

# Robust possibilistic production planning under temporal demand uncertainty with knowledge on dependencies

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# Outline of the presentation

- 1 Context and Motivations
- 2 Production Planning Problem
- 3 Robust possibilistic production planning taking into account the dependencies belief
- 4 Solving the robust possibilistic production planning
- 5 Experimental results

## Production planning

The production planning is composed of three levels of decisions:

- the strategical level:
  - long horizon (e.g. 5 year)
  - large discretisation (e.g. 1 month)
  - decisions taken with a low frequency (e.g. capacity decisions)
- the tactical level:
  - middle horizon (e.g. 1 years)
  - middle discretisation (e.g. 1 week)
  - decisions taken to anticipate the production quantity
- the operational level
  - short horizon (e.g. 1 week)
  - small discretisation (e.g. 1 hour)
  - precise decision of production

## Motivations and solution approach

- Knowledge on demand is uncertain due to fast market evolution.
- Uncertainty over the date on which demand will be requested impacts production planning
- Decision-makers have a good knowledge of possible changes and modify demand forecast according to their beliefs before computing the optimal solution

### Approach proposed

The decision-maker defined his knowledge on possible set of demands from the forecast and then optimize taking into account the imprecise knowledge.

## Formulation of Production Planning Problem

Our problem can be modeled by the following linear program:

$$\begin{aligned} \min \quad & \sum_{t \in [T]} (c^I l_t + c^B B_t + c^P x_t - b^P s_t) \\ \text{s.t.} \quad & B_t - l_t = D_t - X_t && t \in [T], \\ & \sum_{i \in [t]} s_i = D_t - B_t && t \in [T], \\ & B_t, l_t, s_t \geq 0, \mathbf{x} \in \mathbb{X} \subseteq \mathbb{R}_+^T && t \in [T] \end{aligned}$$

where  $D_t = \sum_{i \in [t]} d_i$  and  $X_t = \sum_{i \in [t]} x_i$ ,  $D_t$  and  $X_t$  stand for the cumulative demand up to period  $t$  and the cumulative production up to period  $t$ , respectively.  $l_t$  and  $B_t$  are respectively the inventory and the backordering à period  $t$

## Temporal demand uncertainty

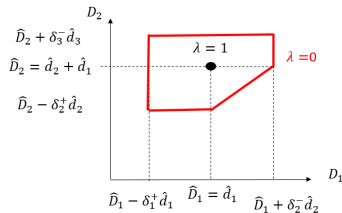
let  $\hat{d}_t$  be the forecasting demand at period  $t$  and  $\hat{D}_t = \sum_{i \in [t]} \hat{d}_i$  the cumulative forecasting demand.

### imprecision on the realization of the demand

The manager can give for each period  $t \in [T]$

- the maximum percent of demand  $\delta_t^- \in [0, 1]$  that can be advanced to the previous period  $t - 1$  and
- the maximum percent of demand  $\delta_t^+ \in [0, 1]$  that can be delayed to the next period  $t + 1$ .
- the level of dependency between horizon periods

$$\begin{aligned}
 D[\lambda] : \quad & \{D[\lambda] \in T \\
 \text{s.t.} \quad & D_t^{[\lambda]} \geq \hat{D}_t - \beta_t^+ \delta_t^+ \hat{d}_t, \forall t \in [T] \\
 & D_t^{[\lambda]} \leq \hat{D}_t + \beta_{t+1}^- \delta_{t+1}^- \hat{d}_{t+1}, \forall t \in [T] \\
 & \beta_t^- \leq 1 - \lambda, \forall t \in [T] \\
 & \beta_t^+ \leq 1 - \lambda, \forall t \in [T] \\
 & \beta_t^+ \delta_t^+ + \beta_t^- \delta_t^- \leq 1, \forall t \in [T] \\
 & \beta_t^-, \beta_t^+ \in [0, 1], \forall t \in [T] \}
 \end{aligned}$$



Robust possibilistic optimization maximize the degree of certainty that a solution cost is lower than a given threshold  $g$ .

$$\max_{\mathbf{x} \in \mathbb{X}} N(\mathcal{C} \leq g)$$

The necessity measure is computed from the marginal possibility distribution and a function  $H_\alpha : [0, 1]^T \rightarrow [0, 1]$  (eq.1) where  $\alpha \in [0, 1]$  is the degree of belief that they is negative dependencies, i.e.

if  $\alpha = 0$  we do not have negative dependencies between uncertainty,

if  $\alpha = 1$  we know that there is negative dependencies between uncertainty of each periods.

$$H_\alpha(\mathbf{u}) = \alpha \cdot W(\mathbf{u}) + (1 - \alpha)M(\mathbf{u}), \alpha \in [0, 1] \quad (1)$$

with  $W(\mathbf{u}) = \max\{\sum_{i=1}^T u_i - T + 1, 0\}$  and  $M(\mathbf{u}) = \min_{i=1, \dots, T}(u_i)$ .

