Scheduling maintenances of nuclear power plants, from 2-stage robust programming to multi-objective optimization

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Aim/highlight of this presentation

- An industrial problem with many types of constraints and variables.
- A 2-stage robust optimization model to fulfill industrial requirements.
- Some hypothesis are different from the state-of-the-art: identifying the methodological and numerical difficulties.
- Bi-objective optimization to overcome these difficulties, and to lead to an industrializable model.

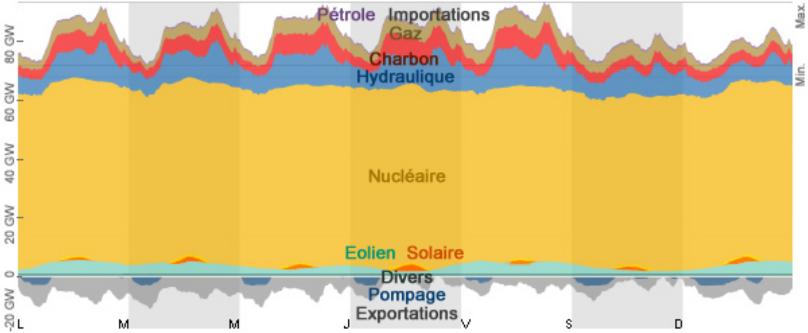
Plan

Plan

Problem presentation

- Nuclear reactors must be shut down periodically for maintenance and refueling.
- A two level problem:
  - Main decisions: dates of outages, refueling quantities. Coupling constraints on outages.
  - Second Level: production and stocks variables, to compute the economic cost of the main decisions, fulfilling the technical constraints.
- Stochastic problem modeled for the Challenge EURO/ROADEF 2010.
- Robust extension: maintenance operations are submitted to uncertainty in their durations, try to minimize the impact of these uncertain lateness.

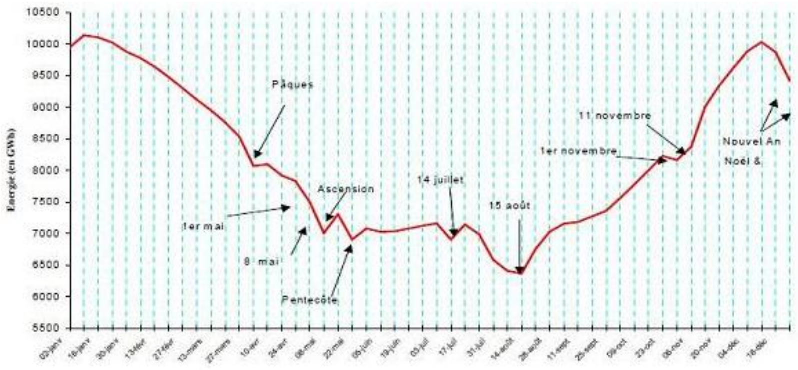
Power generation in a week



données RTE

$\Longrightarrow$ Nuclear power is a “basis” power production mean, few modulation capacities

Power demand in a year



$\Longrightarrow$ First fact: trying to place mainly maintenances (and so outages) mainly in Summer periods, avoid Winter periods.

Sets and few notations

$j \in \mathcal{J} = [\![1, J]\!]$	Flexible (Type 1, T1) power plants.
$i \in \mathcal{I} = [\![1, I]\!]$	Nuclear power plants (Type 2, T2).
$t \in \mathcal{T} = [\![1, T]\!]$	Production time steps, index t corresponds to period $[t, t+1]$
$w \in \mathcal{W} = [\![1, W]\!]$	Weekly time steps to place outage dates.
$k \in \mathcal{K} = [\![0, K]\!]$	Cycles related to T2 units, $k = 0$ for initial conditions.
$s \in \mathcal{S} = [\![1, S]\!]$	Stochastic scenarios for demands, production costs and capacities.

$\mathbf{Da}_{i,k}$	Outage duration for maintenance and refueling of T2 unit i at cycle k.
$\overline{\mathbf{P}}_i^t$	Maximal generated power for T2 unit i at time step t .
$\overline{\mathbf{P}}_{jt}^s$	Maximal generated powers for T1 unit j at scenario s.

