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Production planning in automotive powertrain plants: A case study

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Abstract:

Based on a real case study from the automotive industry, this paper deals with production planning in powertrain plants. We present an overview of the production planning process and propose a mixed integer linear program to determine the production quantities of each product over a planning horizon of several days. Then, using real data of an engine assembly line, we simulate the performance obtained through the proposed model within a rolling horizon planning process. We perform multiple tests in order to evaluate the impact of two parameters involved in this process: planning frequency and frozen horizon length. Furthermore, in order to illustrate the value of improving coordination between engine plants and their customers, we evaluate the impact of the quality of demand information (orders and forecasts). We analyze the simulation results and provide insights and recommendations in order to achieve a good tradeoff between service level, inventory, and planning stability.

Keywords: Production Planning; Mixed Integer Linear Program; Rolling horizon; Planning Frequency; Frozen horizon; Automotive industry.

1 Introduction

As product variety and demand volatility increase, a major challenge for automotive companies is to coordinate effectively the flow of material in their supply chain. In recent years, several studies have been carried out in this field by automotive companies in order to improve their supply chain processes (see for example Souilah 2008; Sali and Giard 2015; Garcia-Sabater, Maheut, and Garcia-Sabater 2011; Volling et al. 2013). Our research falls within this scope. It was conducted together with the automotive company PSA Peugeot Citroën and aims at improving the production planning performance of powertrain plants. A powertrain plant can be either an engine plant, a gearbox plant, or a chassis part plant. These plants supply mainly the car assembly plants but also other customers such as spare parts centers and plants belonging to other automakers. In this paper, we particularly focus on engine plants.

An engine plant is usually composed of multiple workshops. Each workshop contains several production lines dedicated to produce components and products of the same product family (a set of products having common technological characteristics). The production process inside each workshop is independent from the other workshops. Figure 1 gives a typical example of an engine production workshop that contains an assembly line and multiple machining lines producing the main engine components (engine block, cylinder head, crankshaft, and connecting rods).

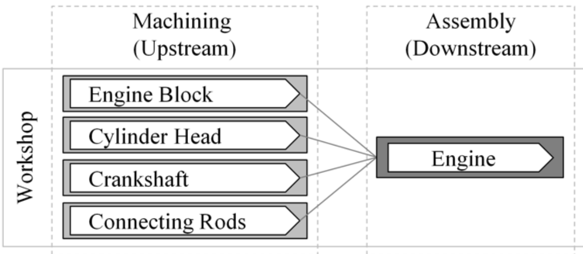

Figure 1 Engine production process

In the context of this study, the powertrain plants are implementing a hierarchical planning system which includes three main processes: the Sales and Operations Planning (S&OP), the Master Production Scheduling (MPS), and the Production Sequencing. Each hierarchical level has its own characteristics, including the execution frequency, the level of product aggregation, the length of the planning horizon, and the size of the time buckets in which the planning horizon is divided. The S&OP process is performed each month. It provides an aggregate planning (at product family or subfamily level) over 18 months divided in months. The MPS process is performed every week or every day and provides a detailed production (at product reference level) over 16 weeks divided in days and weeks. The sequencing process is performed every day and provides the detailed production sequence over 10 days.

The remainder of this article is organized as follows. Section 2 presents a literature review on production planning models and rolling horizon planning systems. Section 3 describes the production planning model that we designed according to the requirements stated by powertrain plants. A numerical example is provided in order to illustrate how this planning model works. Section 4 provides a simulation of rolling horizon planning, which is based on a real case study of an engine assembly line. The impact of planning frequency, frozen horizon length, and quality of demand information will be analyzed. The article ends with the conclusion and further research.

2 Literature review

This literature review focuses on production planning problems and rolling horizon planning systems.

2.1 Production planning models

The aim of production planning is to determine the production quantity of each product, the time at which such quantities have to be produced, and often the production facility on which the production must take place. According to Pochet and Wolsey (2006, page 3), it is usually an operational to tactical problem (short to medium-term) where the usual objective is to meet forecast demand at minimum cost. The authors explain that “the goal of production planning is thus to make planning decisions optimizing the trade-off between economic objectives such as cost minimization or maximization of contribution to profit and the less tangible objective of customer satisfaction.”

Comelli, Gourgand, and Lemoine (2008) give an overview of mathematical models used to solve tactical planning problems. This review classifies the models according to five parameters: mono or multi-level, mono or multi product, with or without capacity constraints, constant or variable demand, and small or big time buckets. The authors distinguish three types of planning problems. The first problem is sales and operations planning (S&OP). It is about balancing sales and production level on a midterm horizon. Production capacity is then usually considered as a decision variable. The second problem is master production scheduling (MPS). It is a more detailed production planning process that provides dates and production quantities of each item. The third problem is material requirements planning (MRP). It is the simultaneous planning of final products and their components using bills of materials. According to the authors, the MPS and MRP are considered as the main problems of tactical planning and are usually modeled as extensions from two well-known models: the capacitated lot sizing problem (CLSP), and the multi-level capacitated lot sizing problem (MLCLSP). See Drexl and Kimms (1997) for a literature review on lot sizing models. These problems are usually solved using mathematical programming (branch and bound, and branch and cut) and approximated methods (heuristics and metaheuristics).

Many commercial software tools called Advanced Planning Systems (APS) have been developed to solve planning problems. These software tools use methods of operational research to support the decision making on a large scope of supply chain processes such as procurement, production, transport, and demand planning (see Meyr, Wagner, and Rohde 2015). Nevertheless, according to Stadtler (2005, page 583), “it does not seem wise to find an overall tool adequate for any possible type of production.” The author indicates that “production planning and detailed scheduling have to be adapted to the specific needs and conditions.”

In the automotive industry, several papers have studied capacity and production planning. Meyr (2009) discusses supply chain planning in the German automotive industry and reviews methods of operational research (linear programming, and mixed integer programming) able to support the planning tasks in car assembly plants. Garcia-Sabater, Maheut, and Garcia-Sabater (2011) present a case study from automotive industry and provide a description of the planning process of an engine plant. They present mixed integer linear programming (MILP) models that integrate production with transport planning and take into account objectives and constraints related to lean manufacturing practices (such as production leveling). Volling et al. (2013) provide an overview of operational research models used for the planning of capacities and orders in build-to-order automobile production. Dörmer, Günther, and Gujjula (2013, 2015) study MPS and sequencing in car assembly lines. They propose a mathematical model and heuristic solution procedures for the MPS that attempt to minimize the workload variability and anticipate decisions on the sequencing problem. Wochner, Grunow, Staeblein and Stolletz (2016) develop a MILP to coordinate sales and ramp-up operations in the automotive industry.

