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Improving the robustness of a supply chain tactical plan

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Abstract

Based on linear and linear integer programming techniques, Advanced Planning Systems (APS) enable a tactical plan to be established each time the plan deviates from reality. Thus, planning is more reactive but may lead to a loss of robustness when making a decision.

This article presents a specific approach to increase robustness and stability for tactical plans. Several methods have already been discussed to achieve this robustness target. This proposed new policy is called the “reference plan”.

Keywords: Robustness, Stability, Tactical planning, Advanced Planning System

1. Introduction

A supply chain is a network of entities which supplies material, transforms it into an intermediate and then finished product, and distributes the finished products to the customers (Lee and Billington, 1995). Historically, these three activities were managed independently. The complex links of the supply chain were ignored (Thomas and Griffin, 1996). Supply Chain Management (SCM) arose in this context in order to ensure the management of both material and data flows at the same time, within and between those entities, so as to synchronize their activities (Christopher, 1992).

Distribution, production and procurement are operationally coordinated at the tactical planning level (Stadtler and Kilger, 2000). The levels of resources and the flows between the entities of the supply chain, etc., are determined in order to synchronize the capacities and

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the flows simultaneously. For this purpose, different scenarios are often evaluated by indicators aggregated in a cost function. The resulting plan defines the reasonable and feasible levels in terms of production and transfer between entities, as well as the required resource level in the supply chain for planned finished products. The plan established a compromise that minimises service costs (backlogs, non-delivery, and profitability of products), inventory levels (holding costs, additional storage capacity) and resources (costs of production, capacity, transport, subcontracting...). Hence tactical planning partially covers Sales and Operations Planning, which ensures the coordination between the various functions of the firm and determines the optimal scenario which will minimize the various expenses and maximize the sales (Vollman *et al.*, 1997).

Advanced Planning Systems (APS) support tactical planning (Stadtler and Kilger, 2000). The technical progress made in computing power enables the calculation of a plan within a few minutes. By using these tools, management can re-optimize the model each time an event puts the current tactical plan into question. The plan is always « optimal » for all variations in the input data. Doing so, they can reach the desired reactivity while maximizing profitability, but without being concerned with modifications made in the plan. These practices induce strong disturbances on the productive system and on the partners of the supply chain by generating the bullwhip effect (Forrester, 1958). The overcosts created by these variations are not taken into account in the system global optimisation.

From another point of view, the calculation of tactical plans by commercial software is based on linear and linear integer programming optimisation techniques (Stadtler and Kilger, 2000). These calculations are relatively well adapted to the problem at hand (Johnson and Montgomery, 1974), (Yu and Li, 2000), as long as we assume a linear

relationship between cost and volume. Yet, these techniques are known for determining optima which are sensitive to fluctuations of the parameters or the costs of the model. The above-mentioned method, consisting of re-optimising the model when an event influences its parameters, leads to reactive but non-robust planning.

Sensitivity analysis is the main approach used to evaluate the effects of changes in the coefficients of the objective function (the costs) and in the members of the constraints vector (the constraints), as well as the range of validity of these effects (Koltai and Terlaky, 2000). It determines the value of the parameters of the model for which a given solution remains optimal. However, this sensitivity analysis studies the impact of independent variations of different parameters. It doesn't enable the manager to study sub-optimal solutions which are less sensitive to simultaneous fluctuations of the factors and are, therefore, more robust.

When the system is subjected to the effects of “noncontrollable” factors, Taguchi (1987) recommends the use of cross-designed orthogonal plans. Thomas and Lamouri (2000) used Taguchi's method to analyse the impact of uncontrollable factors on a tactical plan cost calculated by linear optimisation. They demonstrate that robust optimal solutions could be found using this technique. They determine the strategies, i.e. the decisions to be made, for a better plan robustness on the cost function by choosing the set of controllable parameters minimizing the “quality loss” function. They show that it is possible to find a robust tactical plan. However the time of implementing such an experimental design (even fractional) is limited for industrial use.

In this paper, we propose to study how the process used to elaborate the tactical plan influences its robustness. In doing so, we compare two different processes changing only the

policy used. We highlight the effects of each one on several indicators. For the purposes of our study, the next section defines the terms of robustness and stability. In section 3, we describe the linear model used to compare the two policies. Section 4 presents an iterative method which simulates the elaborating processes. The results of the simulation will be presented in section 5. Section 6 will deal with our conclusions and prospects.

2. Underlying concepts of robustness and stability

In a supply chain, uncertainty appears through demand (volume and mix), process (yield, scrap...) and procurement (quality and reliability of the delivery lead times). Inventories or buffers generally compensate it. Other researchers have shown that the structure of the supply chain itself may generate fluctuations (Simchi-Levi *et al.*, 2000). Indeed, a decision concerning an industrial activity generally causes adjustment decisions for other activities. The effects of the first decision tend to reduce quickly with time, but the combination of the following decisions taken by the same or other associates influence the system overall. The complexity of managing the supply chain due to all the variations was highlighted by the phenomenon usually called the “bullwhip effect” which is an amplification effect (Forrester, 1958). The solution proposed is a better synchronisation amongst the entities and is supported by cooperation and reinforced communication between the entities of the logistic network (Simchi-Levi *et al.*, 2000). However, the compromises have to go behind divergent targets (inventory availability, costs...). Moreover, Holmström (1997) shows that these effects amplify as companies cooperate more.

In such a fluctuating and uncertain context where the terms robustness and stability are used, the definition of these words proves to be necessary.

a) Stability

The term *stability* is generally associated, by opposition, with that of nervousness: De Kok

and Inderfurth (1997) have defined “nervousness” as “a lack of stability in the material requirements planning”.

