Tool for nervousness analysis in a rolling planning environment via historical data

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Abstract. This paper analyses the modifications of plans exchanged between supply chain actors in a tactical planning rolling horizon process. A particular focus is on the changes of planned quantities in order to respond to fluctuating demand or to adapt to internal contingencies of the organization. They create instability and nervousness in the planning system. This paper presents a data-driven study to compare the behavior of planning decision makers in a context of certain and uncertain demand. We show through simulation and statistical analysis the effect of decision characteristics of one actor on the system nervousness and the resulting uncertainty for the other actors.

Keywords: Tactical planning · Rolling horizon · Instability · Nervousness.

1 Introduction

In the context of a decentralized supply chain, partners use independent MRP (Manufacturing Resource Planning) or DRP (Distribution Resource Planning) information systems to manage their cost and service planning. Their planning contains uncertain information that is naturally subject to changes in a rolling horizon process. In general, these variations in planned quantities during rescheduling lead to an undesirable phenomenon called instability or nervousness [1, 2], consider MRP system nervousness as "instability in planned orders".

The instability can generate significant problems such as higher production and inventory costs [3],inefficient relationships between partners [4], a general loss of confidence in planning [5, 6], and generally a bullwhip effect [7]. To make this complex planning system more stable, many solutions have been identified in the literature. Based on these techniques, some have proposed the use of safety stocks to cope with fluctuating sales forecasts, and safety lead times to cope with fluctuating delivery times [8]. [9] proposed to add an instability cost factor to the mathematical model which may mean that the solution is less optimal in terms of cost. [10] suggest improving the information sharing infrastructure between partners. The adaptation of the planning of each actor thus becomes very complicated, because the source of nervousness can come from many different types of uncertainties [1]. some are related to the uncertainties due to sales forecasting, others to the internal processes, see the following Figure, the studies in this context have been suggested in the work [11] and they were questioned in this study.

In our study, we assess the nervousness associated with the plans received from partners in a rolling horizon process. Our objective is to study whether the nervousness is influenced by the choices of planners to develop their own planning or by demand variability.

This paper is divided into six sections. In Section 2, we present the type of supply chain to be treated in our case and the associated uncertain models for each actor. In Section 3, we present the Parameterized Simulation tool and the experimental protocol for data transformation in Section 4. The results of the experiment are detailed in Section 5. Finally, Section 6 is devoted to concluding remarks, including new directions for the simulation work.

2 Problem description

The structure of the supply chain considered in this study is illustrated in Fig. 1. This chain involves three types of independent actors during the planning cycle and 4 actor decision situations. It starts with the elaboration of the supply requirement (SR) by the wholesalers in relation to the external requests received. The central distribution center receives it and issues a production plan (PP) to the factory. The factory plans production and sends a master production schedule (MPS). The central distribution center responds at the end of each cycle with a supply plan (SP) to the wholesalers. In rolling horizon planning,

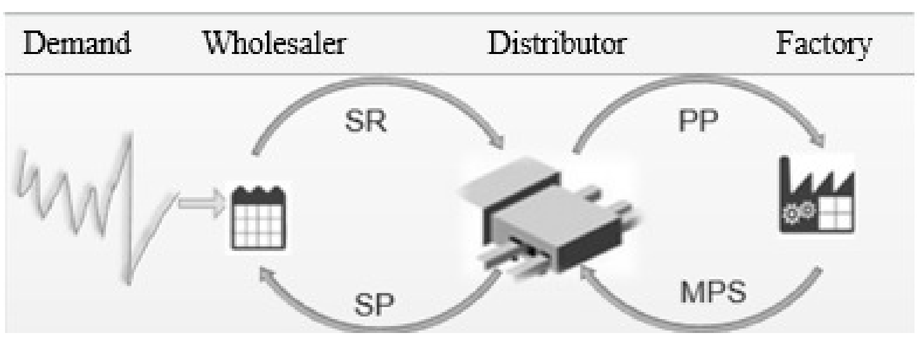

Fig. 1. Variability management in players of the studied supply chain.