Regarding the automotive industry, there are still few papers in the scientific literature giving a comprehensive overview of the production planning process and mathematical models. Moreover, automotive powertrain plant case studies are rare with the exception of Garcia-Sabater, Maheut, and Garcia-Sabater (2011). Most of the papers focus on car assembly plants.

2.2 *Rolling horizon planning*

Rolling horizon planning is a common practice in the industry and has received a lot of attention in the literature during the last decades. Several authors have studied the impact of different planning parameters and rules on the performance of the supply chain in terms of production cost, service level, and stability. A literature review done by Sahin, Narayanan, and Robinson (2013) shows that research on rolling horizon planning problems is still incomplete. Despite its importance and its extensive application in the industry, there is a lack of recent studies, and in particular studies that consider complex supply chain configurations (for example a supply chain involving multiple production levels, multiple products, under capacity constraints and demand uncertainty).

In a rolling horizon planning context, the production plan is updated periodically by using the most reliable information available. According to Tang and Grubbström (2002), there are two basic reasons to update the production plan. The first one is the shift of planning horizon. The planning horizon is usually composed of a finite number of periods. As time moves, some periods of the production plan are executed and become past periods, other periods become closer in time, and new periods must be placed to maintain the planning horizon length. The second reason is uncertainty. When production planning is performed using demand forecast, it should be regularly reviewed in order to react to forecast errors and take advantage of the latest demand information available. This reactivity contributes to reduce costs and improves service level.

Dolgui and Prodhon (2007) examine the appropriate rules to deal with uncertainties in both demand (forecast errors) and production system (machine breakdown, supply delays, etc.). The authors explain that under uncertainties, the production plan needs to be updated quite frequently in order to optimize production decisions. However, too frequent changes provoke disruptions in the supply chain and generate costs related to scheduled orders adjustment (personnel scheduling, machine loading, etc.). The negative effect due to production planning instability is well-known in the literature. It is usually referred to as “nervousness” (Blackburn, Kropp, and Millen 1986; Carlson, Jucker, and Kropp 1979; Ho 1989).

Studies dealing with rolling planning horizon often raise two fundamental questions: how often should the production plan be updated (refers to planning frequency)? Should all the production plan be updated (refers to freezing part of the production plan)? The performance indicators usually considered in the literature are: service level (measure of customer demand satisfaction), production cost (including setup, variable production and inventory costs), and stability (reflects the impact of the modifications in the production plan).

To ensure a relative planning stability, a common practice is to establish a frozen horizon. Thus, the planned periods that belong to the frozen horizon are not changed when the production plan is updated (Sridharan and Berry 1990; Sridharan, Berry, and Udayabhanu 1987; Zhao and Lee 1993). However, other techniques to reduce instability have been proposed in the literature such as using a mathematical model that minimizes instability when the production plan is calculated (Blackburn, Kropp, and Millen 1986; Blackburn, Kropp, and Millen 1987; Herrera 2011; Ho and Carter 1996; Kadipasaoglu and Sridharan 1995).

Barrett and Laforge (1991) study the impact of planning frequency on the performance of a production system with multiple products and multiple levels in MRP context. Using a simulation model, the authors evaluate the performance of different planning frequencies (monthly, twice monthly, weekly, twice weekly, daily, and twice daily). The performance is measured through service level, stock level, and the number of changes made in the production plans. The results show that the rule of thumb that suggests a weekly planning does not provide the best performance tradeoff. In a similar context, Zhao and Lee (1993) examine different parameters involved in a rolling horizon planning system. The authors evaluate the impact of forecast errors. Under deterministic demand conditions, they show that freezing the entire planning horizon improves performance in terms of stability, cost, and service level. However, under demand uncertainty, the determination of frozen horizon length is a tradeoff between stability, cost, and service level. Regarding planning horizon length, the authors state that its prolongation improves the performance when demand is deterministic while it degrades it when demand is uncertain.

Ho and Ireland (1998) study the impact of forecast errors on planning instability. The authors show that the existence of forecast errors increases instability. To mitigate this effect, they suggest using appropriate criteria when calculating the production plan. In others words, a proper lot-sizing rule can help to reduce the instability generated by forecast errors. The same conclusion is stated by Venkataraman and D'Itri (2001) who conducted a similar study.

Xie et al. (2003) study the case of a production system under capacity constraint and demand uncertainty. The production system involves a single stage with multiple products. Regarding planning frequency, the authors find that less frequent planning provides a better performance, both in terms of stability, cost, and quality service. They explain that frequent changes in the production plan in successive planning cycles do not really help to improve service level. This conclusion that recommends less frequent planning is also stated by other authors like Sridharan and Berry (1990), however this does not receive a wide consensus in the literature.

When looking at the findings of numerous articles dealing with rolling horizon planning, there are different recommendations, sometimes contradictory, especially regarding the choice of planning frequency. According to Hozak and Hill (2009, page 4955), “empirical research shows that companies that frequently reschedule perform better, despite some theoretical research that has discouraged high frequencies." The authors explain that providing systems with the timeliest information possible allows a better planning optimization and a better responsiveness to unexpected events.

As a conclusion, rolling horizon planning is a classic topic that received a large attention in the literature. Various articles study the impact of different parameters (length of the planning horizon, length of the frozen horizon planning frequency, forecast errors, and lot-sizing rules) on performance of the production system. Various production contexts were considered: single level or multiple levels, single product or multiple products, deterministic or uncertain demand, with or without resource constraints. However, there is no consensus regarding some conclusions (especially regarding the choice of planning frequency). Furthermore, there is a lack of recent studies on this subject, and in particular case studies coming from the industry.

2.3 Contributions

Our first contribution herein is to provide an overview of the production planning problem of automotive powertrain plants. These plants have specific requirements such as maximizing the usage of capacity, satisfying some lean objectives such as production leveling while maintaining low inventories, production by batch, and satisfying minimum and maximum production quantity constraint. We consider in this paper more specifically the case of engine plants. Based on the needs stated by the plant planning team, we propose a mathematical model (a mixed integer linear program) that aims at optimizing four objectives. The first objective is to **satisfy the forecast demand**. The second one is to **reach safety stock levels**. The third is to **balance the stock level between all products**. The fourth is to **level the production of each product**. Two of these four objectives, namely stock balancing and production leveling, are important in many industrial applications. However, they are rarely studied in the literature within the context of a production planning model. This model was tested in the case of an engine assembly line and also gearbox assembly and other production workshops. We think that this model can be extended to other manufacturing contexts with similar requirements (for example: units producing mechanical parts having similar constraints and/or having objectives like production leveling and stock balancing).

Our second contribution is to study how that planning model should be implemented in a rolling horizon planning context. We analyze in particular the impact of two parameters: **planning frequency** and **length of the frozen horizon**. In addition, we analyze the impact of the **quality of demand information** (orders and forecasts) on the performance of the production system. Our simulation is based on the real data coming from an engine assembly line. We analyze the results and provide insights and recommendations in order to achieve a good tradeoff between service level, inventory, and planning stability.