Planning nervousness is often treated in the literature at the MRP level (Yano and Carlson, 1987), (Minifie and Davis, 1990), (Sridharan and Laforge, 1990), (Kadipasaoglu and Sridharan, 1995), (Blackburn *et al.* 1986), (Ho, 1989), (Jensen, 1993), (Heisig, 1998).

Several authors have explained MRP systems’ nervousness (Orlicky, 1975) and the difficulties induced by "schedule nervousness caused by uncertainty in demand or supply or by dynamic lot-sizing that can be an obstacle to effective execution of material requirements planning systems" (Kadipasaoglu and Sridharan, 1995). Several strategies to dampen nervousness or to increase planning stability in MRP systems were proposed:

- to lengthen the planning horizon (Carlson *et al.* 1982), to freeze the Master Production Schedule within this planning horizon (Zhao and Lee, 1993) and to position buffers (Blackburn *et al.* 1986),
- to distinguish between small and large changes (Ho, 1989).

In their article, De Kok and Inderfurth (1997) study the stability of the plan in volume. They use, as did Kimms (1998), the expected value of variation in the quantities between two periods in the planning. Donselaar *et al.* (2000) study the stability of the plan in buckets. They compare the nervousness of the plan generated by MRP with that of their heuristics. The indicator considered is the number of “re-plannings” encountered. The instability studied is the change within the periods. If a quantity appears or disappears in a time bucket, the indicator is incremented. However, if quantities are only modified, the indicator does not change.

The instability of a plan is often defined by the number of modifications made on the decision variables of the model between two successive versions of the plan. The term stability is related to the decision variables. In MRP context, it is the quantity by bucket to be produced or supplied.

b) Robustness

The term *robustness* is associated with that of risk and decision-making (Kleijnen and Gaury, 2003). The underlying idea of system robustness is that the measured function does not diverge significantly from a given value. A system is known as robust if it provides a weak dispersion of the target performances in spite of the variations of the non-controllable factors. The robustness relates to the dispersion of several functions subject to uncertain parameters and costs (Lee and Yu, 1997). Kleijnen and Gaury (2003) studied the robustness of a kanban loop according to two functions: average wip in the loop and the delivery performance.

c) Robustness and stability approaches

Thus, a system can give a robust answer, i.e. a weak dispersion of the cost function, but be unstable by systematically varying the decisions variables of the system to obtain an identical cost. In the same way, a system can be stable, i.e. few variations of the variables of decisions, while not being robust since the function cost can diverge because of significant fluctuations in conditions.

Taguchi (1987) considers robustness of a function by making the hypothesis that it can be controlled by the quadratic functions "losses" or by the signal-to-noise functions which combines the mean and the variance of result.

Frequently, APS vendors limit themselves by delivering to their customers the mathematical models that provide "optimal" plans (Stadtler and Kilger, 2000). However, the *robustness* of these plans is not considered. An optimal solution for a scenario is not exploitable if it becomes inefficient with a small change in parameters. It will lead to higher costs.

Linear programming requires the user to describe deterministic models. It is complex to describe the majority of concrete logistic problems containing uncertainty, "noise", and incomplete information in linear programming models (Graves *et al.*, 1993). The traditional approach for optimising problems containing probabilistic parameters is stochastic programming. Many theoretical developments were made since the work of the pioneers Dantzig (1955) and Beale (1955). The objective of stochastic programming is to optimise the expected value of performance indicators. However, these techniques are not yet able to solve problems of realistic size at the tactical level (Mulvey and al., 1995).

Mulvey *et al.* (1995) proposed an approach called "robust programming", which is able to simulate the sensitivity to risk of a manager or to guarantee a level of service, to lead to a series of solutions which are gradually less sensitive to the variations of model data. They introduce penalties into the linear model so that the modifications of the decisions variables are an optimisation criterion.

3. Our model

a) General description

The studied supply chain delivers transportation and power systems (turbochargers) to automotive constructors. This supply chain contains one raw material plant (turbo body)

several assembly firms and a distribution system. Thus, the company supply one raw material for each delivered product. In this context, the tactical plan is useful to define the forecasted production, inventory and workforce, essential for financial objectives.

The model describes a simplified situation of decision-making for a production level and capacity changes for a product group. The manager seeks the best compromise between service levels, inventories, and production costs related to the adjustments of capacity.

At each period and for each optimisation of the basic model, all the decision variables are adjusted according to the modifications in demand. It does not take into account the decisions taken during the previous period in supplied quantities, levels of production, and the possible recruitment. It can therefore negate decisions, from one period to another, without taking into account the costs associated with these changes (generation of the model P_{0n} – figure 1).

This basic model is modified to simulate another planning process limiting the modifications made to a “reference plan”. The reference plan (Figure 1) is the tactical plan validated by the concerned departments, at least production, sales, and supply chain during a meeting. It is implemented at the previous period (plan P_{Rn-1}). It is used as a framework to set up the new tactical plan of the current period n (P_{Rn}).

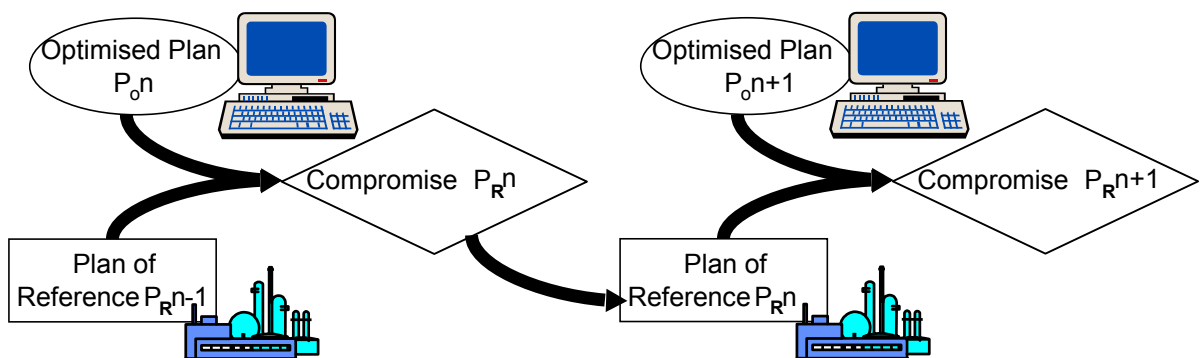


Figure 1: the reference plan

This plan remains a reference as long as the control factors influencing it have not evolved significantly, i.e. remains below a defined threshold.