at each cycle, one actor can adjust his planning decisions, based on his own preferences. [12] considers 4 sources of variability: on demand, on supply, on the operational process, on management decisions. For other actors, these adjustments can be interpreted as uncertainty on their input information.it questioned the uncertainties of demand and with those distributed by the different actors. This generally increases the nervousness in the chain and generates a loss of confidence of the partners in the received plans. Therefore, an actor is facing a dilemma between stability of his decisions and adaptation to changes. [13] has given a special attention in decision-making approaches to adapt to variations in demand, by defining a robust plan that minimizes the difference between the reference plan and the re-schedule. [14] proposed a flexible planning model based on different planning strategies that are proposed to the decision maker (Min, Mean, Max) in the re-schedule calculation. Several other methods have been defined to mitigate nervousness. However, how can we face the management variation associated with the decision maker element?

Such complexity in analyzing the variation of quantities in the rescheduling process underlines the need to provide assistance to decision makers. The idea is to help the manager to (i) analyze the historical data of plans sent and received with the quantification of uncertainties, and (ii) understand his behavior and that of his partners.

In the present study, we were specifically interested in the planning process between a wholesaler, a distributor and a factory, while focusing on uncertainties assessment and the strategies adopted by each one to face the variation of the demand and/or the hazards.

3 Distributor-to-Wholesaler model under uncertainty

Different forms of interaction between the stakeholders can be identified. These interactions are distinct by the nature of the objectives that the stakeholders set for themselves over certain planning horizon periods. We proceed in a similar way to model the successive 4 types of decisions identified in Figure 1 and replicated in a rolling horizon process. For readability purposes, only one linear chain (Wholesaler Distributor Factory) has been treated in our study.

Parameters

H : Planning-horizon length
P : Number of products $p \in [1, P]$ is the product index
K : Planning index (k-th planning step)
F : Number of wholesaler $f \in [1, F]$ is the index of the wholesaler
HF : Length of the frozen horizon (expressed in number of periods
HL : Length of the liquid horizon (expressed in number of periods)

Deterministic data

$D^k_{p,t}$: Demand for product p in period t at cycle k
$TS^k_{p,t}$: Target of product p at the end of period t at cycle k
ω^{TS}_t : Weight assigned to deviation from the target stock in period t
ω^{PP}_t : Weight assigned to deviation from previous plan in period t
ω^{S}_t : Weight assigned to Shortage in period t

Decision variables at cycle k

$I^k_{p,t}$: Inventory of product p at the end of period t
$SR^k_{p,t}$: Scheduled quantity (Supply requirement) of product p for period t
$S^k_{p,t}$: Shortage of product p in period t
$I^{k(+)}_{p,t}$: Upper target stock quantity (overstock) for product p in period t
$I^{k(-)}_{p,t}$: Lower target stock quantity (Under-stock) for product p in period t
$Q^{k(+)}_{p,t}$: Quantity added to planned quantity for product p in period t
$Q^{k(-)}_{p,t}$: Quantity reduced to planned quantity for product p in period t

$$Min \sum_{t \in HL-1, p \in P} \omega^{PP}_t * (Q^{k(+)}_{p,t} - Q^{k(-)}_{p,t}) + \omega^{TS}_t * (I^{k(+)}_{p,t} - I^{k(-)}_{p,t}) + \omega^{S}_t * S^k_{p,t} \quad (1)$$

