Exact and Heuristic Methods to Optimize Maintenances and Flight schedules of Military Aircraft

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Outline

Maintenance

- Maintenance is important.

Maintenance

- Maintenance is important.
- Maintenance is costly.

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- Complexity and durability needs are growing with time.

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  - buildings that need to last 100 years.

Maintenance

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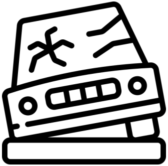
- Maintenance is costly.
- Complexity and durability needs are growing with time.
  - buildings that need to last 100 years.
  - green energy needs lasting infrastructure.

Maintenance planning

Three types:

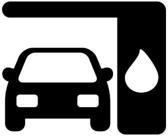
- Corrective.



Maintenance planning

Three types:

- Corrective.
- Preventive.



Maintenance planning

Three types:

- Corrective.
- Preventive.
- Predictive.

Maintenance planning

Three types:

- Corrective.
- **Preventive**.
- Predictive.

Maintenance planning

Three types:

- Corrective.
- **Preventive**.
- Predictive.

Applications

Production, transportation.

Maintenance planning applications

Three elements:

- Tasks (planned over time).

Maintenance planning applications

Three elements:

- Tasks (planned over time).
- Resources (to do the tasks).

Maintenance planning applications

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Maintenance planning applications

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In transportation:

- Tasks: flights, train schedules, routes.

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In transportation:

- Tasks: flights, train schedules, routes.
- Resources: aircraft, trains, vehicles.

Maintenance planning applications

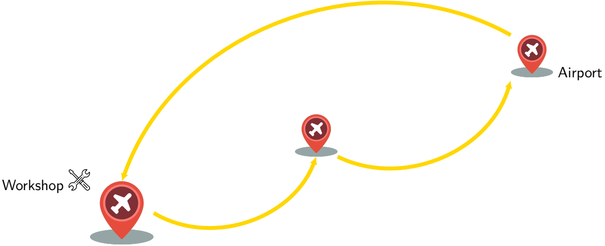
Three elements:

- Tasks (planned over time).
- Resources (to do the tasks).
- Recovery tasks (to care for resources).

In transportation:

- Tasks: flights, train schedules, routes.
- Resources: aircraft, trains, vehicles.
- Recovery tasks: checks (=maintenances).

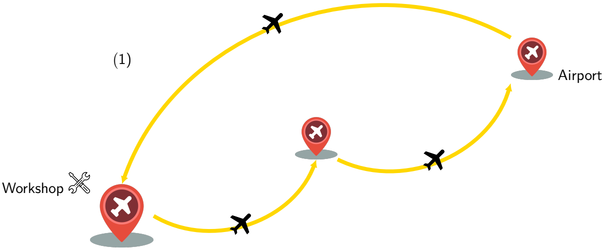
The Flight and Maintenance Planning (FMP) problem



The Flight and Maintenance Planning (FMP) problem

Tail Assignment:
assign aircraft to flights

(1)



State of the art : FMP

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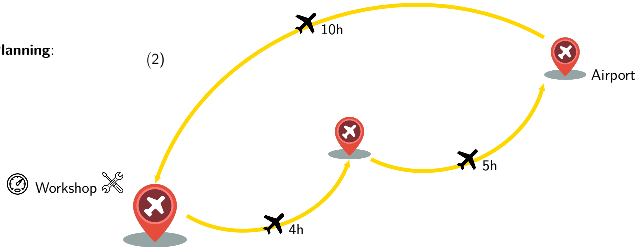
The Flight and Maintenance Planning (FMP) problem

Flight and Maintenance Planning:
assign aircraft to flights

+capacity in workshop
+hour-dependent checks



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(2) A. Sarac, R. Batta, and C. M. Rump. A branch-and-price approach for operational aircraft maintenance routing. European Journal of Operational Research, 175(3):1850–1869, dec 2006.

The Military Flight and Maintenance Planning (MFMP) problem

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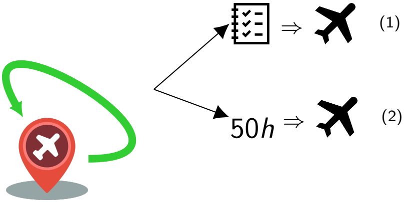

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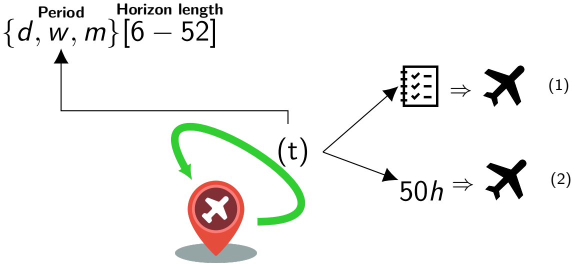

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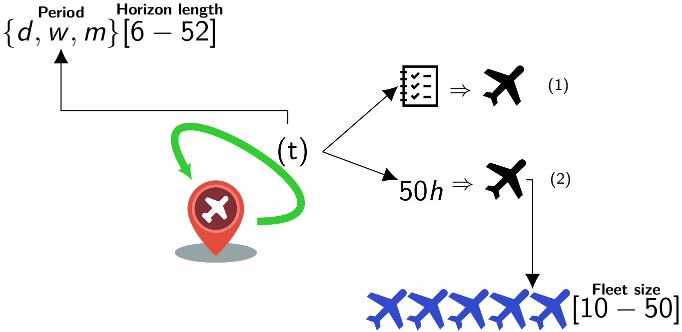