In a planning policy with a “reference plan”, the model takes into account the decisions made in this reference plan to find the best compromise between modification of these decisions and optimisation of an “ideal” model. Thus, the manager’s reluctance to modifications of these decisions is represented by a weight on the difference between the new level of the decisions variables and those of the reference plan. The model minimises the cost generated by the variations on the decision variables compared to the reference plan, while minimising the total cost of the plan.

An alternative approach would be to optimise the model by constraining the number of modifications made to the reference plan. The term modification has then to be defined: it can be a simple variation or a variation exceeding a certain threshold defined by the manager. This last case approaches the theory of the control where there is a "dead" zone around the value of a decision variable in which no action is taken. This approach results in modifying the linear model to introduce integer variables. In this article, we used weightings to preserve a reasonable processing time for the problem.

Several decision variables can be taken into account (production quantity, overtime, employees...). In the model described below, we chose the forecasted supply quantities transmitted to the raw material plant as the decision variables to stabilise, because they correspond with one of the top priorities in tactical plans. That is why only the costs of changing raw material quantity have been introduced.

The quality of demand forecasts strongly influences the global optimisation of the logistic processes (Lee and Billington, 1995). Disney and Towill (2003) determined how their approach of inventory control impacts the bullwhip effect in a supply chain. They measured the variations in the behaviour of the objective function of their simulation model when faced with changes in demand volume. For that, the difference between the forecast and the demand was modelled by a normal law. In another study, Rota *et al.* (2002) modelled the forecasted demand between a mini and maxi in opposition to firmed demands for which the expression was constant.

In our case, using the same experimental logic, uncertainty is created by forecast error. The forecasts generation is made according to the simple exponential smoothing model with a coefficient of sensitivity (fixed at 0.3) reflecting a variable market in order to simulate a certain nervousness. Indeed, the model of exponential smoothing (see Equation (0)) takes into account the recent past with a more significant weighting, which leads to more realistic values.

$$\begin{aligned}
 F_{p+1}(t+1) &= \alpha F_{p+1}(t) + (1-\alpha)F_p(t+1) \quad \forall t > p \\
 F_{p+1}(p+1) &= \alpha D(p) + (1-\alpha)F_p(p+1) \\
 \alpha &= 0.3
 \end{aligned}
 \tag{0}$$

This phenomenon is also explained by Simampo and Ryan (2003) and is an assumption necessary to the specification of the context. Zhao *et al.* (2002) studied the impact of forecasting models on information necessary to manage the supply chain. Our purpose was to analyse the impact of a reference plan on the robustness of the tactical plan, we did not desire to vary the parameters of demand. However, in a future work, we will complete the analysis by taking into account, in an experimental design, all these parameters.

The exponential smoothing model takes into account the recent past (the demand of past period $D(p)$) with a more significant weighting, which leads to more realism in the forecasted values. However this model induces consequently more nervousness in demand (the phenomenon we want to simulate). With regard to the real demand, the normal distribution generates good variability. The forecasts established for the subsequent periods are recomputed by taking into account the real demand. Table 1 shows an example of forecast calculations for a set of real demand. The forecasts calculated for period p have been used for model optimisation at period p .

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Forecast p = 1	65	20	30	30	15	20	20	20	60	90	75	55									
Real Demand p = 1	62																				
Forecast p = 2		33	31	30	20	20	20	20	48	77	76	61	64								
Real Demand p = 2		35																			
Forecast p = 3			32	31	23	21	20	20	40	66	73	65	64	42							
Real Demand p = 3			38																		
Forecast p = 4				33	26	22	21	20	34	56	68	66	65	49	37						
Real Demand p = 4				29																	
Forecast p = 5					27	24	22	21	30	48	62	65	65	54	42	36					
Real Demand p = 5					26																
Forecast p = 6						24	23	21	27	42	56	62	64	57	46	39	30				
Real Demand p = 6						34															
Forecast p = 7							26	23	26	37	50	59	62	58	50	42	34	27			
Real Demand p = 7							45														
Forecast p = 8								29	27	34	46	55	60	59	53	45	37	30	27		
Real Demand p = 8								38													
Forecast p = 9									30	33	42	51	57	58	54	48	41	33	29	29	
Real Demand p = 9									51												
Forecast p = 10										38	41	48	54	57	55	50	43	36	31	30	30

Table 1: uncertainty in demand, $\alpha=0.3$, horizon=12

10'000 sets of rolling forecasts and associated real demands were generated prior to any simulation. These sets were used with both processes of elaborating tactical plan.