3 Planning model

The planning model was developed according to the requirements (objectives and constraints) stated by different powertrain plants. In this model, the production capacity over the planning horizon is considered as an input set by the planning team.

3.1 Objectives

A work conducted together with the powertrain plant teams has led to a list of four objectives (by decreasing priority):

- The first and main objective is to satisfy the forecast demand.
- The second objective is to reach the safety stock levels.
- The third objective is to balance the stock levels between all the products. This objective aims to balance the risk of being out of stock between all products. The stock levels are considered as perfectly balanced when the ratio between the stock level and the safety stock is identical for all products.
- The last objective is to level the production. The production percentage of each product has to be as stable as possible over the planning horizon. The main goal of this objective is to achieve a much more stable schedule and reduce demand variability on upstream supply chain processes.

3.2 Constraints

We have also listed the production constraints that need to be considered when the production planning is made:

- Constraint 1: the production line capacity constraint. For economic reasons (minimizing idle time), the total production quantity on each production line must equal the capacity set by the planning team.

- Constraint 2: the packing unit constraint. The production quantity of each product has to be a multiple of its packing unit. For example, the packing unit is 6 for the engines and 8 for the gearboxes.
- Constraint 3: the minimum production quantity constraint for one product.
- Constraint 4: the minimum production quantity constraint for a set of products.
- Constraint 5: the maximum production quantity constraint for a set of products.
- Constraint 6: the production day constraint for a set of products. Some specific products (e.g. products dedicated to spare part centers) need to be produced on specific days of the planning horizon.

Among all these six constraints, the first two constraints are always considered for all production lines. The other constraints can be considered or not, depending on the production line characteristics. For example: an engine assembly line has only the constraints 1 and 2. A gearbox assembly line usually has the constraints 1, 2, and 3. To limit the length of the paper, only constraint 1 and 2 are considered in the rest of the paper.

3.3 Mathematical formulation

A mixed integer linear program was developed according to the objectives and constraints stated above.

3.3.1 Notations

Let us consider an engine assembly line producing N different products (references). The goal is to calculate the production plan over a planning horizon of H periods (in days). The index i denotes the different products (i=1..N) and h denotes the planning horizon periods (h=1..H).

The model parameters (model inputs) are described below:

$K(h)$	Production capacity of the engine assembly line in period h.
$U(i)$	Packing unit size of product i.
$D(i,h)$	Customer order or demand forecast of product i in period h.
$x(i,0)$	Initial stock of product i.
$SS(i,h)$	Safety stock of product i in the period h.
$TS(i,h)$	Target stock of product i in the period h.
p	Number of consecutive periods considered for production leveling (1<p<=H).
$WB(i,h)$	Cost of backorder for product i in period h.
$WS(i,h)$	Cost of not reaching safety stock for product i in period h.
$WT(i,h)$	Cost of not balancing the stock level for product i in period h.
$WL(i,h)$	Cost of not leveling the production of product i over the periods from h to h+p-1.

The decision variables (model outputs) are the following:

$q(i,h)$	Production quantity of product i in period h.
$q^u(i,h)$	Number of packing units of product i to produce in period h.
$x(i,h)$	Stock level of product i at the end of period h. In case of backorder, this variable is negative.
$b(i,h)$	Backorder of product i at the end of the period h.
$e^{ss}(i,h)$	Difference between the stock level and the safety stock, regarding product i in period h, when the stock level is under the safety stock.
$e^{ts}(i,h)$	Difference between the stock level and the target stock regarding product i in period h.
$m(i,h)$	Production percentage of product i in period h.
$m^{max}(i,h)$	Maximum value of the production percentage of product i over the periods from h to h+p-1.
$m^{min}(i,h)$	Minimum value of the production percentage of product i over the periods from h to h+p-1.

3.3.2 Objective function

The objective function is a weighted sum that can be decomposed in four terms:

$$\sum_{h=1}^{H}\sum_{i=1}^{N} WB(i,h) * b(i,h) \quad (1)$$

$$+\sum_{h=1}^{H}\sum_{i=1}^{N} WS(i,h) * e^{ss}(i,h) \quad (2)$$

$$+\sum_{h=1}^{H}\sum_{i=1}^{N} WT(i,h) * e^{ts}(i,h) \quad (3)$$

$$+\sum_{h=1}^{H-p+1}\sum_{i=1}^{N} WL(i,h) * (m^{max}(i,h) - m^{min}(i,h)) \quad (4)$$

(1) is related to the objective of satisfying the forecast demand. (2) measures the difference between the stock level and the corresponding safety stock. This difference is set to zero if the stock level is greater than the safety stock. (3) is related to the objective of balancing the stock levels between products. Stock levels are perfectly balanced when each stock level equals the corresponding target stock. The target stock levels are calculated before the model is launched, so as to allocate the overall stock level between the different products in proportion to the corresponding safety stocks as shown in equation (5). As the overall production equals the capacity, the overall stock level for each period is calculated with (6).

$$\forall h, \forall i, \quad TS(i,h) = \frac{SS(i,h)}{\sum_{i=1}^{N} SS(i,h)} * \sum_{i=1}^{N} x(i,h) \quad (5)$$

$$\forall h, \quad \sum_{i=1}^{N} x(i,h) = \sum_{i=1}^{N} x(i,0) + \sum_{h'=1}^{h} K(h') - \sum_{h'=1}^{h}\sum_{i=1}^{N} D(i,h') \quad (6)$$

(4) penalizes the difference between the maximum and the minimum value of the production percentage of product i over each p consecutive periods. The parameter p is usually set equal to 5 working days (one week).

3.3.3 Constraints

The main constraints of the model are described by the following equations:

$$\forall h, \forall i, \quad q(i,h) = q^{u}(i,h) * U(i) \quad (7)$$

$$\forall h, \forall i, \quad q^{u}(i,h) \text{ is a non-negative integer} \quad (8)$$

$$\forall h, \quad K(h) - \varepsilon \le \sum_{i=1}^{N} q(i,h) \le K(h) \quad (9)$$

$$\forall h, \forall i, \quad x(i,h) = x(i,h-1) + q(i,h) - D(i,h) \quad (10)$$

$$\forall h, \forall i, \quad b(i,h) \ge -x(i,h) \quad (11)$$

$$\forall h, \forall i, \quad b(i,h) \ge 0 \quad (12)$$

$$\forall h, \forall i, \quad e^{ss}(i,h) \ge SS(i,h) - x(i,h) \quad (13)$$

$$\forall h, \forall i, \quad e^{ss}(i,h) \ge 0 \quad (14)$$

$$\forall h, \forall i, \quad e^{ts}(i,h) \ge TS(i,h) - x(i,h) \quad (15)$$

$$\forall h, \forall i, \quad e^{ts}(i,h) \ge x(i,h) - TS(i,h) \quad (16)$$

$$\forall h, \forall i, \quad m(i,h) * K(h) = 100 * q(i,h) \quad (17)$$

$$\forall h \le H - p + 1, \forall h' = 0..p-1, \forall i, \quad m^{max}(i,h) \ge m(i,h+h') \quad (18)$$

$$\forall h \le H - p + 1, \forall h' = 0..p-1, \forall i, \quad m^{min}(i,h) \le m(i,h+h') \quad (19)$$

The production quantity of each product must be a non-negative integer and be a multiple of the packing unit size. This is expressed with (7) and (8). The total production quantity must equal the capacity of the assembly line. This is expressed through (9). To avoid infeasibility due to the packing units, a small tolerance ε is considered (the value of ε is based on the size of the smallest packing unit among products). Equation (10) describes the inventory dynamic.