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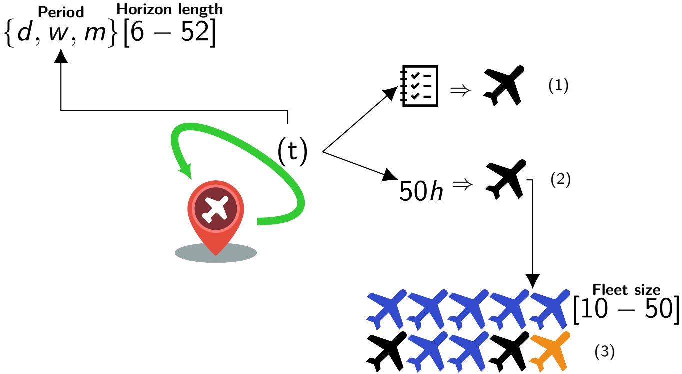

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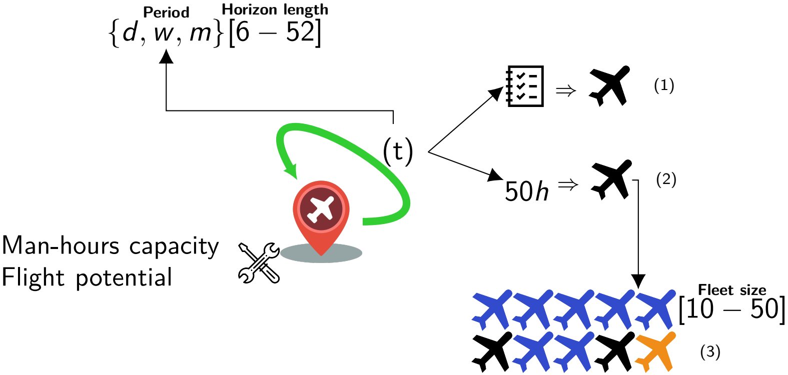

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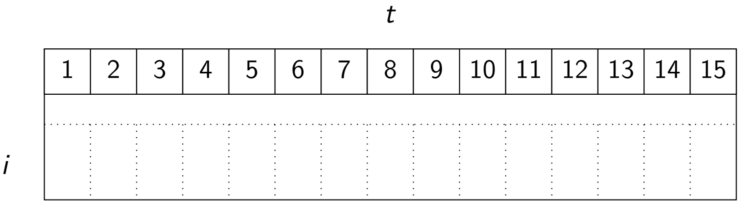
Maintenance example



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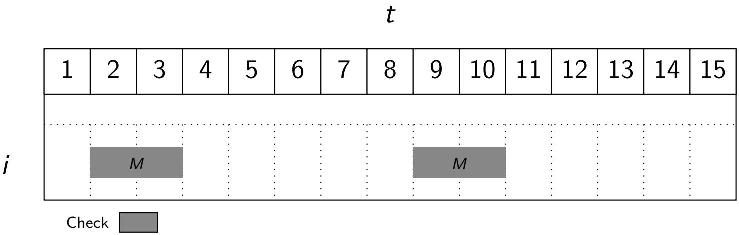

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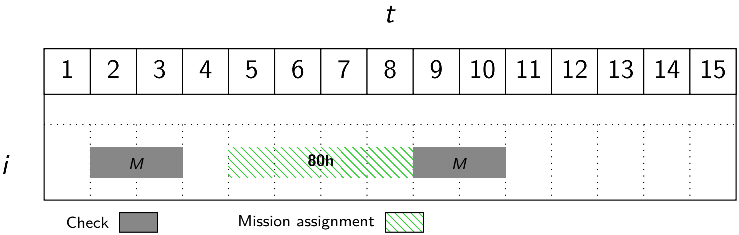

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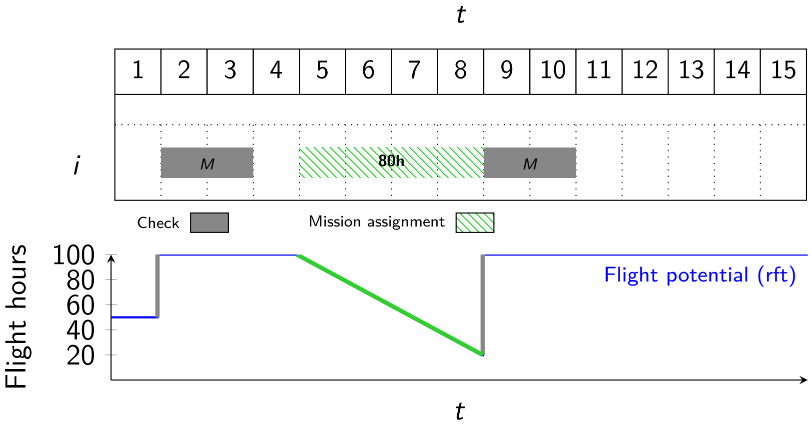

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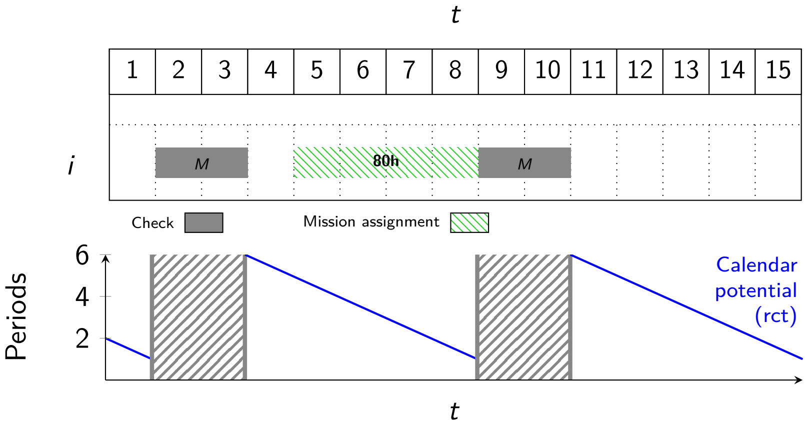

The long term Military Flight and Maintenance Planning problem

The French Air Force variant of the MFMP for the Mirage 2000 series.