b) Notation

n: number of periods incremented during simulation,

h: horizon of the tactical plan,

p: the current period index of simulation $p = 1, 2 \dots n$,

t: index of the period of the plan $t = p, p+1, \dots, p+h-1$,

$F_p(t)$: demand forecast for period t calculated in period p ,

D_p : real demand for period p ,
 $CR(t)$: maximum resource capacity usable in period t in production unit,
 $CS(t)$: maximum storage capacity usable in period t in production unit,
 $u(t)$: quantity of production units in period t per operator,
 $uo(t)$: quantity of production units per overtime hour in period t ,
 $CO(t)$: maximum of overtime hours per operator in period t ,
 I_0 : Beginning inventory (positive or null),
 B_0 : Beginning backorders (positive or null),
 IM_0 : Raw material beginning inventory (positive or null),
 O_0 : beginning number of operators (positive or null),
 I_h : target level of inventory (positive or null),
 R_h : target level of backorders (positive or null),
 O_h : target numbers of operators (positive or null),
 $C_S(t)$: storage cost per production unit in period t ,
 $C_B(t)$: cost of backorders per production unit for one period in period t ,
 $C_H(t)$: cost of hiring one operator in period t ,
 $C_L(t)$: cost of one layoff in period t ,
 $W(t)$: wages per operator in period t ,
 $C_O(t)$: cost of one overtime hour in period t ,
 $C_{SU}(t)$: supply cost of one unit in period t ,
 $C_{MS}(t)$: storage cost per unit of raw material in period t ,
 $OH_p(t)$: numbers of overtime hours in period t planned in period p ,
 $O_p(t)$: numbers of operators in period t planned in period p ,
 $H_p(t)$: number of hired operators in period t planned in period p ,
 $L_p(t)$: number of layoffs in period t planned in period p ,

$I_p(t)$: level of inventory at the end of period t planned in period p ,

$B_p(t)$: level of backorders at the end of period t planned in period p ,

$IM_p(t)$: level of raw material inventory at the end of period t planned in period p ,

$P_p(t)$: numbers of production units manufactured in period t planned in period p ,

$S_p(t)$: numbers raw material units to be supplied in period t planned in period p .

c) *Linear model*

The manager seeks to optimise resource use, minimising the costs over the whole horizon of his plan $CT(p)$ at each period p under constraints of the equations (2)-(10).

$$CT(p) = \sum_{t=p}^{p+h} C_S(t) \times I_p(t) + C_B(t) \times B_p(t) + C_H(t) \times H_p(t) + C_L(t) \times L_p(t) + W(t) \times O_p(t) + C_O(t) \times OH_p(t) + C_{MS}(t) \times IM_p(t) + C_{SU}(t) \times S_p(t) - \forall p \quad (1)$$

These costs are the storage cost of finished products, the cost of backorders, the costs of hiring and layoffs, wages, overtime, storage cost and supply costs of raw materials. Equation (1) can also be rewritten in equation (1'):

$$CT(p) = \sum_{t=p}^{p+h} C_p(t) \quad \forall p \quad (1'),$$

where $C_p(t)$ is the monthly cost in period t of the optimised plan in period p :

$$C_p(t) = C_S(t) \times I_p(t) + C_B(t) \times B_p(t) + C_H(t) \times H_p(t) + C_L(t) \times L_p(t) + W(t) \times O_p(t) + C_O(t) \times OH_p(t) + C_{MS}(t) \times IM_p(t) + C_{SU}(t) \times S_p(t) - \forall p, t \quad (1'')$$

$$\begin{aligned} \text{Inventories balance: } I_p(t-1) - B_p(t-1) + P_p(t) &= I_p(t) - B_p(t) + F_p(t) \quad \forall p, t \\ IM_p(t-1) + S_p(t) &= IM_p(t) + P_p(t) \quad \forall p, t \end{aligned} \quad (2)$$

$$\text{Material availability: } P_p(t) \leq IM_p(t-1) \quad \forall p, \forall t \quad (3)$$

$$\text{Number of operators balance: } O_p(t-1) + H_p(t) = L_p(t) + O_p(t) \quad \forall p, t \quad (4)$$

$$\begin{aligned} & I_p(p+h-1) = I_h \quad \forall p \\ \text{Targets for inventory, backorders, and number of operators: } & B_p(p+h-1) = B_h \quad \forall p \quad (5) \\ & O_p(p+h-1) = O_h \quad \forall p \end{aligned}$$

$$\text{Resource constraint: } 0 \leq P_p(t) \leq CR(t) \quad \forall p, t \quad (6)$$

$$\text{Labour constraint: } 0 \leq P_p(t) \leq u(t) \times O_p(t) + uo(t) \times OH_p(t) \quad \forall p, t \quad (7)$$

$$\text{Storage constraint: } 0 \leq I_p(t) + IM_p(t) \leq CS(t) \quad \forall p, t \quad (8)$$

$$\text{Overtime constraint: } 0 \leq OH_p(t) \leq CO(t) \times O_p(t) \quad \forall p, t \quad (9)$$

$$\text{Positive variables: } 0 \leq O_p(t), H_p(t), L_p(t), B_p(t), P_p(t), S_p(t), OH_p(t) \quad \forall p, t \quad (10)$$

Equation (3) assumes that one unit of product consumes one unit of raw material. Also it introduces one period lead-time between supply and consumption of raw material: production in period t is constrained by raw material put in stock in period $t-1$. These two hypotheses can easily be changed depending on the industrial context.

In the first policy, the costs induced by cancellations or additional purchases are not taken into account when elaborating the plan, but are calculated as a result of the decision in order to compare the two policies.

d) Linear Model with reference plan

To model this policy, the following notations are introduced:

$C_{EX}(t)$: overcost per additional raw material unit purchased compared to the reference plan,

$C_{CA}(t)$: overcost per raw material unit cancelled compared to the reference plan,

$EX_p(t)$: number of raw material units supplied in addition to the quantity of reference in period t planned in period p ,

$CA_p(t)$: number of raw material units cancelled in period t planned in period p

$EX_p(t)$ and $CA_p(t)$ represent the difference to the reference plan. A variation exists if one of these variables is positive. These additional variables are determined by optimisation of the

model. This optimisation consists of providing a compromise between the stability ($EX_p(t)$ and $CA_p(t)$ are null) and the delay costs.

The planning objective remains the same: to minimize the costs on the planning horizon. Now, the costs induced by cancellation or additional purchases are taken into account when elaborating the plan. They represent weightings, i.e. the manager aversion to carry out these modifications.