(11) and (12), together with term (1) of the objective function which is minimized, allow the evaluation of backorder quantities. The (13) and (14), together with (2) of the objective function, allow the evaluation of the difference between the net stock and the safety stock. This difference is set to zero if the net stock level is greater than the safety stock. (15) and (16), together with (3) of the objective function, allow the evaluation of the positive difference between the net stock level and the target stock.

(17) allows the evaluation of the production percentage of product i in period h. The total production quantity for a given period is approximated by the production capacity. (18) and (19) together with (4) allow to penalize the production unevenness of product i over the periods h to h+p-1.

3.4 *Numerical example*

In order to show how this planning model works, we give a numerical example based on theoretical data. We consider an engine assembly line producing five products (N=5). We suppose that the planning horizon is equal to two weeks. As we exclude weekends, the planning horizon is equivalent to ten working days (H=10).

We suppose that the production planning is performed on Monday, at the beginning of the day, in order to plan the quantities to produce over the two coming weeks.

The production capacity over the planning horizon is constant and equals 540 engines per day. For each product, the packing unit is equal to 6. The demand data are created randomly using a normal distribution with different parameters in order to have some products with high demand and others with lower demand. These data are given in Table 1. Initial stocks and safety stocks are also provided in Table 1.

Table 1 Demand Forecast, initial stocks, and safety stocks

Parameters		Product i=1	Product i=2	Product i=3	Product i=4	Product i=5
Demand forecasts	$D(i,1)$	156	168	102	30	48
	$D(i,2)$	168	114	132	72	54
	$D(i,3)$	162	102	150	48	48
	$D(i,4)$	156	114	156	60	54
	$D(i,5)$	198	108	132	60	60
	$D(i,6)$	120	156	120	66	54
	$D(i,7)$	162	144	72	42	84
	$D(i,8)$	168	198	126	84	48
	$D(i,9)$	126	162	120	54	60
	$D(i,10)$	192	162	102	48	66
Initial stocks	$x(i,0)$	306	282	258	132	102
Safety stocks	$SS(i,h)$	234	204	180	102	78

As the first priority is given to satisfy the demand forecast (minimize backorders), the highest weight parameter is given to this objective. The second objective is to reach safety stock levels. A lower weight is then given to this objective. The third objective is to reach safety stocks and the last one is production leveling. The chosen weight values are given in (20).

$$\forall h, \forall i, \quad WB(i,h) = 10^5,\ WS(i,h) = 10^3,\ WT(i,h) = 10^2,\ WL(i,h) = 1 \qquad (20)$$

The calculation of the production plan was performed using CPLEX Solver. The obtained solution is illustrated by two figures. Figure 2 illustrates the production quantities of each product over the planning horizon. Since leveling the production is considered as having less priority, we can see that the proposed quantities are not stable over the planning horizon. Note that as the production capacity is constant, it is correct to look at the production quantity instead of the percentage that it represents.

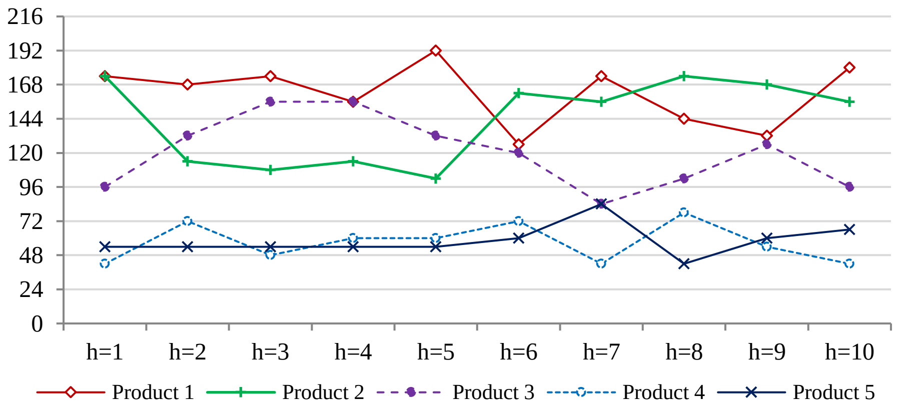

Figure 2 Production

Figure 3 presents the ratio between the stock level and safety stock, for each product and each period. In this figure, we can see that all stock levels are positive and are higher than the safety stocks (stock ratio≥1). This shows that the two most important objectives (satisfying demand forecast and reaching safety stocks) are achieved.

Furthermore, for each period, the ratio between stock and safety stock is almost identical for the all products. This means that the stock levels are well balanced.

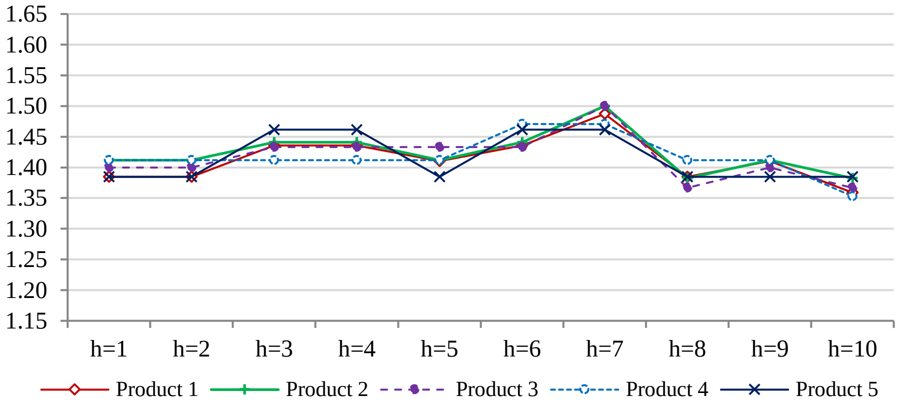

Figure 3 Stock Ratio (Stock level/Safety stock)

If the weight parameters of the objective function are modified, a different production plan can be calculated. For example, we modified the weight parameters in order to give a higher priority to production leveling. The obtained results are illustrated in Figure 4 and 5. Figure 4 shows that the production quantity becomes more stable than in Figure 2. In the other hand, Figure 5 shows that the stocks become less balanced than in Figure 3.