N.B: in this talk, we assume $\mathcal{T} = \mathcal{W}$ (aggregating $\mathcal{T}$ time steps to weeks), and only one stochastic scenario (just to avoid a supplementary index, the robust extension applies with several stochastic scenarios)

Problem Constraints

- Power demand constraints coupling all production units
- Production constraints for generating units:
  - Production bounds for T1 and T2 units
  - Decreasing profile when fuel level of nuclear units is low
- Fuel constraints:
  - Bounds on fuel stocks and refueling levels
  - Maximal threshold of fuel to operate an outage
- Scheduling constraints for outages: resource constraints, different spacing constraints, maximal capacity offline ...

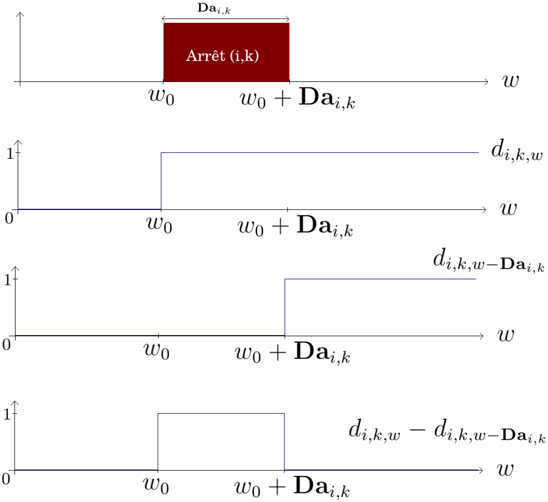
Competing approaches for the 2010 ROADEF Challenge

- Best results: simple aggressive and frontal local search heuristics with local moves on outages dates. (Gardi et al and Kuiper et al)
- Heuristics and matheuristics iterating in the natural 2 level structure were not efficient.
- Approaches based on exact methods required model simplifications and reduction sizes(scenarios and time steps aggregated, hierarchical approaches, relaxed constraints and heuristic fixations in postprocessing)
- Only one exact approach did not aggregate the scenarios (Lusby et al for a Benders decomposition approach).

Gardi, F., Nouioua, K.: *Local search for mixed-integer nonlinear optimization: a methodology and an application*. Lecture Notes in Computer Science 6622, 167–178 (2011)
Rozenknopf, A., Calvo, R.W., et al.: *Solving the electricity production planning problem by a column generation based heuristic*. Journal of Scheduling 16(6), 585–604 (2013)
Lusby, R., Muller, L., Petersen, B.: *A solution approach based on benders decomposition for the preventive maintenance scheduling problem of a stochastic large-scale energy system*. Journal of Scheduling 16(6), 605–628 (2013)

Variable definition

- Binaries: Outage decisions $d_{i,k,w}$ for outage (i,k) and week w: $d_{i,k,w} = 1$ if the outage i,k began before w. (for efficient standard branching)
- Continuous variables:
  - $r_{i,k}$: refueling quantities for the refueling in outage (i,k).
  - $p_{i,k,s,t}$ nuclear (T2) productions T1.
  - $p_{j,s,t}$ non nuclear (T1) productions levels.
  - Residual stocks $x^{fin}_{i,s}$ (for cost function, to avoid end-of-side effects)
- Dependent variables: fuel stocks $x^{init}_{i,k,s}, x^{fin}_{i,k,s}$.



Définition des variables, illustration

A glance at the problem structure

$$\min_{d \in \{0,1\}^n \times \mathbb{R}_+^m, p_s \geqslant 0} \quad \sum_s c_s \, p_s$$
$$A \, d \leqslant b$$
$$\forall s \quad T \, d + W \, p_s \leqslant h_s$$
$$\forall s \quad B \, p_s \leqslant b_s$$

d: decisions on outages (binaries) and refueling levels (continuous), independent decisions valid for all scenarios (1st stage)

p_s: production decisions (continuous) and implied fuel levels to have a linear formulation (2nd stage, distinguished over the scenarios s).