The optimised cost function becomes:

$$CT(p) = \sum_{t=p}^{p+h} C_S(t) \times I_p(t) + C_B(t) \times B_p(t) + C_H(t) \times H_p(t) + C_L(t) \times L_p(t) + W(t) \times O_p(t) + Co(t) \times OH_p(t) + C_{MS}(t) \times IM_p(t) + C_{SU}(t) \times S_p(t) + C_{EX}(t) \times EX_p(t) + C_{CA}(t) \times CA_p(t) - \forall p \quad (11)$$

It is optimised under constraints of the equations (2)-(10) and (12)-(13).

$$\text{Raw material balance: } IM_p(t) = IM_{p-1}(t) - CA_p(t) + EX_p(t) \quad \forall p, t \quad (12)$$

$$\text{Positive variables: } 0 \leq EX_p(t), CA_p(t) \quad \forall p, t \quad (13)$$

e) Indicators

The real costs generated on the n simulated periods are obviously monitored. The robustness is described by the standard deviation of the induced costs. This indicator allows one to observe the variability of the measured function.

The service performance, I_{SP} , is the average over n simulated periods of the quantity delivered divided by the quantity to be delivered, I_{pSP} . The quantity to be delivered is the backorders of the previous period plus the demand of the period.

$$\begin{aligned} \text{if } I_p(t) \geq 0 \text{ then } I_{pSP} &= 1 \quad \forall p \\ \text{if } I_p(t) < 0 \text{ then } I_{pSP} &= \frac{B_{p-1}(t) + D_p - B_p(t)}{B_{p-1}(t) + D_p} \quad \forall p \end{aligned}$$

In our case, the measured instability, I_s , relates to the volume supplied over each period. This indicator is different from that of De Kok and Inderfurth (1997) or of Kimms (1998). It relates to the variation of volume between the forecast of period $t+1$ decided in t , and the quantity actually supplied in $t+1$ period.

f) Values and costs used

	1	2	3	4	5	6	7	8	9	10	11	12
Holding costs	20	20	20	20	20	20	20	20	20	20	20	20
Backorders costs	60	60	60	60	60	60	60	60	60	60	60	60
Hiring costs	400	400	400	400	400	400	400	400	400	400	400	400
Layoff costs	500	500	500	500	500	500	500	500	500	500	500	500
Regular Wages	1600	1600	1600	1600	1600	1600	1600	1600	1600	1600	1600	1600
Overtime costs	15	15	15	15	15	15	15	15	15	15	15	15
Supply costs	200	200	200	200	200	200	200	200	200	200	200	200
Material holding costs	10	10	10	10	10	10	10	10	10	10	10	10
Qty. cancel cost	60	30	0	0	0	0	0	0	0	0	0	0
Qty. Express supply costs	60	30	0	0	0	0	0	0	0	0	0	0

Table 2: costs of decision variables

$n=12$ $h=12$
 $\alpha=0.3$

Beginning inventory (UN) $t=0$:	0	Ending inventory	0
Beginning Nbr of workers $t=0$:	5	Ending number of workers :	5
Hours/month/worker :	160		
UN/month/worker	8		
Max. overtime/month/worker :	20	Resource capacity (UN/mois) :	200
Labour hours (H/UN) :	20	Storage capacity (UN):	400
alpha	0.3		
Material Beginning inventory (UN) $t=0$:	0		

Table 3: constraints parameters

As mentioned previously, controllable factors exist for a tactical plan (Thomas and Lamouri, 2000). By using an experimental design, these controllable factors can be fixed at levels which make it possible to minimize the total cost of the plan. In this article, the values of these factors are fixed to levels found in Thomas and Lamouri (2000).

4. Simulation

Simulation is an approach which reproduces the dynamic behaviour of the decision-making model. To examine the dynamic nature of the supply chain, an approach using a rolling horizon is adopted. That means that as time increases, new information becomes available (the current demand and new forecasts), and the decision variables and performance indicators are re-valued.

The current demand follows a normal distribution with a mean equal to the forecast and a standard deviation equal to 6. The forecasts established for the following periods are recomputed by taking into account the current demand according to an exponential model with a coefficient α . The initial forecasts $F_0(t)$ are represented on figure 2.

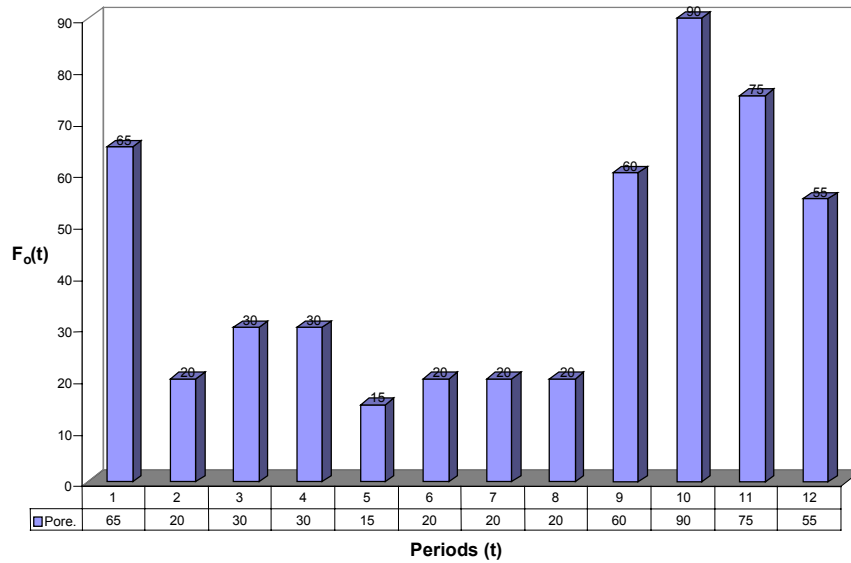


Figure 2: Initial Forecasts $p=0$

10'000 simulations were carried out for each of the two cases, with or without a reference plan, according to the values indicated previously. Values were held constant for both cases. At each period, the model is optimised according to the calculated forecasts. It gives the tactical plan from which the first period is implemented: production, overtime, hiring are executed and raw material forecasts are transmitted. Then, the current demand is introduced making it possible to calculate the real costs for the period. New forecasts are then given, and the index is incremented (Figure 3).

