almost of base-stock type (i.e. with $s = S - 1$). Moreover, this result holds for all 135 instances. The very slight differences between BS and (s, S) could be explained by the approximations due to the step size for exploring the state-space and the precision of the simulation module. Moreover, we note that using a linear flexibility instead of static flexibility has a positive impact and reduces the stock levels.

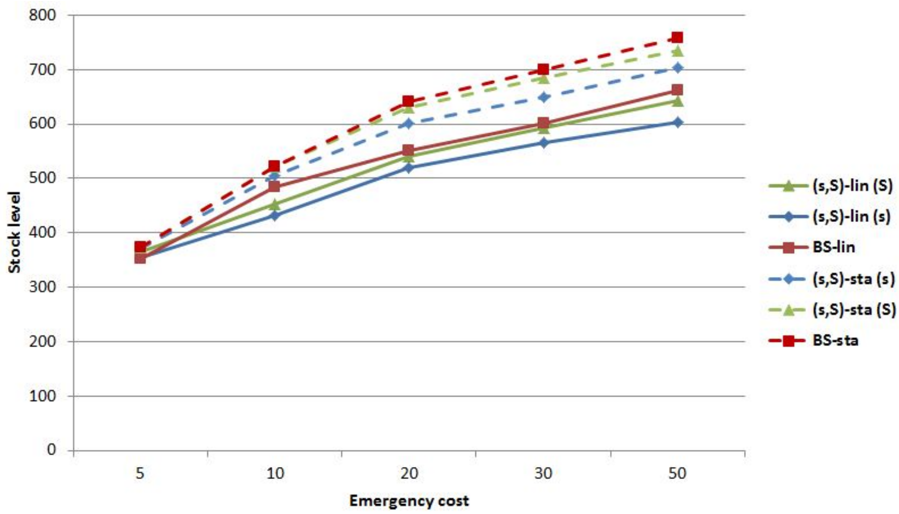

Figure 9: Optimal stock parameters vs. emergency cost ((s, S) and BS policies)

Figure 10 presents the optimal stock parameters for MRP and CONWIP strategies. We note that using a linear flexibility reduces significantly the safety stock level for MRP policies. However, it does not change significantly the CONWIP level (about less than 1% of reduction with the use of linear flexibility). This explains why CONWIP-sta and CONWIP-lin lead to very close performances in terms of logistic costs.

6.3 Managerial insights

Our study suggests that coupling inventory strategies with a flexible S&OP leads to various computation time and cost performances. Depending on the industrial context, the computation time could be an issue. In some situations, practitioners may need fast solutions to find good parameter values. We show that the use of linear flexibility significantly increases the computation time but this might be worthwhile, especially if the cost reduction, thanks to the linear flexibility, is significant for the company. For the case of Renault, the computation time is not an issue since calculations can be performed on dedicated servers and the benefits of using linear flexibility are worthwhile, especially for expensive components with long procurement lead times. We note that adequate optimization settings, depending on the instance and the policy, can reduce significantly the computation time.

Our numerical experiments suggest that the simple strategies for managing inventories such as BS and (s, S) do not perform well when they are coupled with a flexible S&OP, compared to other policies.

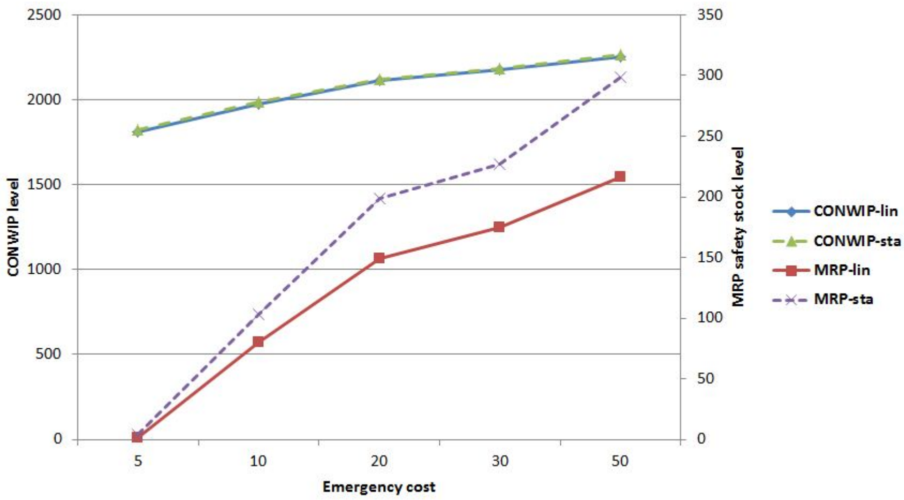

Figure 10: Optimal stock parameters vs. emergency cost (MRP and CONWIP policies)