$A \, d \leqslant b$: especially scheduling constraints for outages

$B \, p_s \leqslant b_s$: production/ fuel level constraints (can be included in $T \, d + W \, p_s \leqslant h_s$)

Main constraints $T \, d + W \, p_s \leqslant h_s$, coupling maintenance decisions to null T2 production:

$$\forall i, k, s, w, \quad p_{i,k,s,w} \leqslant \overline{\mathbf{P}}_{i,w}(d_{i,k,w-\mathbf{Da}_{i,k}} - d_{i,k+1,w}) \tag{1}$$

Solving limits

- Strong limiting factor: the sizes of instances
- LP relaxation: not computable in 1h for difficult instances (B8-B9) even with deterministic problem and aggregated production time steps to weeks with Cplex 12.3. OK with 12.5
- With restricted time windows, good B& B convergence
- B&B search efficient restricting the size (1 stochastic scenario, time steps aggregated to weeks, 3 cycles and 120 weeks max with time windows)
- Dual heuristics compute high quality dual bounds for the whole problem.
- Efficient matheuristics to tackle the size of the full problem.

$\Longrightarrow$ In this talk, for the robust extension, we consider (reduced) instances where straightforward B&B solving is efficient.

Dupin, N., Talbi, E.: *Dual Heuristics and New Lower Bounds for the Challenge EURO/ROADEF 2010*. Matheuristics 2016 pp. 60–71 (2016)
Dupin, N., Talbi, E.: *Dual heuristics and new dual bounds to schedule the maintenances of nuclear power plants*, submitted, preprint available in arXiv.

Plan

Robust problem

- Outage durations are uncertain due to possible delays of the maintenance operations.
- Impact on the planning with linking constraints on outages, production capacities . . .
- We consider here only the outage prolongation as uncertain.
- We want to face off the worst scenario of prolongation in the whole planning considering outages prolongation in a given uncertainty set.

$\Longrightarrow$ Operational/industrial requirements meet robust optimization

Uncertainty sets

- Each prolongation $\delta_{i,k}$ has a maximal duration $\overline{\delta_{i,k}}$.
- Interval uncertainty: $\Omega_{worst} = \prod_{i,k} [\![0, \overline{\delta_{i,k}}]\!]$.
- Maximal budget maximal of extreme delays:
  $\Omega^{\Gamma}_{budget} = \left\{ \delta \in \Omega_{worst} \middle| \sum_{i,k} \delta_{i,k} \leqslant \Gamma \right\}$.
- Cardinality restriction:
  $\Omega^{N}_{card} = \left\{ \delta \middle| \exists (\varepsilon_{i,k}) \in \{0,1\}, \forall i,k, \delta_{i,k} \leqslant \overline{\delta_{i,k}} \varepsilon_{i,k} \text{ and } \sum_{i,k} \varepsilon_{i,k} \leqslant N \right\}$

$\Longrightarrow$ Discrete uncertainty sets, Ω in the following, discretizing all the possible scenarios.
$\Longrightarrow$ main case: $N = 1$ (or $\Gamma = 1$) and $\overline{\delta_{i,k}} = 1$ (and will make enough difficulties . . .)

Robustness definition

Robustness: We want to face off the worst case in the uncertainty set Ω, minimizing the worst expected cost.

Second level decisions can be adjusted after the uncertainty outcomes. It leads to a Min-Max-Min scheme:

$$\begin{array}{ll} \min_d \quad c_D.d + \mathcal{Q}(d) & \quad \text{with:} \\ A.d \leqslant b & \end{array}$$

$$\mathcal{Q}(d) = \quad \max_{\delta \in \Omega} Q(d,\delta) \quad \text{and} \quad Q(d,\delta) = \quad \begin{array}{l} \min_x \quad c_p.p \\ T(\delta).d + W.p \leqslant h(\delta) \end{array}$$

Uncertainty set, why not a continuous uncertainty set?

- Nicer with Bertsimas and Sim model, to use duality and usual 2-stage robust framework: $\Omega^{\Gamma}_{budget} = \left\{ \delta \in \prod_{i,k} [0, \overline{\delta_{i,k}}] \middle| \sum_{i,k} \delta_{i,k} \leqslant \Gamma \right\}$.
- Uncertainty in constraints, implying feasibility issues (it would have been better with cost uncertainty)
- WORSE: Uncertainty is non linear in constraints (and absolutely discrete in the w' indexes of $d_{i,k,w'}$):

$$\forall i, k, \delta \in \Omega, w, \quad p_{i,k,\delta,w} \leqslant \overline{\mathbf{P}}_{i,w}(d_{i,k,w-\mathbf{Da}_{i,k}-\delta_{i,k}} - d_{i,k+1,w}) \qquad (2)$$