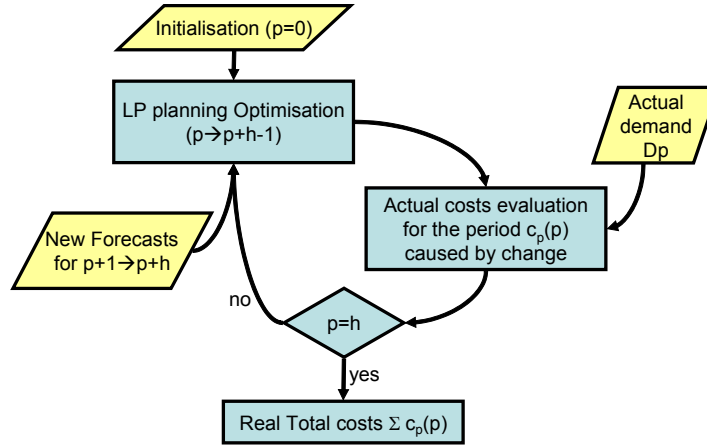


Figure 3: Simulation process with the basic model

In the case of simulation with a “reference plan”, the plan of the period is preserved in order to be used as the input for the model optimised in the following period (Figure 4).

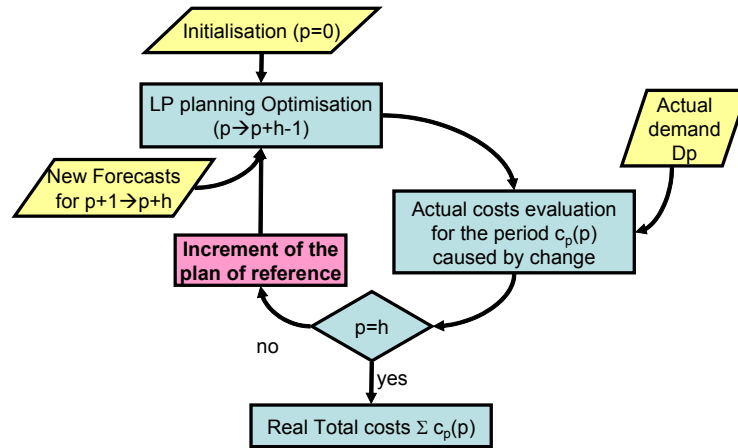


Figure 4: Simulation process with reference plan model

At each period, the indicators are incremented.

The only parameters that change from one simulation to another, is the set of demands and forecasts. However, the same sets are used for each policy. Therefore, only the processes used to establish the tactical plan changes from one case to the other.

The difference between the two processes is in the way the costs of a change in variables enclosed within the reference plan are taken into account. In the process with a reference plan, costs of change are clearly evaluated in the decision-making procedure. For the other process, they are evaluated after the decision-making.

5. Results

We are comparing two different processes of establishing a tactical plan and highlight their impacts on several indicators. Figure 5 resumes the impact of each process on each indicator.

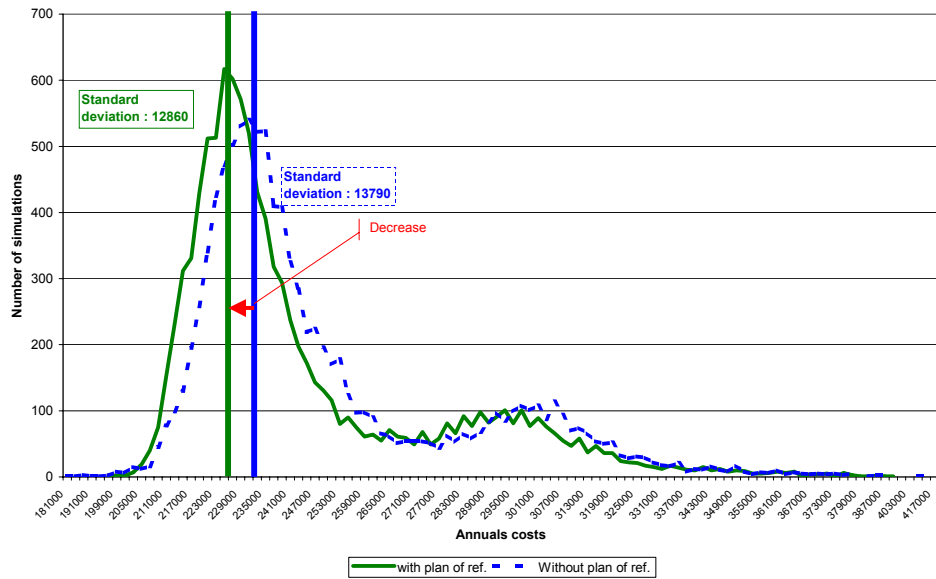
Indicators	Without Reference plan	With reference plan
Costs	235 000	228 000 (decrease)
Robustness	13 790	12860 (increase)
Customer service	62%	71% (increase)
Stability	11	3 (increase)

Figure 5: Indicators comparison

The first graph (Figure 6) represents the number of simulations with the same range of annual costs. Each curve represents one of the processes.