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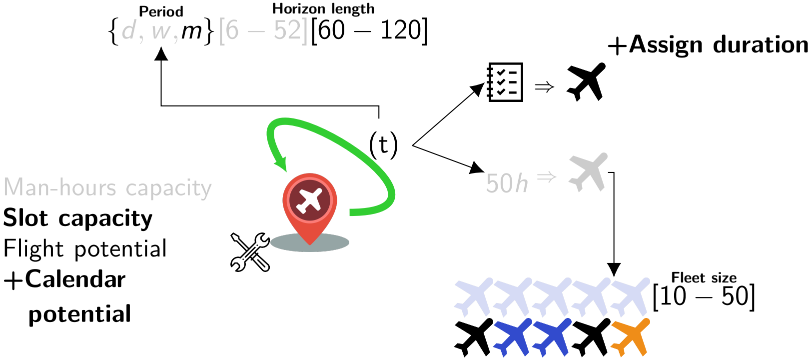

Comparison of several MFMP problems

Table with most relevant characteristics of variants of the MFMP in the literature. C= Constraint; O=Objective.

Reference	Maintenance					Missions					Fleet	
	CP	**FD**	**MS**	**RC**	**MT**	**DA**	**HD**	**HF**	**MD**	**HT**	**AV**	**SU**
Kozanidis				C			C				O(c)	O(d)
Hahn et al.		C				C	C		O	C		C(a)
Winata		C				C	C		O			
Cho		C				C						C(a)
Verhoeff et al.				C			C			C	C(b)	O(d)
Li et al.		C				C						
Shah et al.		C					C				O(a)	C(a)
Gavranis et al.				C			C					O(e),O(f)
Marlow and Dell				C			C			O		O(b)
Seif and Yu			C	C	C		C	C				O(e)
This thesis	C	C				C		C	C		O(a),O(b)	O(c)

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Gavranis et al.				C			C					O(e),O(f)
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[illegible]			C	C	C		C	C				[illegible]
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Objectives

- Formulate the French Air Force variant of the MFMP and study its complexity.

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- Build exact methods to solve the French Air Force MFMP problem.
- Expand solution methods to cope with large scale real-life MFMP problems.
- Deliver a decision making prototype for test in real-life data sets.

Outline

1. Context and state of the art
2. **Exact methods**
3. Valid bounds and learned constraints
4. Graph-based VND matheuristic
5. General conclusions and perspectives

The long term MFMP problem

Basic problem

The long term MFMP problem

Basic problem

- $j \in \mathcal{J}$ **missions**.

j	MT_j^{min}	$Start_j$	End_j	H_j	R_j
0	2	1	4	24	1
1	2	5	7	34	3
2	3	8	11	18	3
3	3	12	15	30	3
4	2	16	18	35	3
5	2	19	20	25	1

The long term MFMP problem

Basic problem

- $j \in \mathcal{J}$ missions.
- $i \in \mathcal{I}$ **aircraft**.

i	Rct_i^{Init}	Rft_i^{Init}
0	7	120
1	13	220
2	7	140
3	8	140
4	6	160

The long term MFMP problem

Basic problem

- $j \in \mathcal{J}$ missions.
- $i \in \mathcal{I}$ aircraft.
- **Maintenances**.

Frequency (in time, in flight hours).
Duration.
Capacity.

The long term MFMP problem

Basic problem

- $j \in \mathcal{J}$ missions.
- $i \in \mathcal{I}$ aircraft.
- Maintenances.

More constraints

Fleet-status, mission-aircraft compatibility.

The long term MFMP problem

Basic problem

- $j \in \mathcal{J}$ missions.
- $i \in \mathcal{I}$ aircraft.
- Maintenances.

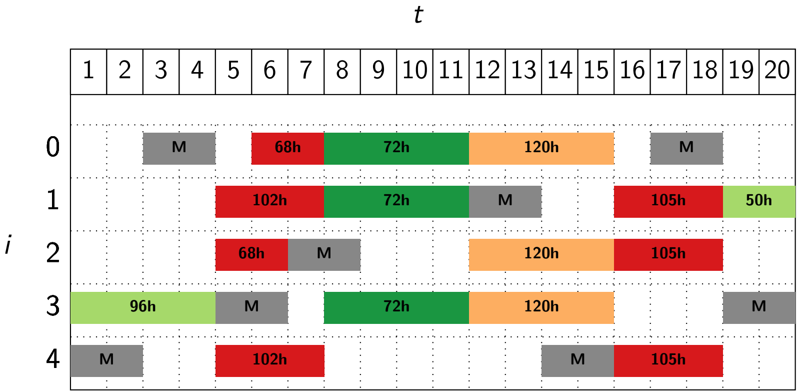
More constraints

Fleet-status, mission-aircraft compatibility.

Objectives

Maximize the availability, minimize the number of checks, minimize maintenance capacity.

An example of an MFMP solution



Complexity analysis

Take an instance I from the MFMP problem.

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- Take out maintenances needs.