$\Longrightarrow$ No alternative to consider a discrete set of scenarios

Linearization having discrete scenarios

Linearization with discrete scenarios $\delta \in \Omega$, MIP to be solved with Benders decomposition:

$$
\begin{array}{rrl}
\min_{d \in \{0,1\}^n \times \mathbb{R}_+^m, p_\delta \geqslant 0} & cd + C^{rob} & \\
 & A\, d & \leqslant b \\
\forall \delta & T_\delta\, x + W\, p_\delta & \leqslant h \\
\forall \delta & q\, p_\delta & \leqslant C^{rob}
\end{array}
$$

Benders decomposition for our MIP

- Variable partitioning: first level variables 'z': $d_{i,k,w}$, $r_{i,k}$ and C^{robust}. Other variables 'y' depend on the scenarios.

$$\min_{z,y \geqslant 0} \quad cz \tag{3}$$

$$Az \geqslant a \tag{4}$$

$$Tz + Wy \geqslant b \tag{5}$$

- Master Problem $\min cz$ s.t $Az \geqslant a$ and cuts generated by the subproblems. (projection of the constraints $Tz + Wy \geqslant b$ in the space of z variables) .

Generating Benders cuts

- Here just feasibility cuts: z^0 given, is it possible for all the prolongation scenarios to have a production planning with cost at most C^{robust}?
  Transforming into optimization problem and using duality:

$$\begin{aligned} \min \eta \qquad & \qquad \max(b - T.z^0).v > 0? && (6) \\ Wy + \eta \geqslant b - T.z^0 \qquad = & \qquad W^T.v \leqslant 0 && (7) \\ & \qquad \sum_i v_i \leqslant 1 && (8) \\ \eta, y \geqslant 0 \qquad & \qquad v \geqslant 0 && (9) \end{aligned}$$

- Benders Reformulation: for all extreme ray v of W^T, we have cuts $(d - T.z).v \leqslant 0$.

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  - Residual stocks $x^{fin}_{i,s,\delta}$ (for cost function, to avoid end-of-side effects)
- Dependent variables: fuel stocks $x^{init}_{i,k,s,\delta}, x^{fin}_{i,k,s,\delta}$.

$$\begin{array}{lll}
\min & \sum_{i,k} \mathbf{C}^{rld}_{i,k} r_{i,k} + \sum_{i,k,w} \mathbf{C}^{pen}_{i,k,w}(d_{i,k,w} - d_{i,k,w-1}) + C^{robust} & (10) \\
\forall i,k,w, & d_{i,k,w-1} \leqslant d_{i,k,w} & (11) \\
\forall i,k, & \mathbf{Rmin}_{i,k}\ d_{i,k,W} \leqslant r_{i,k} \leqslant \mathbf{Rmax}_{i,k}\ d_{i,k,W} & (12) \\
\forall \delta, & \sum_{j,s,t} \pi_s \mathbf{C}^{prd}_{j,s,t} \mathbf{D}^t\ p_{j,s,\delta,t} - \sum_{i,s} \pi_s \mathbf{C}^{val}_i x_{i,s,\delta,T} \leqslant C^{robust} & (13) \\
\forall i,s,\delta, & x^{init}_{i,-1,s} = \mathbf{Xi}_i & (14) \\
\forall j,t,s,\delta, & \mathbf{Pmin}^s_{j,t} \leqslant p_{j,s,\delta,t} \leqslant \mathbf{Pmax}^s_{j,t} & (15) \\
\forall i,t,s,\delta, & 0 \leqslant p_{i,k,s,\delta,t} \leqslant \mathbf{Pmax}^t_i (d_{i,k,w_t - \mathbf{Da}_{i,k,\delta}} - d_{i,k+1,w_t}) & (16) \\
\forall i,t,s,\delta,m, & \frac{p_{i,k,s,\delta,t}}{\mathbf{Pmax}^t_i} \leqslant \frac{\mathbf{c}_{i,k,m-1} - \mathbf{c}_{i,k,m}}{\mathbf{f}_{i,k,m-1} - \mathbf{f}_{i,k,m}} (x_{i,s,\delta,t} - \mathbf{f}_{i,k,m}) + \mathbf{c}_{i,k,m} & (17) \\
\forall s,t,\delta, & \sum_{i,k} p_{i,k,s,\delta,t} + \sum_j p_{j,s,\delta,t} = \mathbf{Dem}^{t,s} & (18) \\
\forall i,k,s,\delta, & 0 \leqslant x^{init}_{i,k,s,\delta} \leqslant \mathbf{Smax}_{i,k} & (19) \\
\forall i,t,s,\delta, & x^{fin}_{i,k,s,\delta} = x^{init}_{i,k,s,\delta} - \sum_t \mathbf{D}^t\ p_{i,k,s,\delta,t} & (20) \\
\forall i,k,s,\delta, & x^{fin}_{i,k,s,\delta} \leqslant \mathbf{Amax}_{i,k+1} + (\mathbf{Smax}_{i,k} - \mathbf{Amax}_{i,k+1})\ d_{i,k+1,W} & (21) \\
\forall i,t,s,\delta, & x^{init}_{i,k,s,\delta} - \mathbf{Bo}_{i,k} = r_{i,k} + \frac{\mathbf{Q}_{i,k-1}}{\mathbf{Q}_{i,k}} (x^{fin}_{i,k-1,s,\delta} - \mathbf{Bo}_{i,k-1}) & (22) \\
\forall i,k,s,\delta,t, & x_{i,s,\delta,t} \leqslant x^{init}_{i,k,s,\delta} - \sum_{t' \leqslant t} \mathbf{D}^{t'}\ p_{i,k,s,\delta,t'} + M_i\ (1 - d_{i,k,w_t} + d_{i,k-1,w_t}) & (23) \\
\forall w,\delta, & \sum_{i,k} \mathbf{Pmax}^w_i (d_{i,k,w} - d_{i,k,w-\mathbf{Da}_{i,k,\delta}}) \leqslant \mathbf{Imax} & (24)
\end{array}$$