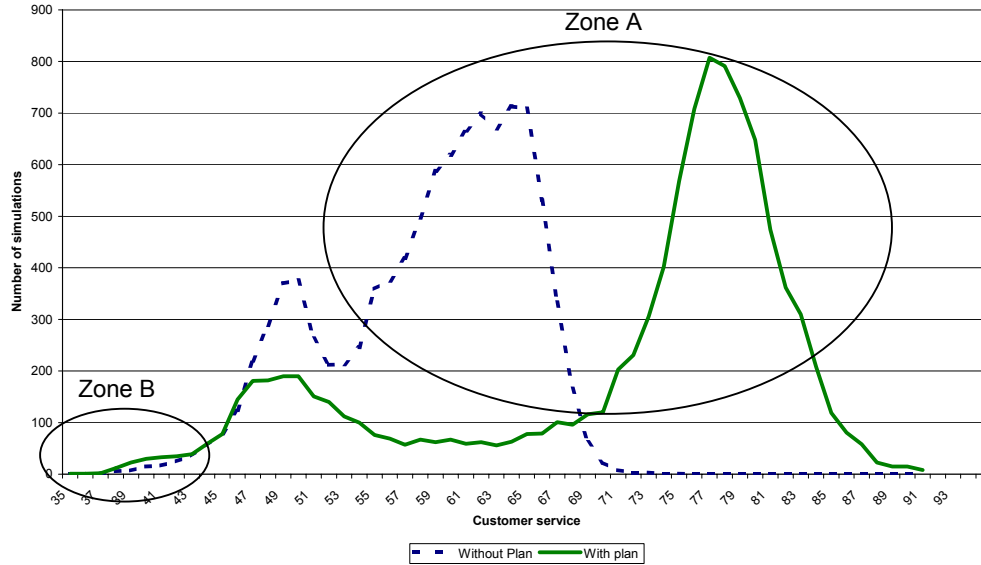
The first notable result is that a strategy of planning with a reference plan reduces annual costs, while improving the robustness in costs. Indeed, the standard deviation for this strategy is smaller.

As in our experimental method, the only factor that changes is the process to elaborate a tactical plan, we conclude here that this factor influences the robustness of tactical planning.



Annuals costs	Whitout Plan	With plan	Annuals costs	Whitout Plan	With plan	Annuals costs	Whitout Plan	With plan
181000	0	1	257000	75	97	327000	17	29
185000	0	1	259000	61	98	329000	15	22
189000	0	3	261000	64	90	331000	12	18
191000	0	1	263000	55	66	333000	17	16
195000	0	1	265000	71	62	335000	14	21
197000	3	2	267000	61	51	337000	11	8
199000	2	8	269000	59	54	339000	10	12
201000	2	6	271000	49	54	341000	15	11
203000	7	15	273000	68	54	343000	10	16
205000	19	12	275000	49	51	345000	12	11
207000	40	16	277000	58	44	347000	8	8
209000	75	45	279000	81	63	349000	10	17
211000	153	78	281000	66	53	351000	9	8
213000	231	99	283000	92	65	353000	5	4
215000	312	130	285000	77	58	355000	5	7
217000	331	195	287000	98	68	357000	6	6
219000	429	258	289000	82	84	359000	8	10
221000	512	341	291000	91	97	361000	6	4
223000	513	425	293000	101	85	363000	8	7
225000	617	471	295000	81	99	365000	1	5
227000	602	502	297000	101	108	367000	4	4
229000	571	530	299000	77	101	369000	4	5
231000	520	540	301000	89	108	371000	5	4
233000	431	522	303000	76	87	373000	1	5
235000	391	523	305000	66	114	375000	6	3
237000	318	410	307000	55	94	377000	3	5
239000	294	408	309000	47	70	379000	1	
241000	237	325	311000	58	74	381000	1	1
243000	197	284	313000	37	66	383000	2	2
245000	172	219	315000	47	54	385000	1	2
247000	143	224	317000	36	50	387000	1	0
249000	131	196	319000	36	52	389000	0	1
251000	116	170	321000	24	33	391000	1	0
253000	80	178	323000	22	28	393000	0	1
255000	90	124	325000	21	31	395000	0	

Figure 6: annual costs variability



Service level	Without Plan	With plan	Service level	Without Plan	With plan	Service level	Without Plan	With plan
35	0	1	55	212	76	75	3	568
36	0	1	56	213	69	76	3	708
37	0	2	57	246	57	77	1	807
38	0	12	58	359	67	78	1	791
39	0	23	59	375	62	79	0	729
40	1	30	60	419	67	80	0	648
41	6	33	61	497	59	81	0	474
42	7	35	62	588	62	82	0	362
43	15	39	63	619	56	83	0	310
44	17	59	64	666	63	84	0	208
45	25	78	65	699	78	85	0	119
46	36	145	66	670	79	86	0	81
47	56	181	67	713	101	87	0	58
48	79	182	68	709	96	88	0	23
49	124	190	69	531	116	89	0	15
50	220	190	70	333	120	90	0	15
51	289	151	71	166	203	91	0	8
52	370	140	72	62	231	92	0	0
53	376	112	73	23	306	93	0	0
54	263	100	74	8	402	94	0	2

Figure 7: Customer service indicator

The I_{SP} indicator, or service performance, shows a strong difference between the two strategies (Figure 7). The strategy with a reference plan lead to an increase of more than 10% in service performance with the data set used (Zone A). This result is obtained by a strategic buffer of raw materials (Figure 8). Indeed, the model supports additional raw material inventory even if it means high storage costs. It makes it possible to react more quickly to unforeseen demand without risking costs of change. A service level around 80% can appear low compared to current standards. The data file makes the simulation begin with a null stock in the period of high demand. The initial conditions thus impose a degraded service level. Further work must be done to analyse the impact of initial conditions on robustness of the plan.