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Becomes the NP-Complete Shift Satisfaction Personnel Task Scheduling Problem $\star$.

$\star$ E. M. Arkin and E. B. Silverberg. Scheduling jobs with fixed start and end times. Discrete Applied Mathematics, 1987.

Solution approaches

Mixed Integer Programming model

Simulated Annealing: initial solution

Solution approaches

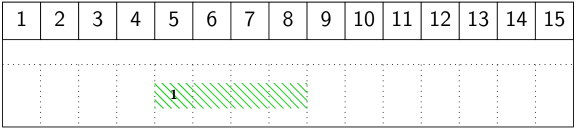
Mixed Integer Programming model

Simulated Annealing: initial solution

Mixed Integer Programming model

Binary variables

a^s_{ijt} : assignment of mission j to aircraft i starts in period t.



Mixed Integer Programming model

Binary variables

a^s_{ijt} : assignment of mission j to aircraft i starts in period t.

a_{ijt} : mission j assigned in period t to aircraft i.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
				1	1	1	1							

Mixed Integer Programming model

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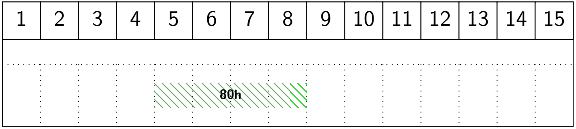
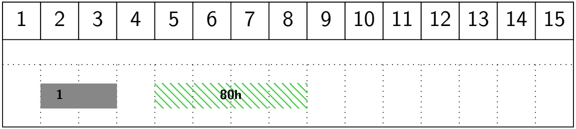


Mixed Integer Programming model

Binary variables

a^s_{ijt} : assignment of mission j to aircraft i starts in period t.
a_{ijt} : mission j assigned in period t to aircraft i.
m_{it} : aircraft i starts a check in period t.



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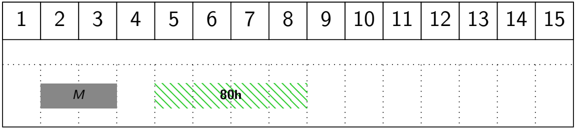

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$$\underbrace{\sum_{t' \in \mathcal{T}^s_t} \sum_{i \in \mathcal{I}} m_{it'}}_{\text{Number of aircraft in maintenance in period } t} + N_t \leq C^{max} \qquad t \in \mathcal{T}$$

Maintenance capacity

Mixed Integer Programming model

Binary variables

a^s_{ijt} : assignment of mission j to aircraft i starts in period t.
a_{ijt} : mission j assigned in period t to aircraft i.
m_{it} : aircraft i starts a check in period t.

$$\sum_{t' \in \mathcal{T}^s_t} \sum_{i \in \mathcal{I}} m_{it'} + N_t \leq C^{max} \qquad t \in \mathcal{T}$$

$$\underbrace{\sum_{i \in \mathcal{I}_j} a_{ijt}}_{} \geq \mathrm{R_j} \qquad j \in \mathcal{J}, t \in \mathcal{T}_j$$

Number of aircraft assigned to mission j in period t

Mission needs of mission j

Mixed Integer Programming model

Binary variables

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$$\sum_{i \in \mathcal{I}_j} a_{ijt} \geq R_j \qquad j \in \mathcal{J}, t \in \mathcal{T}_j$$

$$\underbrace{\sum_{t' \in \mathcal{T}^s_t} m_{it'} + \sum_{j \in \mathcal{J}_t \cap \mathcal{O}_i} a_{ijt}}_{} \leq 1 \qquad t \in \mathcal{T}, i \in \mathcal{I}$$

Assignments of aircraft i in period t

Mixed Integer Programming model: Flight hours rule

Continuous variables

u_{it} : flight hours by aircraft i during period t.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0h	0h	0h	0h	20h	20h	20h	20h	0h	0h	0h	0h	0h	0h	0h

Mixed Integer Programming model: Flight hours rule

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1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0h	0h	0h	0h	20h	20h	20h	20h	0h	0h	0h	0h	0h	0h	0h

$$u_{it} \geq \sum_{j \in \mathcal{J}_t \cap \mathcal{O}_i} a_{ijt} H_j \qquad t = 1, ..., \mathcal{T}, i \in \mathcal{I}$$

$$u_{it} \geq U^{min}(1 - \sum_{t' \in \mathcal{T}_t^s} m_{it'}) \qquad t = 1, ..., \mathcal{T}, i \in \mathcal{I}$$

$$u_{it} \in [0, \max_j \{H_j\}] \qquad t = 1, ..., \mathcal{T}, i \in \mathcal{I}$$

Mixed Integer Programming model: Flight hours rule

Continuous variables

u_{it} : flight hours by aircraft i during period t.

rft_{it} : remaining flight hours for aircraft i during period t.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
50h	100h	100h	100h	80h	60h	40h	20h	20h	20h	20h	20h	20h	20h	20h