$$s.t. \quad \begin{cases} SR^k_{p,t} = D^k_{p,t} + S^k_{p,(t-1)} + I^k_{p,t} - I^k_{p,(t-1)} - S^k_{p,t} & \forall t \in H \quad (2) \\ I^{k(+)}_{p,t} - I^{k(-)}_{p,t} = I^k_{p,t} - S^k_{p,t} - TS^k_{p,t} & \forall t \in HL \quad (3) \\ Q^{k(+)}_{p,t} - Q^{k(-)}_{p,t} = SR^k_{p,t} - SR^{(k-1)}_{p,t} & \forall t \in H-1 \; (4) \\ SR^k_{p,t} = \sum_{j=t}^{t+Offset} D^k_{p,j} & \forall t \in H \quad (5) \\ SR^k_{p,t} = SR^{(k-1)}_{p,t} & \forall t \in H \quad (6) \\ SR^k_{p,t}, I^k_{p,t}, I^{k(+)}_{p,t}, I^{k(-)}_{p,t}, Q^{k(+)}_{p,t}, Q^{k(-)}_{p,t}, S^k_{p,t} \geq 0 \in N & \forall t \in HF \quad (7) \end{cases}$$

The objective of the model (1) is to propose a compromise between three forms of strategies : (S1) stability over cycles of the planning (ω^{PP}_t is high), (S2) adjusting plans to maintain targeted inventories (ω^{TS}_t is high), (S3) avoiding shortage (ω^{S}_t is high). In general, (S3) is mandatory but the compromise between (S1) and (S2) is to be studied. The hypothesis here is that depending on parts of the planning horizon (from short term to long term) a decision maker can adapt his strategy and manage his decisions stability. It results a vector of weights [ω^{PP}_t,ω^{TS}_t] that represents his behavior.

The constraints of the model are: (2) The constraint linking the shortages in finished products to their supply requirements and to the deliveries committed to the wholesalers (3) The deviation from the target stock (4) The deviation of the plan from the previous plan (5) Updating the stock level according to the planned receipts from the factory in period $(t + dt)$ (6) The target stock coverage time (7) The quantities fixed on the frozen horizon (8) Non-negativity constraints of the variables.

4 Methodology

The purpose of the simulation is to study the impact of the behavior of supply chain actors in a rolling horizon planning process. The behavior is linked to the mix of strategies in different parts of his planning horizons that an actor can consider: see objective function (1).

In this experimentation, we consider that all the decision makers have the same strategy during the whole rolling horizon process. It can be: Representing an assignment of ω_t for each period $t = 1, ..., H - 1$ by a vector $\omega = (\omega_1, ..., \omega_t)$

$\omega_t \in \{0, 1\}$: 1 maintain stability in the previous plan, 0 respect the target stock,
Let's assume the following strategy : ω_t^{TS} = Big value
ω_t^{PP} =[1,1,1,1,1,1,1,0,0,0,0,0,0,1,1,1,1,1,1,1,1,1,1,1,0,0,0,0,0,0,0]
ω_t^{TS} =[0,0,0,0,0,0,0,1,1,1,1,1,1,0,0,0,0,0,0,0,0,0,0,0,1,1,1,1,1,1,1]

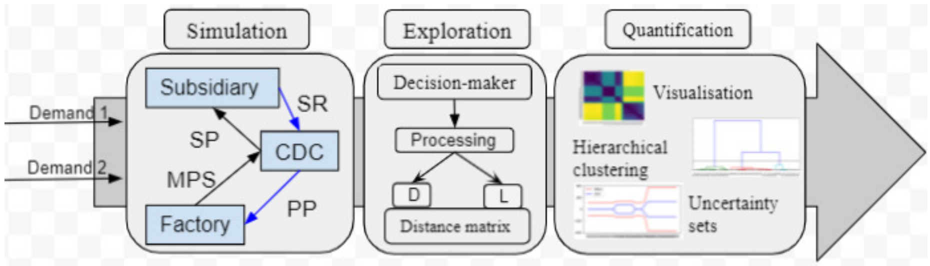

Fig. 2. Process of simulation, exploration and quantification of uncertainty (SEQ).

The methodology is based on a simulation of the rolling horizon process and then an analysis of the instability of the generated plans that can be interpreted as an uncertainty of the decision.