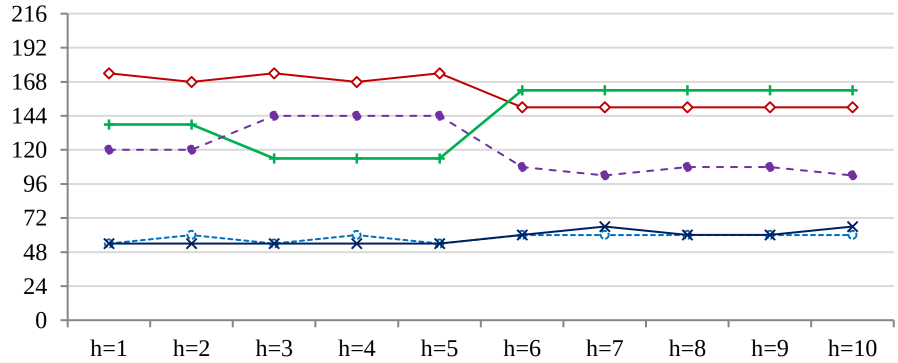

Figure 4 Production

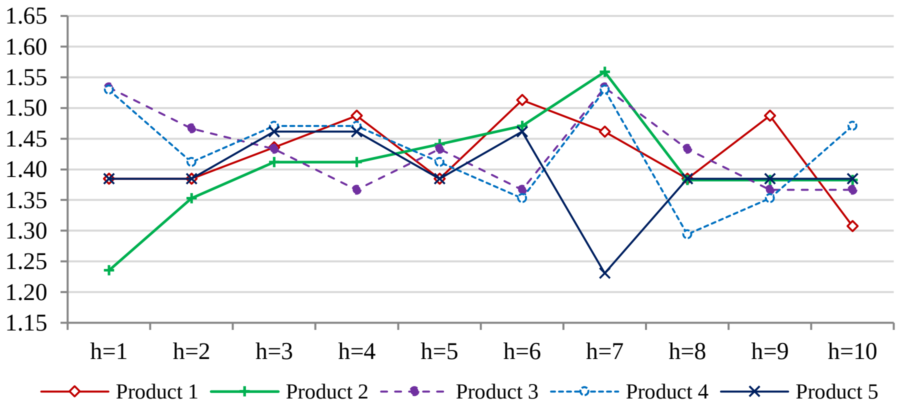

Figure 5 Stock Ratio (Stock level/Safety stock)

Through this numerical example, we showed how the planning model works. This model was tested within the company and was able to properly fulfill the requirements stated by the engine plant, both in terms of solution relevance and computation times.

3.5 Computation times

In order to evaluate the computation times, several tests have been performed with different values of N and H. Based on the previous example, we have designed 49 instances (see Table 2). Initial stocks, safety stocks, and demand information are defined by duplicating the settings of the numerical example we presented previously. The production capacity is then defined in proportion to the number of products. The weights involved in the objective function are time dependent. For each objective and each period h, the weight values are defined by multiplying a constant coefficient by the function $(0.95)^{h-1}$. This is done in order to give higher priority to earlier periods of the planning horizon.

The 49 test instances were solved using IBM ILOG CPLEX Optimization Studio (Version: 12.6.0.0) and using a personal computer (DELL VOSTRO V131 Intel® Core™ i3 2.1GHz, 2 GB RAM). The direct formulation of the model in CPLEX did not provide good computation time results for large-sized instances (i.e. when N*H> 2000). However, we obtained better results thanks to a reformulation we made on the model. As the demand information for each product is always a multiple of the product packing unit, we add a constraint stating that the variation of stock level, for each product, has to be a multiple of the corresponding packing unit. This constraint is provided by (21) and (22).

$$\forall h, \forall i, \quad x(i,h) - x(i,h-1) = \Delta(i,h) * U(i) \qquad (21)$$

$$\forall h, \forall i, \quad \Delta(i,h) \text{ is an integer} \qquad (22)$$

The obtained results are presented in Table 2. Note that the computation time limit was set to 120 seconds.

Table 2 Computation Time

		Number of periods (H)						
		H=5	H=10	H=20	H=40	H=60	H=80	H=100
Number of products (N)	N=5	0.10 [a]	0.10 [a]	0.20 [a]	0.30 [a]	0.50 [a]	0.60 [a]	0.60 [a]
	N=10	0.10 [a]	0.10 [a]	0.10 [a]	0.40 [a]	0.90 [a]	1.90 [a]	1.90 [a]
	N=20	0.00 [a]	0.10 [a]	0.40 [a]	4.70 [a]	8.70 [a]	13.00 [a]	17.20 [a]
	N=40	0.10 [a]	0.30 [a]	5.50 [a]	95.90 [a]	0.05% [b]	0.17% [b]	0.17% [b]
	N=60	2.20 [a]	5.40 [a]	20.90 [a]	0.37% [b]	0.34% [b]	0.35% [b]	0.35% [b]
	N=80	0.40 [a]	3.40 [a]	21.40 [a]	0.24% [b]	0.26% [b]	0.31% [b]	0.36% [b]
	N=100	0.60 [a]	4.60 [a]	89.20 [a]	0.43% [b]	0.43% [b]	0.39% [b]	0.81% [b]

[a] Computation time needed to obtain the optimal solution (in seconds)

[b] Relative gap to the lower bound when the optimal solution is not obtained within 120 s

Table 2 shows that for 34 instances, the optimal solution is obtained within 120 seconds. The average computation time for these instances is 9 seconds. For 15 instances, the solution we obtain after 120 seconds is not guaranteed to be optimal. Nevertheless, the relative gap to optimum is lower than 0.81%.

4 Rolling horizon planning simulation

4.1 Simulation procedure

We consider an engine assembly line that produces N engine references. Every day, the customers provide demand forecasts that the engine assembly line uses to perform its production planning (In this case, more than 97% of the demand comes from car assembly plants). The planning horizon length set by the engine assembly line is H days. We denote by T the simulation time length and by t a specific day in the simulation time (t=0..T).

The first calculation of the production plan (initialization) is performed at t=0. The time between two successive planning updates determines the planning periodicity and is denoted by δ. As time moves, a part of the production plan is executed and new information becomes available (demand forecast, stock levels, and capacity). At t=δ, a new calculation of the production plan is made. This is the second iteration in the simulation. This procedure is then repeated at t=2δ, t=3δ, t=4δ, …, until the end of the simulation time.