Mixed Integer Programming model: Flight hours rule

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1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
50h	100h	100h	100h	80h	60h	40h	20h	20h	20h	20h	20h	20h	20h	20h

$$rft_{i0} = Rft_i^{Init} \qquad i \in \mathcal{I}$$

$$rft_{it} \leq rft_{i(t-1)} + H^M m_{it} - u_{it} \qquad t = 1, ..., \mathcal{T}, i \in \mathcal{I}$$

$$rft_{it} \geq H^M m_{it'} \qquad t \in \mathcal{T}, t' \in \mathcal{T}_t^s, i \in \mathcal{I}$$

$$rft_{it} \in [0, H^M] \qquad t \in \mathcal{T}, i \in \mathcal{I}$$

Solution approaches

Mixed Integer Programming model

Simulated Annealing: initial solution

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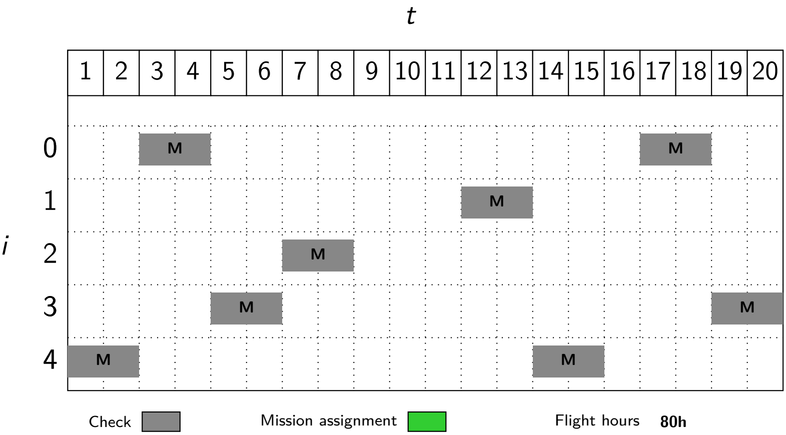

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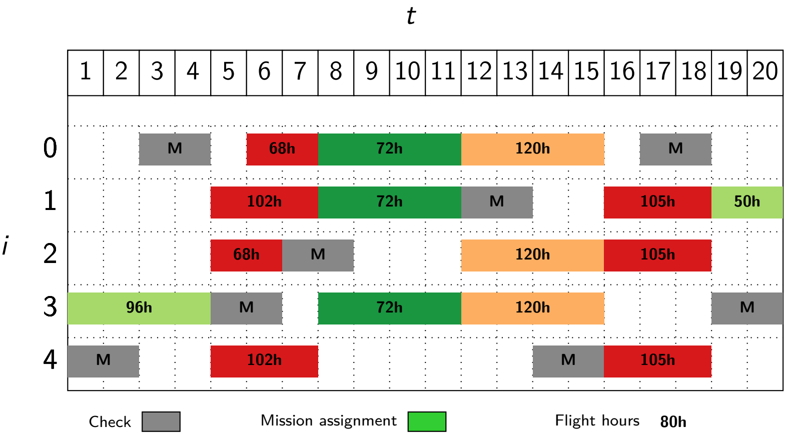

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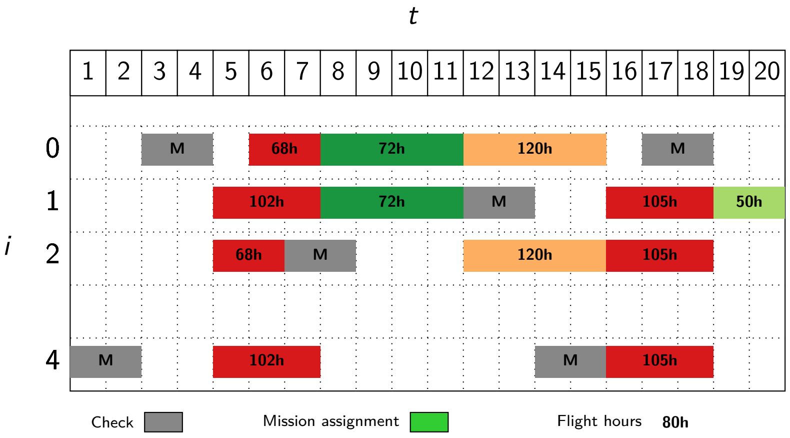

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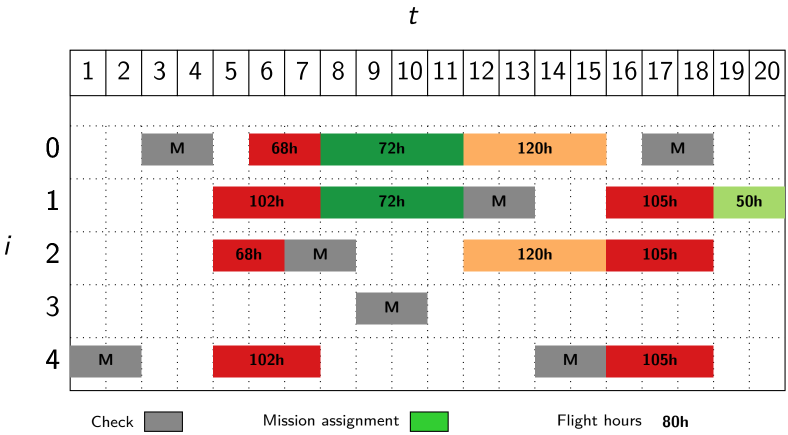

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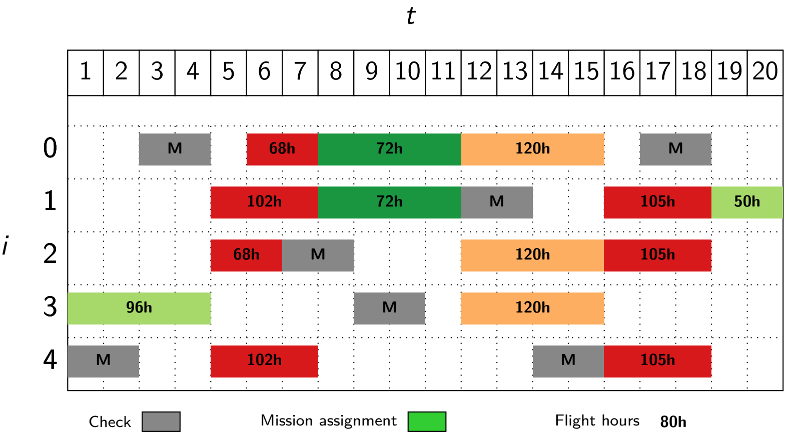