4.1 Simulation

This rolling horizon planning process replicates 260 planning cycles, over a 30-week horizon. The demand plans are updated weekly. Two types of demand are considered:
Case 1: stable demand: is randomly generated using a uniform distribution within the following interval U(50, 100), two seasonality: one during the summer period (week 23 to week 36) and the other during the new year (week 51 and 52). In addition, during the 260 planning cycles, the demand does not change.
Case 2: unstable demand: is the same as the stable demand for the initial plan, and during the following planning cycles changes according to the following perturbations summarized in Table 1.

Table 1. Perturbations applying to each period.

Period (t)	[1 - 2]	[3 - 15]	[15 - 29]	[30]
Random uniformly in range	frozen	(-10, 10)	(-100, 100)	(-100, 100)

The tool was developed using the Python 2.6 programming language, and the models defined above were solved using GLPK LP/MIP Solver v4.45 and Pyomo, a library available on Python for open-source constrained optimization. The choice of this simulation is justified, on one hand, by the current absence of massive data to analyze the different behaviors of the actors with all its complexity, and on the other hand, by the power of the simulation to generate behaviors in a logistics chain.

4.2 Exploration and Quantification

[15–17] measures of standard nervousness (max, mean, percentage and number of changes) are not horizon dependent. The mathematics of this step was elaborated in [18]. The idea is to store the series of plans generated in a rolling horizon process. So that, Euclidean distance matrices between plans can be computed. Then, an automatic classification method allows producing groups of horizons with similar degrees of variation. The following two distance matrices can be considered:

- The D matrix quantifies the absolute difference in cumulative quantities between two successive plans by the following equation: $D_{i,h} = Q_{i,i+h} - Q_{i+1,i+h}$ where Q is the cumulative quantity expected in plan i at period $i + h$. Over the re-planning cycles, D_{1,h_1} represents the first observation of difference of the cumulative quantities between two consecutive plans at first period.
- The L matrix, represents the absolute difference in cumulative quantities between the planned quantity and the really executed quantity (last planned) by the following equation: $L_{i,h} = Q_{i,i+h} - Q_{i+h,i+h}$. Similarly, $L_{1,h1}$ represents the first observation of difference between the cumulative quantities of plan 1 and plan realized, for this period. Finally, the information obtained in each horizon group is used to estimate the uncertainties of a plan. Different types of uncertainty estimation methods are possible: Mini max interval, or interquartile range [18].

5 Analyses and results interpretation

5.1 Case 1

While demand is stable, the idea of this study is to visualize the influence of both strategies mixed by each actor during the planning process. Therefore, instabilities only result of the actors'strategies.

In each cycle, the actors exchange plans over a rolling 30-week horizon. The first period of supply plan (SR) corresponds to the reception of really launched productions in the previous cycle. Now, let's look at the deviation matrices (see Fig. 2). For Wholesaler (SR), distribution (PP and SP) and factory (MPS), according to their distance matrices, we identify three clusters of periods. Two clusters have stable plans (green rectangles): one shows the frozen short term periods in which the decision-maker does not change his decisions. The other stable zone corresponds to the long term horizon in which the decision-maker tends to smooth out the deviation along the periods. The zone in the middle (rectangle red) corresponds to the period in which the decision-maker seeks to satisfy his local requirement, to respect the objective stock. In that way the