Even if BS policies are widely applied in practice and are very fast to optimize, they only provide very poor cost performance for all instances considered in this article. However, MRP and CONWIP provides significantly better cost performances. Choosing between MRP and CONWIP depends on the industrial context. MRP perfoms well when the forecast are relatively accurate. It is also a better solution than CONWIP when the emergency cost or the demand variability is high. In the other situations, CONWIP should be preferred. Moreover, MRP is easily and widely applied in practice but CONWIP requires more efforts to be correctly implemented because it needs a reliable control system for checking the quantity of work-in-process in the whole pipeline. Both require more computation time than BS policies and Π_{static} to find good parameter values.

Π_{static} and Π_{linear} do not perform as well as MRP and CONWIP, but when the number of components is high, they are simpler and more intuitive to use. They also facilitate the coordination between sales and supply chain functions. These are the reasons why Π_{static} and Π_{linear} are preferred at Renault. Indeed, these policies are only defined as percentage values. Using percentages has some drawbacks (as explained in Section 4) but it is simpler to manipulate than many different stock levels for practitioners (of both sales and supply chain departments). For example, managers can use the same percentage for a whole category of components that have the same characteristics of cost and forecast accuracy and they do not need to compute for each component an optimal stock level (they only need the optimal percentages for Π_{static} or Π_{linear}). In practice in Renault, parts are categorised according to their costs (holding and emergency) and forecast type (for example: some forecasts are provided directly by the sales department and are relatively reliable, but for new options or very specific components, demand is very unpredictable). Then, optimal percentages are applied for each category. This avoids using a lot of different stock levels and facilitate the negotiation processes during the S&OP between sales and supply chain functions. Our study suggests that Π_{static} and Π_{linear} are less efficient than MRP and CONWIP, but under certain conditions (for example: low sales requirements), there is only a slight cost difference.

7 Conclusion and research perspectives

Reducing logistic costs while satisfying customers requirements becomes more challenging in a global environment. In this article, we present a simulation-optimization solution to find the best parameters of various policies for managing inventories and the flexibility offered to the sales during the S&OP process. We consider ten different policies based on MRP, reorder point policies, CONWIP systems and Renault's policies. We perform a numerical experiment based on industrial data. This research is particularly relevant for companies that face impatient customers, uncertain demand and distant sourcing.

The contribution of this paper is threefold. First, we investigate the coupling of different inventory strategies with a flexible S&OP, through a stochastic multi-objective optimization model solved by simulation-optimization. Second, we present a detailed numerical comparison of the policies in terms of computation time and logistic cost. We detail how the performances vary as a function of system parameters and policies. Third, we provide practical recommendations to help decision makers to choose the appropriate policy depending on the problem characteristics.

Several research avenues can be derived from this study. First, the optimization algorithm and settings have a strong impact on computation time and cost performances. It would be valuable for both practitioners and academics to investigate on more efficient algorithms and settings. Second, safety stock and flexibility parameters could be determined by using heuristic formulas or approximations. It would be interesting to compare performances obtained via simulation-optimization and several heuristics. Finally, research could be conducted on different strategies (instead of static and linear policies) for managing the flexibility in S&OP.

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References

S. Andradóttir. An overview of simulation optimization via random search. *Handbooks in operations research and management science*, 13:617–631, 2006.

K. J. Arrow, T. Harris, and J. Marschak. Optimal inventory policy. *Econometrica: Journal of the Econometric Society*, pages 250–272, 1951.

E. S. Bernardes and M. D. Hanna. A theoretical review of flexibility, agility and responsiveness in the operations management literature. *International Journal of Operations & Production Management*, 29(1):30–53, 2009.

Y. Carson and A. Maria. Simulation optimization: methods and applications. In *Proceedings of the 29th conference on Winter simulation*, pages 118–126. IEEE Computer Society, 1997.