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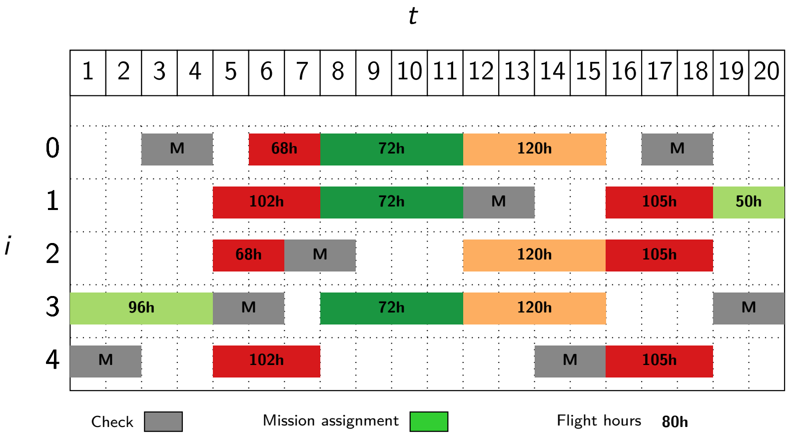


Experiments

Instance simulator.

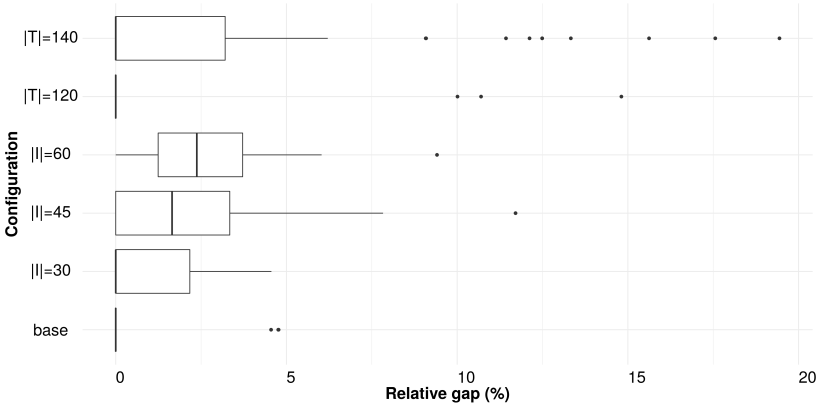
Experiments

Instance simulator.

- Several parameters and configurations.
  - Fleet sizes ($|\mathcal{I}|$): 15 (base), 30, 45, 60.
  - Planning horizons ($|\mathcal{T}|$): 90 (base), 120, 140.
- Number of instances per dataset: 50.
- Resolution: CPLEX with a time limit of 1 hour.

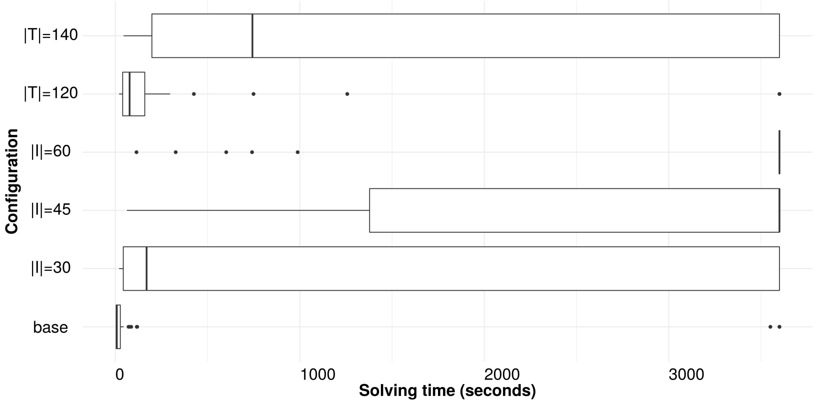
Results

- Small gaps overall.



Results

- Small gaps overall.
- Solution times highly sensible on the size of the instance.



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Submission: Franco Peschiera, Olga Battaïa, Alain Haït, Nicolas Dupin. Long term planning of military aircraft flight and maintenance operations. Annals of Operations Research.

Outline

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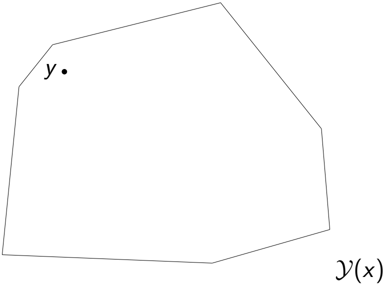
Contents

Predicting learned-cuts

Predicting learned-cuts

Optimization problem $y^*(x) :\equiv arg\ \min_{y \in \mathcal{Y}(x)} C(x, y)$



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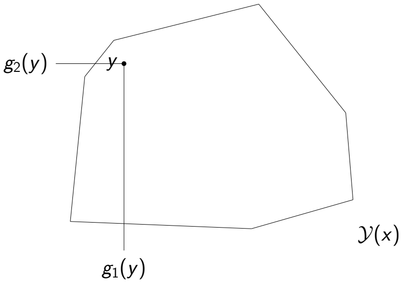