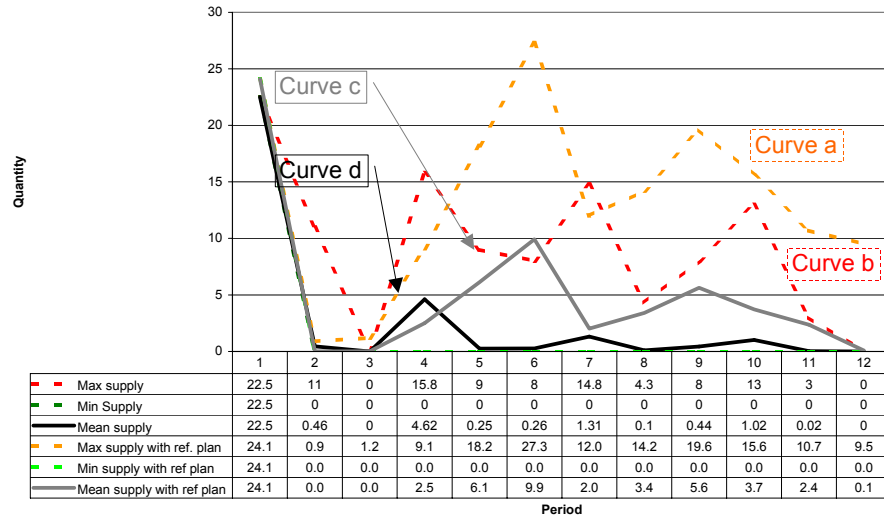


Figure 8: Raw material inventory level at the end of each period

The curve “c” represents the average level of raw material inventory over all the scenarios for periods with a reference plan. The curve “d” represents that obtained without a reference plan. Figure 8 shows that this inventory is, on average, higher with a reference plan. The same conclusion is obtained when the maximum raw material inventory is analysed. Curve “a” represents the maximum inventory generated on all the simulations using the model with a reference plan. Curve “b” represents the same data for the other case. The first curve is higher than the second. If the storage costs are higher than the costs of change, or if demand is decreasing, the model reacts as in the basic case.

We also found that the model with reference plan generates some cases of a bad service performance (Figure 7, Zone B). The model chooses in these cases stability by keeping the quantity of raw material to be supplied unchanged, and thus degrades the service performance by limiting the production.

With regard to the indicator of stability, I_s , the profit of a strategic "reference plan" is obvious. Figure 9 represents the number of simulations according to the number of changes in the supplied quantities of raw materials. From permanent modifications, a quasi stability

is reached. It should be noted, however, that the model allows for changes when the difference is too large. With this kind of model, a degree of freedom is conserved. This is not possible with the frozen time fences used traditionally to reduce nervousness (Vollman *et al.*, 1997).

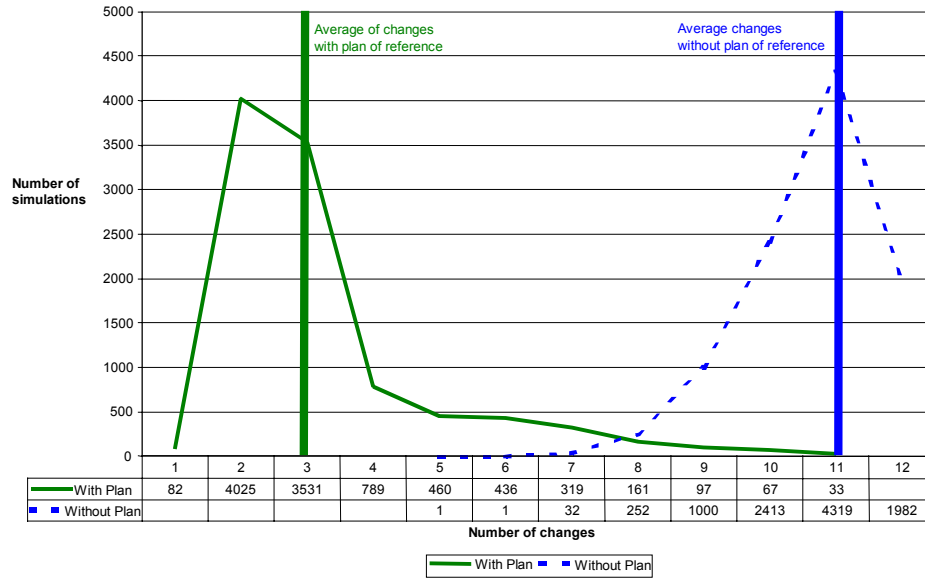


Figure 9: distribution of the number of changes in supplied quantities

6. Conclusions

In this article, we have analysed the influence of the tactical planning process on robustness and stability. We have also proposed an approach to reduce planning nervousness while allowing a certain level of reactivity. Establishment of tactical planning uses a reference plan from the previous cycle as a constraint during the re-optimisation of the model. A limited number of modifications can be done this way, according to the horizon, thus making it possible to ensure stability in supply while improving the robustness in costs.

Always based on linear or mixed-integer programming, this planning logic can be implemented in an APS by adapting the models already employed.

Being a promising approach, future work includes more extreme cases treated by experimental design in order to analyse the impact of controllable factors as the standard deviation of the demand (α), the holding costs, the delays cost, the modifications and the demand pattern. It will also have to be adapted to other decisional situations modelled in APS.

However, it should be noted that in many cases the impact of plan instability cannot be evaluated by costs. Indeed, the “costs” associated with re-planning depend on the level on flexibility in capacities at various horizons. They also depend on the modifications of production in the short-term, which are induced by re-planning processes. Moreover, the loss of confidence in the planning system or in the supply chain department cannot be easily expressed financially. Thus, the suggested approach appears to have the potential for considerable benefit, if not always easy to evaluate financially. It is, however, necessary to study the impact of these changes to current practices, for example:

- on the variability of demand on a supplier which is an external capacity constraint,
- on confidence in the case of annual contracts,
- on the utilisation rate of the related departments (warehousing, purchasing, ...)

Other approaches to reduce planning nervousness can be adapted to our situation by modifying the model. They do not use the concepts of cost. In particular, fuzzy logic computes robustness and “smoothed” plan changes under constraints. Future work will apply this method to the tactical planning model discussed in this article.

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