V. Chankong and Y. Y. Haimes. *Multiobjective decision making: theory and methodology.* Number 8. North-Holland, 1983.

M. Christopher and M. Holweg. Supply Chain 2.0: managing supply chains in the era of turbulence. *International Journal of Physical Distribution & Logistics Management*, 41(1):63–82, 2011.

M. Christopher and H. Peck. Building the resilient supply chain. *International Journal of Logistics Management*, 15(2):1–14, 2004.

A. Dolgui and C. Prodhon. Supply planning under uncertainties in MRP environments: A state of the art. *Annual Reviews in Control*, 31(2):269–279, 2007.

Q. Feng, G. Gallego, S. P. Sethi, H. Yan, and H. Zhang. Optimality and nonoptimality of the base-stock policy in inventory problems with multiple delivery modes. *Journal of Industrial and Management Optimization*, 2(1):19, 2006.

J. M. Framinan, P. L. González, and R. Ruiz-Usano. The CONWIP production control system: review and research issues. *Production Planning & Control*, 14(3):255–265, 2003.

M. C. Fu. Optimization via simulation: a review. *Annals of Operations Research*, 53(1):199–248, 1994.

M. C. Fu. Gradient estimation. *Handbooks in operations research and management science*, 13:575–616, 2006.

M. C. Fu, F. Glover, and J. April. Simulation optimization: a review, new developments, and applications. In *Proceedings of the 32nd conference on Winter simulation*, pages 83–85. Institute of Electrical and Electronics Engineers, Piscataway, New Jersey, USA, 2005.

F. Glover, J. P. Kelly, and M. Laguna. New advances for wedding optimization and simulation. In *Proceedings of the 1999 Winter Simulation Conference*, volume 1, pages 255–260. IEEE, 1999.

J. A. Grimson and D. F. Pyke. Sales and operations planning: an exploratory study and framework. *The International Journal of Logistics Management*, 18(3):322–346, 2007.

V. Guide Jr and R. Srivastava. A review of techniques for buffering against uncertainty with MRP systems. *Production Planning & Control*, 11(3):223–233, 2000.

Y. Y. Haimes, L. S. Lasdon, and D. A. Wismer. On a bicriterion formulation of the problems of integrated system identification and system optimization. *IEEE Transactions on Systems, Man, and Cybernetics*, 1(3):296–297, 1971.

R. M. Hill. On the suboptimality of (S-1,S) lost sales inventory policies. *International Journal of Production Economics*, 59(1):387–393, 1999.

M. Holweg, S. Disney, P. Hines, and M. Naim. Towards responsive vehicle supply: a simulation-based investigation into automotive scheduling systems. *Journal of Operations Management*, 23(5):507–530, 2005.

F. R. Jacobs and D. C. Whybark. A comparison of reorder point and material requirements planning inventory control logic. *Decision Sciences*, 23(2):332–342, 1992.

S. Koh, S. Saad, and M. Jones. Uncertainty under MRP-planned manufacture: review and categorization. *International Journal of Production Research*, 40(10):2399–2421, 2002.

L. H. Lee, E. P. Chew, P. I. Frazier, Q.-S. Jia, and C.-H. Chen. Advances in simulation optimization and its applications. *IIE Transactions*, 45(7):683–684, 2013.

L. L. Lim, G. Alpan, and B. Penz. Reconciling sales and operations management with distant suppliers in the automotive industry: A simulation approach. *To appear in International Journal of Production Economics*, 2014a. doi: 10.1016/j.ijpe.2014.01.011. URL `http://dx.doi.org/10.1016/j.ijpe.2014.01.011`.

L. L. Lim, G. Alpan, and B. Penz. A simulation-optimization approach for managing the sales and operations planning in the automotive industry. *Les Cahiers Leibniz*, (212):1–26 (submitted to publication), 2014b.

U. Merschmann and U. W. Thonemann. Supply chain flexibility, uncertainty and firm performance: an empirical analysis of German manufacturing firms. *International Journal of Production Economics*, 130(1):43–53, 2011.

M. Nakano. Collaborative forecasting and planning in supply chains: The impact on performance in japanese manufacturers. *International Journal of Physical Distribution & Logistics Management*, 39 (2):84–105, 2009.