The necessity degree to have a vector  $\mathbf{x} \in \mathbb{X}$  lower or equal to a given vector  $\mathbf{a}$  is:

$$N(\mathbf{x} \leq \mathbf{a}) = 1 - H_\alpha(\Pi(a_1 < x_1), \dots, \Pi(a_T < x_T))$$

## Problem formulation

The problem with time uncertainty can be formulated as a particular case of production planning with uncertain cumulative demands  $\tilde{\mathbf{D}} = (\tilde{D}_t)_{t \in [T]}$ :

$$\min_{\mathbf{x} \in \mathbb{X}} \mathcal{C}(\mathbf{x}, \tilde{\mathbf{D}}) = \min_{\mathbf{x} \in \mathbb{X}} \sum_{t \in [T]} C_t(x_t, \tilde{D}_t) = \quad (2)$$

$$\sum_{t \in [T]} \max\{c^I(x_t - \tilde{D}_t), c^B(\tilde{D}_t - x_t)\} + c^P x_T - b^P \min\{x_T, \tilde{D}_T\}. \quad (3)$$

Using  $\Pi$ -RO:

$$\min_{\mathbf{x} \in \mathbb{X}} \quad \epsilon \quad (4)$$
$$\begin{aligned} & \max_{\{\mathbf{c} \mid H_\alpha(\mathbf{c}) \geq \epsilon\}} \sum_{t \in [T]} c_t \leq g \\ & C_t = c_t \quad \forall t \in [T] \end{aligned}$$

with  $H_\alpha(\mathbf{c}) = H_\alpha(\Pi(c_1 < C_1), \dots, \Pi(c_T < C_T))$



## Solving the adversarial problem

First we focus on the problem :

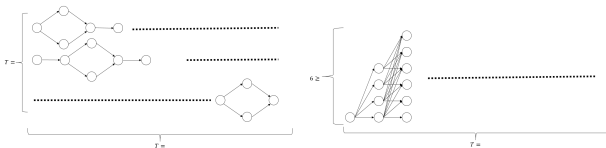
$$\max_{\{C=c \mid H_\alpha(c) \geq \epsilon\}} \sum_{t \in [T]} c_t \quad (5)$$

$D \in D^{[0]}$

### Theorem

*The problem 5 can be computed in  $O(T^2)$  times*

The main idea of the proof is that the problem can be formulated as longest path problem for graphs with one of the following structures :



## Solving Problem

for a given  $\epsilon$

Using the dual formulation of the longest path problem formulation of the adversarial problem we can represent the problem by a linear programme.

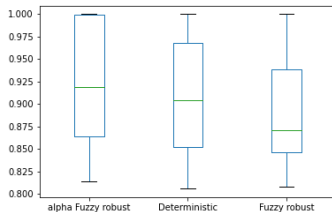
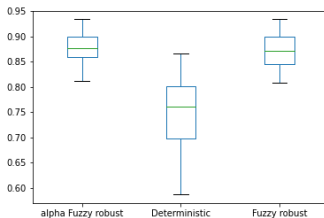
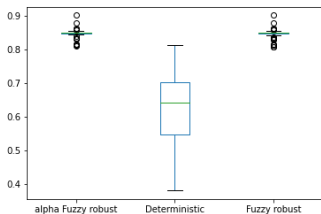
minimize  $\epsilon$

$\epsilon \in [0, 1]$  due to the fact that  $h^\epsilon$  is nonincreasing function of  $\epsilon$ . We can apply binary search on  $[0, 1]$  and at each iteration if they exist a feasible solution which boils down to solving the solve the linear programming formulation of the problem above.

The running time of the above algorithm is  $O(I(T) \log \xi^{-1})$  time, where  $I(T)$  is the time required for solving the linear program,  $\xi > 0$  is the error tolerance.

## Experimental results

Degree of necessity of different types of optimal solutions for  $\alpha = 0.25$ ,  $\alpha = 0.5$  and  $\alpha = 1$



See you at the poster session!!