In addition, the engine plant may establish a frozen horizon. If the frozen horizon length is X days, then the first X days of the planning horizon cannot be modified when the production plan is updated. In other terms, when the production plan is calculated, the first δ+X periods of the production plan cannot be modified in the future.

At each iteration, the production plan is recalculated using the planning model presented in Section 3. This recalculation is made at the end of day t in order to plan the production from day t+1 to t+H. The main input parameters involved in this recalculation are demand information $d_t(i,h)$, production capacity $K_t(h)$, and stock levels $x_t(i)$. $d_t(i,h)$ is the demand forecast at t regarding the day t+h and the product i, $K_t(h)$ is the capacity of the engine assembly line in day t+h, and $x_t(i)$ denotes the stock level of the product i at the end of day t. The calculation output is $q_t(i,h)$ which is the production quantity planned at t regarding the day t+h and the product i.

As the engine plant may consider a frozen horizon of X days, we have added an additional constraint (23) within the planning model which states that for each day that belongs to the frozen horizon, the quantity calculated at t must equal the quantity previously calculated at t- δ.

$$\forall i, \forall t > \delta, \quad \text{if} \quad h \leq X \quad \text{then} \quad q_t(i,h) = q_{t-\delta}(i,h+\delta) \qquad (23)$$

4.2 *Input data*

We gathered real data from the engine assembly line so as to simulate the planning process over T=60 working days (12 weeks) and N=34 references. The average overall production is around 500 engines per day. The production planning horizon length is H=10 working days (2 weeks). In Table 3, we provide indicators about demand variability for each product i.

Table 3 Demand Variability

Product i	Average Demand	Standard deviation of demand	Percentage of periods with demand > 0	Maximum demand quantity	Minimum demand quantity
i=1	73.2	21.1	100%	132	24
i=2	61.4	19.8	100%	108	18
i=3	40.0	20.1	93%	96	0
i=4	32.6	17.8	100%	90	6
i=5	27.3	17.4	92%	78	0
i=6	21.6	10.9	97%	60	0
i=7	23.5	31.1	53%	120	0
i=8	21.3	15.2	95%	60	0
i=9	19.6	19.5	93%	102	0
i=10	17.8	7.7	97%	36	0
i=11	20.8	32.5	51%	138	0
i=12	13.8	10.9	83%	36	0
i=13	16.4	7.4	100%	42	6
i=14	16.7	27.7	37%	114	0
i=15	12.0	8.1	92%	36	0
i=16	12.1	7.6	92%	30	0
i=17	11.2	11.2	80%	72	0
i=18	12.0	9.3	83%	36	0
i=19	9.6	5.8	85%	18	0
i=20	7.6	8.0	63%	30	0
i=21	7.6	4.0	90%	18	0
i=22	6.7	10.0	42%	42	0
i=23	3.8	6.4	34%	24	0
i=24	2.4	3.7	36%	18	0
i=25	2.3	3.0	39%	6	0
i=26	1.3	3.0	19%	12	0
i=27	1.2	2.7	19%	12	0
i=28	0.8	2.6	10%	12	0
i=29	1.1	7.8	3%	60	0
i=30	0.7	2.0	12%	6	0
i=31	0.4	1.5	7%	6	0
i=32	0.4	1.5	7%	6	0
i=33	0.4	1.9	5%	12	0
i=34	0.1	0.8	2%	6	0

Every day, the customers send demand forecasts that indicate the quantity of each product that must be shipped by the engine plant over the next ten working days. The customers usually confirm the real demand by sending orders three days before the shipping date. Thus, the demand information related to the 3 first days of the planning horizon is almost certain (forecast errors exist but are very minor). However, starting from the fourth day of the horizon, the demand is uncertain and forecast errors are more significant. In Figure 6, we indicate, for each period h of the planning horizon, the forecast error expressed as a percentage of actual demand. Thus, we can clearly see that the forecast errors are very low for h=1, h=2 and h=3 (0%, 2% and 8% respectively) and become much higher starting from h=4.

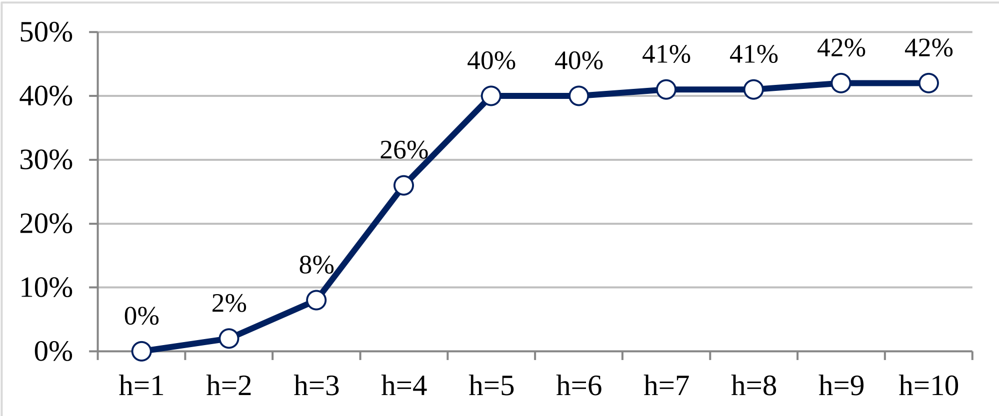

Figure 6 Forecast accuracy over the planning horizon

In our simulations, we assume that, for each week, the production capacity is equal to the average demand of this week. In other words, within each week, we produce exactly the total demand of this week. Accordingly, the overall net stock at the beginning of each week is always the same, and is equal to the initial stock. This is why the overall initial stock is a key parameter in our simulations. This assumption of a weekly demand equal to the weekly capacity is pessimistic, as it assumes no production flexibility. In practice, we have observed that each line has some flexibility on production.

Multiple scenarios were simulated. A scenario is defined by setting a planning periodicity (δ) and a frozen horizon length (X). In order to analyze the impact of δ and X, we simulated 8 different scenarios: scenario 1 (δ=1, X=0), scenario 2 (δ=1, X=1), scenario 3 (δ=1, X=2), scenario 4 (δ=1, X=3), scenario 5 (δ=1, X=4), scenario 6 (δ=1, X=5), scenario 7 (δ=5, X=0), and scenario 8 (δ=5, X=5). In these scenarios, we are testing two planning frequencies which are the most likely to be used in practice: daily planning (scenarios from 1 to 6) and weekly planning (scenarios 7 and 8). In case of a daily planning, we test different frozen horizon length (from X=0 to X=5 days). In case of a weekly planning, we test X=0 and X=5 days.

Thus, for each scenario, we test different initial stock levels so as to determine the amount of stock required to achieve a given service level. Ten initial stock values are tested: 0, 198, 402, 600, 798, 1002, 1200, 1398, 1602, and 1800. These values were defined by considering an increase by step of 200 engines, and taking the closest multiple of 6, since the stock level must be multiple of 6 (size of the engine packing unit). In terms of days of coverage, 200 engines represent approximately 0.4 days. We first start with the zero initial stock value. Then, we gradually increase the value of the initial stock (198, 402, 600, …). We stop when all the values are tested or when the obtained service level is greater than or equal to 99%.