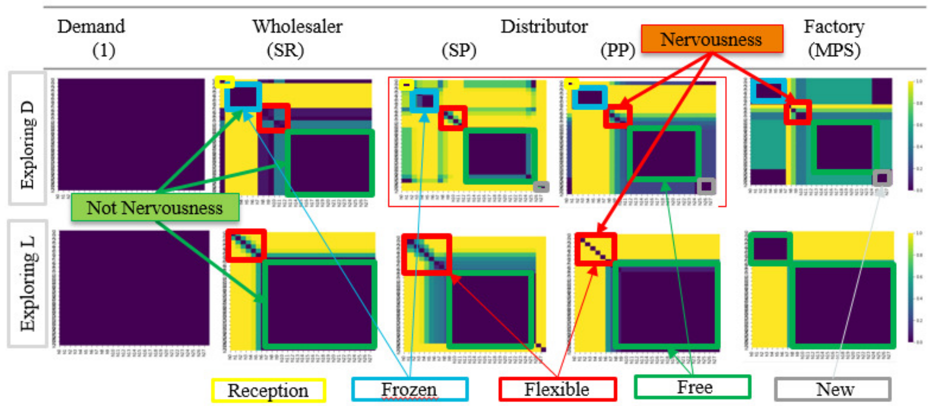

Fig. 3. Multidimensional visualization of management variability with constant demand.

strategy of the decision makers is visible. Moreover, the propagation of variability over the supply chain decisions (from the supply requirements to the other plans) can be noticed looking at the deviations between clusters. The brighter the colors, the more independent are the changes and thus the more variability appears.

5.2 Case 2

In this section, we visualize also the impact of an unstable external demand when facing the same decisions strategy. We consider the stable demand during the [h1-h13] and unstable during the rest of the periods. The demand behavior is not synchronized with the decisions one. Let's explore the effects in Fig. 4). We applied the same decisions strategy as for the stable demand. In horizon (h8-

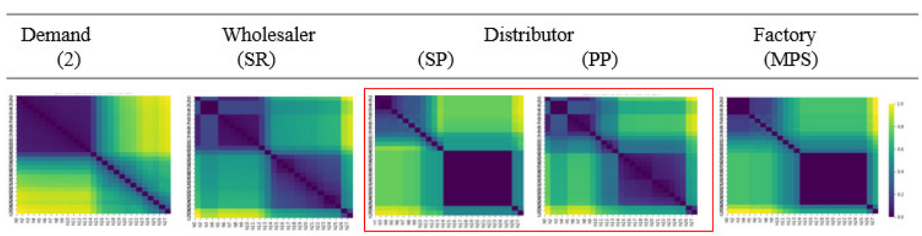

Fig. 4. Multidimensional visualization variability management with varying demand.

h13), a nervousness gradually arrives at the SP decision (throughout SR then PP then MPS) while demand is stable. It is caused by the adaptation strategy of the actors. Conversely, by the end of the horizon, while demand changes the decisions gradually become stable (throughout SR then PP then MPS and finally SP). As a consequence, the decision makers can impose a behavior that is decorrelated from the demand behavior: the farther is the decision in the process from the demand expression, the more decorrelated is the decision.

6 Conclusion

In this paper, we have proposed a simulation approach of a rolling horizon process in a supply chain. It takes into account the actor's preference to transmit planning instability, on some planning periods. It allows a better understanding of the decision makers conception of planning. The results of the analysis of nervousness by the D and L matrix showed that the choice of actor effectively affects the planning system in terms of nervousness and instability and can be measured.

In our research work, this tool aims at enriching the information and completing the existing decision support tools for the partners of the supply chain in terms of nervousness. However, this work can be spread in two ways. Firstly, to analyze the data of several wholesaler and several types of products because, the distributor generally supply their plans under a size of the most important constraints (e.g.: shipping constraint). Secondly, in analyzing the effects of actors that do not have the same decision strategies.

We applied the same decision strategy as for the stable demand. In horizon (h8-h13), a nervousness gradually arrives at the SP decision (throughout SR then PP then MPS) while demand is stable. It is caused by the adaptation strategy of the actors. Conversely, by the end of the horizon, while demand changes the decisions gradually become stable (throughout SR then PP then MPS and finally SP). As a consequence, the decision makers can impose a behavior that is decorrelated from the demand behavior: the farther is the decision in the process from the demand expression, the more decorrelated is the decision.

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