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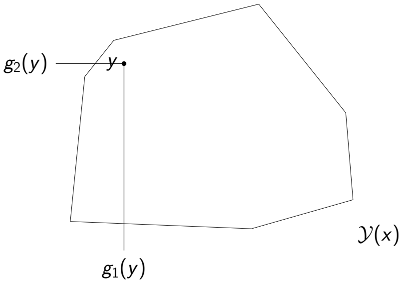

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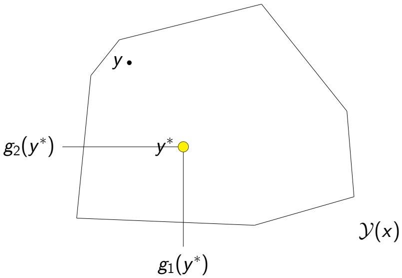

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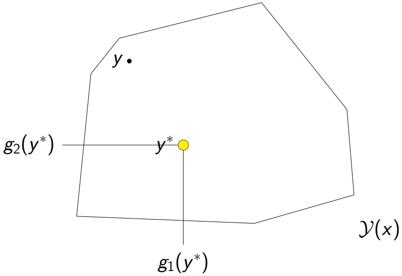
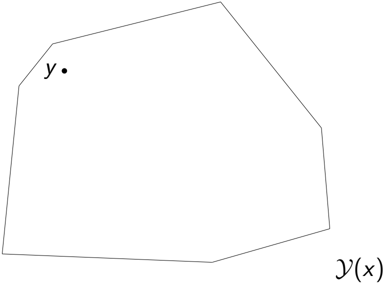
Input features	$H(x) = \{h_m(x)\ \forall m \in \mathcal{M}\}$
Training for optimal	$G(y^*(x)) \approx \hat{G}(x) = f(H(x))\star$



$\star$ E. Larsen, S. Lachapelle, Y. Bengio, E. Frejinger, S. Lacoste-Julien, and A. Lodi. Predicting Tactical Solutions to Operational Planning Problems under Imperfect Information. arXiv, 2018.

Applying learned-cuts



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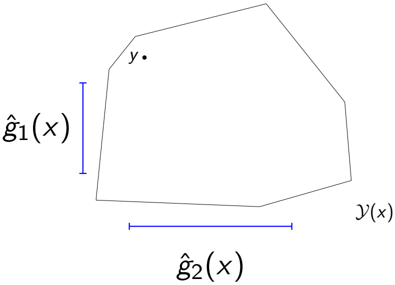

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We predict the optimal features $\hat{G}(x) = \hat{g}_n(x)\ \forall n \in \mathcal{N}$

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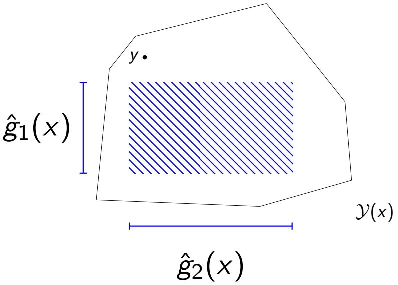

Applying learned-cuts

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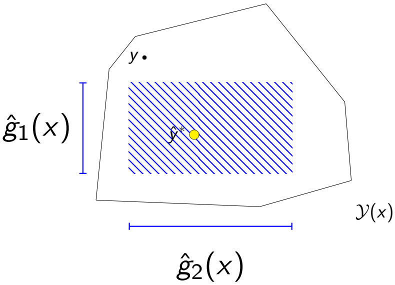
We predict the optimal "zone"	$\mathcal{Y}'(x) = \{y \in \mathcal{Y} \mid \hat{G}(x) = G(y)\}$
We solve the predicted model	$\hat{y}^*(x) :\equiv arg\ \min_{y\in\mathcal{Y}'(x)} C(x,y)$



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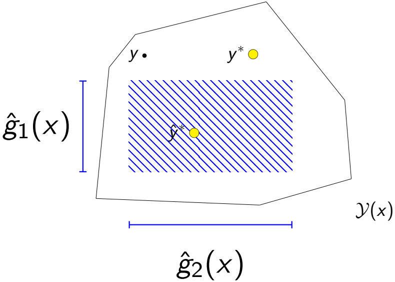
We solve the predicted model	$\hat{y}^*(x) :\equiv arg \ \min_{y \in \mathcal{Y}'(x)} C(x, y)$
With some (hopefully small) loss	$C(x, \hat{y}^*(x)) \approx C(x, y^*(x))$



Motivation

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1. **Performance**: a smaller model is easier to solve.

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2. **User feedback**: direct feedback about the solution without needing to solve any model.

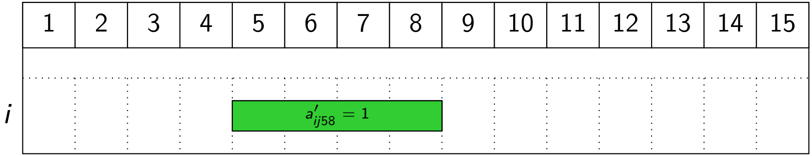
Contents

New formulation

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
i															

New formulation

$a'_{ijtt'}$: aircraft i is in mission j between t and t'.