$$\sum_{i,k,w} \alpha^{(1)}_{i,k,w} \mathbf{Pmax}^w_i (d_{i,k,w-\mathbf{Da}_{i,k,\delta}} - d_{i,k+1,w}) + \sum_{i,k} \alpha^{(4)}_{i,k} \left(\mathbf{q}_{0,k-1}\mathbf{Xi}_i + \sum_{l=0}^{k-1} \mathbf{q}_{l+1,k-1}(r_{i,l+1} - \mathbf{Bo}_{i,l}) \right)$$

$$+ \sum_{i,k} \alpha^{(2)}_{i,k} \left(\mathbf{Smax}_{i,k} \left(1 + d_{i,k+1,W} - d_{i,k,W}\right) + \mathbf{q}_{0,k-1}\mathbf{Xi}_i + \sum_{l=0}^{k-1} \mathbf{q}_{l+1,k-1}(r_{i,l+1} - \mathbf{Bo}_{i,l}) \right)$$

$$+ \sum_{i,k} \alpha^{(3)}_{i,k} \left(\mathbf{Smax}_{i,k} - (\mathbf{Smax}_{i,k} - \mathbf{Amax}_{i,k+1})\, d_{i,k+1,W} - \mathbf{q}_{0,k-1}\mathbf{Xi}_i - \sum_{l=0}^{k-1} \mathbf{q}_{l+1,k-1}(r_{i,l+1} - \mathbf{Bo}_{i,l}) \right)$$

$$+ \sum_{i,k} \alpha^{(5)}_{i,k} \left(\mathbf{Smax}_{i,k} - \mathbf{q}_{0,k-1}\mathbf{Xi}_i - \sum_{l=0}^{k-1} \mathbf{q}_{l+1,k-1}(r_{i,l+1} - \mathbf{Bo}_{i,l}) \right)$$

$$+ \sum_{w} \alpha^{(17)}_{w} \left(1 - \sum_{(i,k)\in \mathbf{A17}} (d_{i,k,w-\mathbf{Da}_{i,k,\delta}} - d_{i,k,w-\mathbf{Da}_{i,k,\delta}-\mathbf{Se17}}) \right)$$

$$+ \sum_{w} \alpha^{(18)}_{w} \left(1 - \sum_{(i,k)\in \mathbf{A18}} (d_{i,k,w} - d_{i,k,w-\mathbf{Se18}}) + (d_{i,k,w-\mathbf{Da}_{i,k,\delta}} - d_{i,k,w-\mathbf{Da}_{i,k,\delta}-\mathbf{Se18}}) \right)$$