In Section 3, we explained that the planning model considers that the overall production must be almost equal to the capacity set by the planning team. In this situation, the simulated performance of the engine assembly line is highly influenced by the capacity level and the initial stocks. For example, if the initial stock and the capacity are too low, many backorders will occur and the obtained service level will be very poor. Therefore, to improve that service level, the initial stock level must be higher or the production capacity must be adjusted. In the simulation model presented herein, we consider that the capacity is fixed. Then, we perform multiple simulations with different initial stock levels so as to determine the stock level which is required to achieve a desired service level (this approach will be discussed in the conclusion of this article). In other words, we consider that the overall initial stock available at the beginning of the simulation (t=0) is set by the user (for example 300 engines). As we also need to determine how this overall stock is allocated to the different products (determine the initial stock $x_0(i)$ for each product i), we introduced a modification within the planning model so as, at the beginning of the simulation (t=0), the allocation of the overall initial stock is optimized automatically according to the planning requirements (3.1).

4.3 Performance indicators

For a given scenario and initial stock value, we simulate the planning process over T=60 days. Then, we measure the performance indicators at the end of the simulation. As is usually done in the literature, we consider three performance indicators: stock level indicator (as a cost indicator), service level (as a customer satisfaction indicator), and a planning stability indicator.

As a stock level indicator, we consider the value of the overall initial stock set by the user. This stock value is expressed in terms of days of coverage. We calculate the ratio between the initial stock level and the average daily demand. This calculation is illustrated by (24) where $d^R_t(i)$ denotes the actual demand of the product i in day t.

$$\frac{\sum_{i=1}^{N} x_0(i)}{\frac{1}{T}*\sum_{t=1}^{T}\sum_{i=1}^{N} d^R{}_t(i)} \tag{24}$$

The service level indicator reflects the percentage of demand satisfaction. The calculation of this indicator is illustrated by (25) where $b_t(i)$ denotes the backorder quantity of the product i in day t.

$$1 - \frac{\sum_{t=1}^{T}\sum_{i=1}^{N} b_t(i)}{\sum_{t=1}^{T}\sum_{i=1}^{N} d^R{}_t(i)} \tag{25}$$

In order to measure planning stability, we compare the quantity that was really produced by the assembly line to the quantity that was planned h days before. Then, we calculate the percentage of the quantity really produced in comparison to the quantity planned h days before. For a given value of h, this calculation is given by (26) where $q^R_t(i)$ denotes the real quantity produced of product i in day t. As an example, for a single product, if the quantity produced in day t is $q^R_t(i)=90$ and the quantity planned h days before was $q_{t-h}(i,h)=100$, then the planning stability indicator is equal to 90%. If the quantity produced in day t was $q^R_t(i)=100$, then the indicator would be equal to 100%.

$$\frac{\sum_{t=1}^{T}\sum_{i=1}^{N} Min\{q_t^R(i), q_{t-h}(i,h)\}}{\sum_{t=1}^{T}\sum_{i=1}^{N} q_t^R(i)} \tag{26}$$

This planning stability indicator can be calculated for different values of h. In our case study, the management was particularly interested in the planning stability regarding the 5 first days of the horizon. Therefore, we measure this indicator for h=1..5 and then we calculate the average in order to obtain a synthetic indicator. This calculation is described in (27).

$$\frac{1}{5} * \sum_{h=1}^{h=5} \frac{\sum_{t=1}^{T}\sum_{i=1}^{N} Min\{q_t^R(i), q_{t-h}(i,h)\}}{\sum_{t=1}^{T}\sum_{i=1}^{N} q_t^R(i)} \tag{27}$$

As the different scenarios and performance indicators were introduced, we will now present the simulation results. The simulation model has been developed in CPLEX (to calculate the production plans) and Excel (to manage input and output data).

4.4 Impact of planning frequency and frozen horizon

For each scenario, we made multiple simulations by testing different initial stock levels in order to determine the minimum stock level needed to obtain a service level greater than or equal to 99%. This target service level was determined together with the engine plant management.

In Table 4, we present the simulation results. For each scenario, this table provides the stock level needed to obtain the desired service level (expressed in days of coverage), the value of the service level, and the value of the planning stability indicator that we previously described in (27).

Table 4 Impact of planning frequency and frozen horizon

Scenario	Planning Periodicity (δ)	Frozen horizon length (X)	Initial stock level needed to obtain a service level ≥ 99%	Obtained service level	Planning stability (over the 5 first days of the planning horizon)
Scenario 1	1 (every day)	0	0.4	99.9%	85%
Scenario 2		1	0.4	99.7%	88%
Scenario 3		2	0.8	100.0%	91%
Scenario 4		3	1.2	99.0%	96%
Scenario 5		4	2.0	99.2%	100%
Scenario 6		5	2.4	99.3%	100%
Scenario 7	5 (every week)	0	1.2	99.2%	96%
Scenario 8		5	3.2	99.4%	100%

In order to analyse the impact of the frozen horizon length, let us look at the scenarios with daily planning (δ=1). The results show that the increase in the frozen horizon length improves planning stability. However, this will require higher stock levels if we desire to maintain a good service level (≥99%). For example, to switch from a frozen horizon of 1 day (X=1) to 5 days (X=5), the stock level passes from 0.4 to 2.4 days of coverage.

To analyze the impact of planning periodicity (δ), we compare the scenarios 7 and 8 (weekly planning) to the scenarios 1 and 6 (daily planning) respectively. The scenarios 7 and 1 do not consider a frozen horizon (X=0) while the scenarios 8 and 6 consider a frozen horizon of 5 days (X=5). The simulation results show that increasing the planning periodicity from daily (δ=1) to weekly planning (δ=5) improves stability. This is observable when comparing the scenario 1 to scenario 7. For the scenarios 6 and 8, the planning stability is identical and equals 100%. This is because the frozen horizon length in these scenarios is 5 days (X=5) and we are measuring the planning stability indicator over the first 5 days of the planning horizon. This being said, the increase in planning periodicity leads to higher stock levels. The needed stock to achieve the desired service level passes, in case of a X=0, from 0.4 days (scenario 1) to 1.2 days (scenario 7), and from 2.4 days (Scenario 6) to 3.2 days (scenario 8) in case of X=5.

As a conclusion, the simulation results showed that the increase in frozen horizon length (X) and planning periodicity (δ) improves the performance in terms of planning stability but worsens it in terms of stock needed to achieve the target service level. Based on the real data of an engine assembly, the simulations we made helped to quantify the performance obtained in different scenarios. The obtained results illustrate the trade-off between stability, stock and service levels, and provide some insights to help the decision makers in choosing the most suitable scenario (planning periodicity and frozen horizon length).