S. Ólafsson. Metaheuristics. *Handbooks in Operations Research and Management Science*, 13:633–654, 2006.

J. Olhager, M. Rudberg, and J. Wikner. Long-term capacity management: linking the perspectives from manufacturing strategy and sales and operations planning. *International Journal of Production Economics*, 69(2):215–225, 2001.

R. Oliva and N. Watson. Cross-functional alignment in supply chain planning: a case study of sales and operations planning. *Journal of Operations Management*, 29(5):434–448, 2011.

J. A. Orlicky. *Material requirements planning: the new way of life in production and inventory management*. McGraw-Hill, Inc., 1975.

E. Presman and S. P. Sethi. Inventory models with continuous and Poisson demands and discounted and average costs. *Production and Operations Management*, 15(2):279–293, 2006.

A. Reichhart and M. Holweg. Creating the customer-responsive supply chain: a reconciliation of concepts. *International Journal of Operations & Production Management*, 27(11):1144–1172, 2007.

D. Rexhausen, R. Pibernik, and G. Kaiser. Customer-facing supply chain practices - The impact of demand and distribution management on supply chain success. *Journal of Operations Management*, 30(4):269–281, 2012.

S. Robinson. *Simulation: the practice of model development and use*. Wiley. com, 2004.

R. O. Roundy and J. A. Muckstadt. Heuristic computation of periodic-review base stock inventory policies. *Management Science*, 46(1):104–109, 2000.

A. M. Sanchez and M. Perez. Supply chain flexibility and firm performance: a conceptual model and empirical study in the automotive industry. *International Journal of Operations & Production Management*, 25(7):681–700, 2005.

C. R. Schultz. On the optimality of the (S-1, S) policy. *Naval Research Logistics*, 37(5):715–723, 1990.

E. A. Silver, H. Naseraldin, and D. P. Bischak. Determining the reorder point and order-up-to-level in a periodic review system so as to achieve a desired fill rate and a desired average time between replenishments. *Journal of the Operational Research Society*, 60(9):1244–1253, 2008.

M. L. Spearman and M. A. Zazanis. Push and pull production systems: issues and comparisons. *Operations research*, 40(3):521–532, 1992.

M. L. Spearman, D. L. Woodruff, and W. J. Hopp. CONWIP: a pull alternative to kanban. *International Journal of Production Research*, 28(5):879–894, 1990.

M. Stevenson and M. Spring. Supply chain flexibility: an inter-firm empirical study. *International Journal of Operations & Production Management*, 29(9):946–971, 2009.

G. Svensson. A conceptual framework for the analysis of vulnerability in supply chains. *International Journal of Physical Distribution & Logistics Management*, 30(9):731–750, 2000.

J. R. Swisher, P. D. Hyden, S. H. Jacobson, and L. W. Schruben. A survey of simulation optimization techniques and procedures. In *Proceedings of the 2000 Winter Simulation Conference*, volume 1, pages 119–128. IEEE, 2000.

J. R. Swisher, P. D. Hyden, S. H. Jacobson, and L. W. Schruben. A survey of recent advances in discrete input parameter discrete-event simulation optimization. *IIE Transactions*, 36(6):591–600, 2004.

V. Tardif and L. Maaseidvaag. An adaptive approach to controlling kanban systems. *European Journal of Operational Research*, 132(2):411–424, 2001.

A. M. T. Thomé, L. F. Scavarda, N. S. Fernandez, and A. J. Scavarda. Sales and operations planning: A research synthesis. *International Journal of Production Economics*, 138(1):1–13, 2012.

A. M. T. Thomé, R. S. Sousa, and L. F. Scavarda. The impact of sales and operations planning practices on manufacturing operational performance. *International Journal of Production Research*, (ahead-of-print):1–14, 2013.

T. E. Vollmann, W. L. Berry, and C. D. Whybark. *Manufacturing planning and control systems*. McGraw-Hill, 1997.

Y. Xu, A. Bisi, and M. Dada. New structural properties of (s, S) policies for inventory models with lost sales. *Operations Research Letters*, 38(5):441–449, 2010.

K. K. Yang. A comparison of reorder point and kanban policies for a single machine production system. *Production Planning & Control*, 9(4):385–390, 1998.

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