$$+ \sum_{w} \alpha^{(20)}_{w} \left(\mathbf{N}^{20}_w - \sum_{(i,k)\in \mathbf{A}^{20}_w} (d_{i,k,w} - d_{i,k,w-\mathbf{Da}_{i,k,\delta}}) \right) + \sum_{w} \alpha^{(21)}_{w} \left(\mathbf{I}^{max} - \sum_{(i,k)} \mathbf{Pmax}^w_i (d_{i,k,w} - d_{i,k,w-\mathbf{Da}_{i,k,\delta}}) \right)$$

$$- \sum_{w} \beta^{(1)}_w \mathbf{P}^{min}_{j,w} + \sum_{w} \beta^{(2)}_w \mathbf{P}^{max}_{j,w} + \sum_{w} \beta^{(3)}_w \mathbf{Dem}^w + \sum_{w} \beta^{(4)}_w (\mathbf{P}^{max}_{0,w} - \mathbf{Dem}^w) + \gamma C^{rob} \geqslant 0$$

Implementation points

Challenging difficulty: very large scale problem.

- Numerical instability due to propagation of rounding errors in Benders cuts.
- Too conservative approach: scheduling constraint induce tight planning in summers, there is frequently no 100% robust solution

$\Longrightarrow$ Needs for another definition of robustness, for modeling and solving issues

Plan

Specific case of constraints CT14 and CT15

Former robust constraints for CT14 and CT15:

$$\forall \delta, w, \quad \sum_{(i,k)\in \mathbf{A14}} (d_{i,k,w} - d_{i,k,w-(\mathbf{Da}_{i,k,\delta}+\mathbf{Se14})^+}) \leqslant 1 \qquad (25)$$

$$\forall \delta, w \in [\mathbf{d}_{15}, \mathbf{f}_{15}], \quad \sum_{(i,k)\in \mathbf{A15}} (d_{i,k,w} - d_{i,k,w-(\mathbf{Da}_{i,k,\delta}+\mathbf{Se15})^+}) \leqslant 1 \qquad (26)$$

The robustness of CT14 and CT15 is equivalent to Soyster's approach Robust CT14 and CT15 constraints are equivalent to the deterministic constraints with $\mathbf{Da}_{i,k} = \overline{\mathbf{Da}}_{i,k}$, using Soyster's results:

$$\forall w, \quad \sum_{(i,k)\in \mathbf{A14}} (d_{i,k,w} - d_{i,k,w-(\overline{\mathbf{Da}}_{i,k}+\mathbf{Se14})^+}) \leqslant 1 \qquad (27)$$

$$\forall w \in [\mathbf{d}_{15}, \mathbf{f}_{15}], \quad \sum_{(i,k)\in \mathbf{A15}} (d_{i,k,w} - d_{i,k,w-(\overline{\mathbf{Da}}_{i,k}+\mathbf{Se15})^+}) \leqslant 1 \qquad (28)$$

$\Longrightarrow$ Trick can be used to reduce the size of previous model $\Longrightarrow$ As CT14 and CT15 predominant to design good robust solutions, robust constraints with deterministic solution still infeasible in most of the instances.

Robustified approach

For all constraints $c \in CT14$ and $c \in CT15$, continuous variables $z^{(14)}_{c,w}, z^{(15)}_{c,w} \geqslant 0$ are introduced to penalize robust violations, paying cost $\mathbf{Cpen}^{rob}$ for violations.

We try to minimize $f^{rob}_{obj} = \sum_w \mathbf{Cpen}^{rob}(z^{(14)}_{c,w} + z^{(15)}_{c,w})$ and also with f^{det}_{obj} the previous objective

We add to the previous deterministic formulation the constraints:

$$\forall w, c \in CT14 \quad \sum_{(i,k)\in \mathbf{A14}^c} \left(d_{i,k,w} - d_{i,k,w-(\overline{\mathbf{Da}}_{i,k}+\mathbf{Se14})^+}\right) \leqslant 1 + z^{(14)}_{c,w}$$