Having a good planning stability is particularly important for the procurement department because it reduces the uncertainty regarding the quantities of components required by the engine assembly line, and thereby reduces upstream safety stocks and associated costs. In our case study, the procurement department requested to freeze the production plan of the engine assembly line over 5 days (X=5), which makes possible to supply just in time the exact amount of the required components. If we put this request as the first priority, the scenarios 6 and 8 may be considered. However, our simulation results suggest that the scenario 6 (daily planning with a frozen horizon of 5 days) leads to better production reactivity and improves the performance in terms of stock and service level. This being said, in this scenario, the stock needed to reach the desired service level is 2.4 days of coverage, which is relatively high. To achieve a better stock performance, a tradeoff solution would be to consider a frozen horizon of 3 days (scenario 4) instead of 5 days (scenario 6). Table 4 shows that the scenario 4 (δ = 1, X = 3) requires half less amount stock (1.2 instead of 2.4 days). Moreover, this scenario provides a very good planning stability (96%). Therefore, we recommend the implementation of scenario 4 which does not meet strictly the request of X=5 but leads to a very good performance tradeoff between service level (99.9%), stock (1.2 days), and planning stability over the 5 first days of the horizon (96%).

4.5 Impact of the quality of demand information

Now, we investigate the impact of the quality of demand information (forecast) that is used by the engine assembly line to perform its production planning. The simulation results presented previously (Table 4) were made with the real demand data (real forecast errors). Now, we reduce the amount of forecast errors and analyze the impact on the performance. We will focus on three scenarios: scenario 4, scenario 6, and scenario 8.

In order to simulate the improvement of forecast accuracy, we multiply the real forecast errors by a coefficient (1-α) where α represents the percentage of improvement of the forecast accuracy. Four different values of α are tested: 20%, 40%, 60%, and 80%. Table 5 gives the simulation results (stock and service level) for each scenario and each value of α.

Table 5 Impact of forecast accuracy improvement

			Without forecast improvement		With forecast improvement		
Scenario	Planning Periodicity (δ)	Frozen horizon length (X)	Initial stock level needed to obtain a service level ≥ 99%	Obtained service level	Percentage of forecast accuracy improvement (α)	Initial stock level needed to obtain a service level ≥ 99%	Obtained service level
Scenario 4	1 (every day)	3	1.2	99.0%	20%	1.2	99.7%
					40%	1.2	99.9%
					60%	0.8	99.8%
					80%	0.4	99.4%
Scenario 6		5	2.4	99.3%	20%	2.0	99.9%
					40%	1.6	99.8%
					60%	1.2	99.2%
					80%	0.8	99.2%
Scenario 8	5 (every week)	5	3.2	99.4%	20%	2.8	99.9%
					40%	2.0	99.4%
					60%	1.2	99.0%
					80%	0.8	99.3%

As we can expect, Table 5 shows that improving forecast accuracy leads to stock reduction and service level improvement. For example, if forecast accuracy is improved by 20%, we can see that a significant stock reduction is achieved in scenario 6 and 8, and service level is improved from 99.0% to 99.7% in scenario 4. These results indicate the prerequisites to establish in terms of forecast accuracy if one desires to implement a specific scenario. For example, if the target is to implement the scenario 6 with a stock level not exceeding 1.6 days, then the forecast accuracy needs to be improved by at least 40%. Finally, let us remark that the scenario 4 requires lower stock levels in comparison to scenarios 6 and 8.

At the beginning of this section, we explained that the engine plant customers usually send their orders three days before the shipping date. Thus, demand information over the 3 first days of the planning horizon is almost certain since forecast errors are very minor. So, we also wanted to simulate a situation in which the customers would send their orders four or five days (instead of three days) before the shipping date. For each scenario (4, 6, and 8), we performed simulations by supposing that the real demand is perfectly known over the λ first days of the planning horizon. Three values of λ were tested: λ=3 (which is very close to the actual situation), λ=4, and λ=5. The obtained results are presented in Table 6.

The results show that passing from λ=3 to λ=4 improves the stock performance. In fact, the stock is reduced from 3.2 to 2.8 days in scenario 8, from 2.4 to 2.0 days in the scenario 6, and from 1.2 to 0.4 days in scenario 4. When passing from λ=4 to λ=5, the service level is improved by 0.2% for scenarios 4 and 8, and by 0.6% for the scenario 6. Finally, note that scenario 4 is systematically better than the scenarios 6 and 8. In particular, an implementation of scenario 4 (δ=1, X=3) with a λ=4 days would lead to a service level of 99.6% with very low stock (0.4 days). Remember that this scenario also provides a very good stability (96%).

Table 6 Impact of sooner receiving of customer orders

Scenario	Planning Periodicity (δ)	Frozen horizon length (X)	Number of days with real demand known (λ)	Initial stock level needed to obtain a service level ≥ 99%	Obtained service level
Scenario 4	1 (every day)	3	3 days	1.2	99.4%
			4 days	0.4	99.6%
			5 days	0.4	99.8%
Scenario 6		5	3 days	2.4	99.5%
			4 days	2.0	99.0%
			5 days	2.0	99.6%
Scenario 8	5 (every week)	5	3 days	3.2	99.5%
			4 days	2.8	99.0%
			5 days	2.8	99.2%

5 Conclusion and further research

In this paper, we have developed a planning model, based on the requirements provided by the engine plant teams of PSA Peugeot Citroën. This model was tested within the company and was able to properly fulfill the requirements stated by the engine plant, both in terms of solution relevance and computation times.

Using the planning model, we developed a simulation model in order to evaluate the performance obtained in rolling horizon planning context. Increasing planning periodicity and frozen horizon length improve the performance in terms of stability but worsen it in terms of stock and service level. In this case study, considering the stability requested by the engine procurement department, we recommended a daily planning with a frozen horizon of 3 (scenario 4). In this scenario, we obtain a service level equal to 99% with a stock level of 1.2 days. Moreover, the planning stability over the 5 first days of the horizon is 96%. When analyzing the impact of demand information, we showed that performance of this scenario could be significantly improved if the customer orders were known 1 day sooner. In fact, in this situation, we could achieve a service level equal to 99.6% with a stock level of 0.4 days. More generally, the analysis of the impact of forecast errors indicates the prerequisites that must be established in order to achieve the desired performance.

The assumption to produce at maximum capacity is not respected in practice and it would be interesting to relax this assumption. In this case, inventory costs should be included in the objective function. Another avenue for research would be to consider production capacity as a decision variable and not as an input of our model. Consequently, a better simulation approach would be to use the actual initial stock of the engine plant and to adjust the production capacity over the simulation time.

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