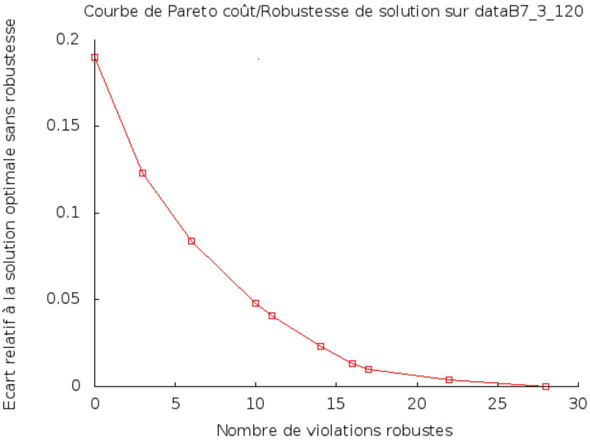
$$\forall c \in CT15, w \in [\mathbf{d}^c_{15}, \mathbf{f}^c_{15}], \quad \sum_{(i,k)\in \mathbf{A15}^c} \left(d_{i,k,w} - d_{i,k,w-(\overline{\mathbf{Da}}_{i,k}+\mathbf{Se15})^+}\right) \leqslant 1 + z^{(15)}_{c,w}$$

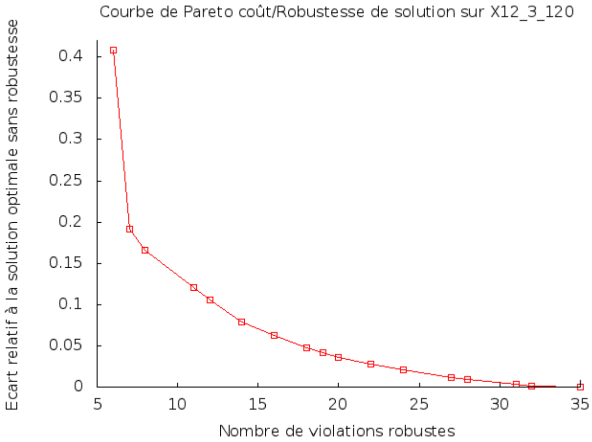
Solving facts

- Weighted-sum robustified MIP problem with a similar size than the deterministic one.
- Same set of feasible solutions than the deterministic MIP: furnish robustified solutions for all instances
- Similar B& B characteristics than the deterministic MIP.
- Robust trade-off can help MIP solvers to cut off solutions. Difficulties in deterministic MIP that lots of solutions have similar cost, known bottleneck for B&B.
- Computation of Pareto fronts of the best compromise solutions to trade off cost/robustness.
- f_{obj}^{rob} has discrete values, a good point for a ε-constraint method for bi-objective optimization. Also dichotomic search (first phase of TPM method) applies in this bi-objective case.

$\Longrightarrow$ Simple approach, but efficient in a operational standpoint and using a simple and efficient methodology.

Courbe de Pareto Cout/Robustesse




Courbe de Pareto coût/Robustesse de solution sur X12_3_120
Ecart relatif à la solution optimale sans robustesse
Nombre de violations robustes
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
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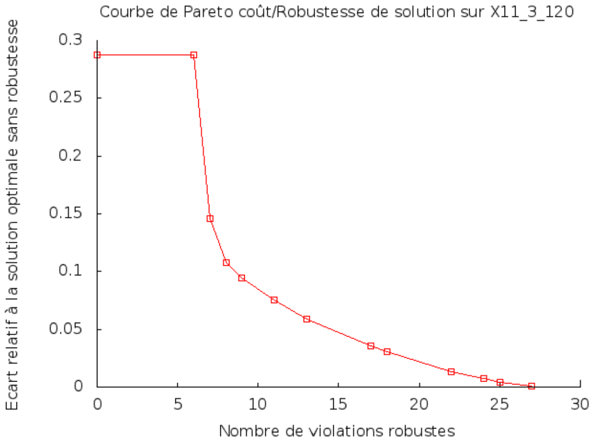
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Plan

Conclusions and perspectives

Conclusions:

- Robust optimization with an hypothesis significantly different from the state of the art: discrete uncertainty.
- Benders approach: numerical difficulties.
- Simple robustified approach: efficient, based on deterministic resolution, consistent to give feasible solutions.
- Robustness is a trade-off to cut off non robust solutions as lots of solutions have similar cost.

Perspectives:

- Stability objective through the dynamic reoptimizations.
- Matheuristic construction of Pareto Fronts for the real-size instances