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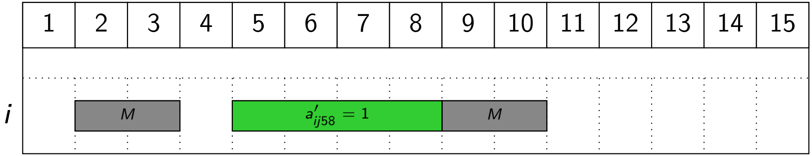

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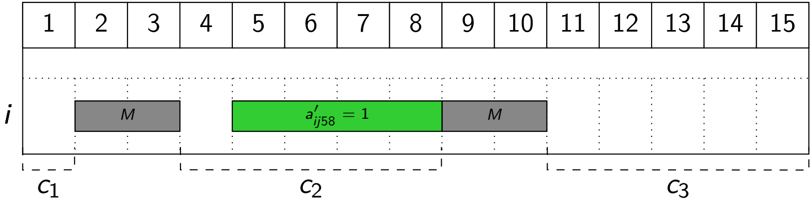

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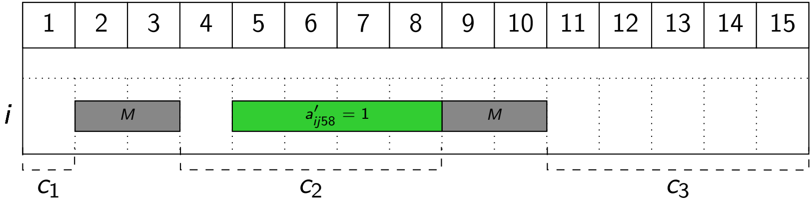
$$\sum_{(j,t,t')\in\mathcal{J}\mathcal{T}\mathcal{T}_{ic}} a'_{ijtt'} H'_{jtt'} + U'_{tc}$$

$$i \in \mathcal{I}, p \in \mathcal{P}, c \in \mathcal{C}_p$$



New formulation

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$$\sum_{(j,t,t') \in \mathcal{JTT}_{ic}} a'_{ijtt'} H'_{jtt'} + U'_{tc} \leq H^M + bigM(1 - m'_{ip})$$

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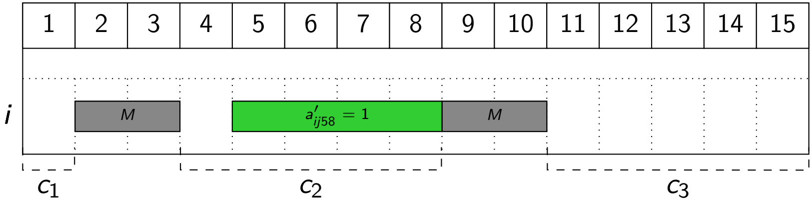
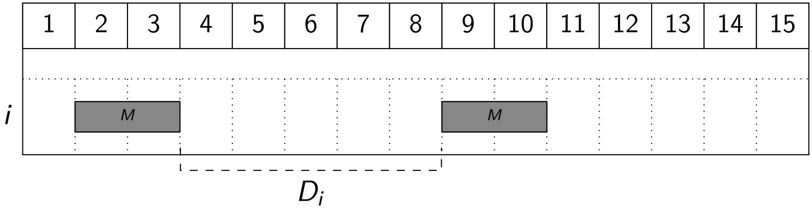


Solution features: G(y)



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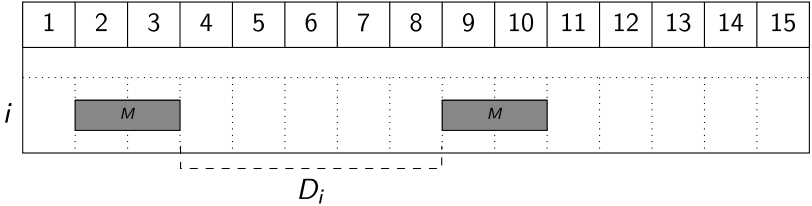

For each aircraft i: $D_i(y) \in [E^{min}, E^{max}]\ \forall y \in \mathcal{Y}(x)$.

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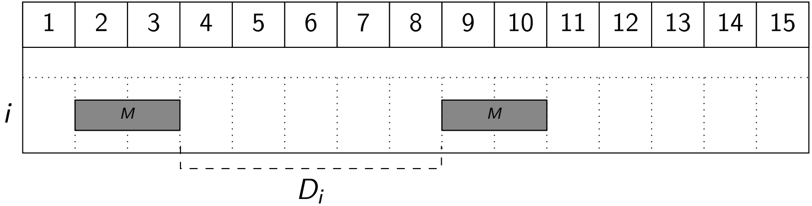

For each aircraft i: $D_i(y) \in [E^{min}, E^{max}]\ \forall y \in \mathcal{Y}(x)$.

Average distance between maintenances

$$g_1(y) = \mu_D = \frac{\sum_{i \in \mathcal{I}} D_i(y)}{I}.$$

Input features: H(x)

Mission related

Max, average, variance of flight hours per period. Median period.

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Fleet related

Sum of initial flight potential.

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Sum of initial flight potential.

Compatibility related

Sum of all special mission flight hours.

Forecasting technique

Quantile regressions

Upper bound and lower bound at 10% and 90%.

$$\mu_D \rightarrow [\hat{\mu}_D^{lb}, \hat{\mu}_D^{ub}]$$

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Training / test set

of 5000 small instances solved to optimal and divided into 70/30.

Applying learned-cuts

Pattern filtering:

$$D_{ip} \in [\hat{\mu}_D^{lb} - tol, \hat{\mu}_D^{ub} + tol] \rightarrow p \in \mathcal{P}_i$$

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Pattern recycling: with probabiliy α

$$D_{ip} \notin [\hat{\mu}_D^{lb} - tol, \hat{\mu}_D^{ub} + tol] \wedge P(\alpha) \rightarrow p \in \mathcal{P}_i$$

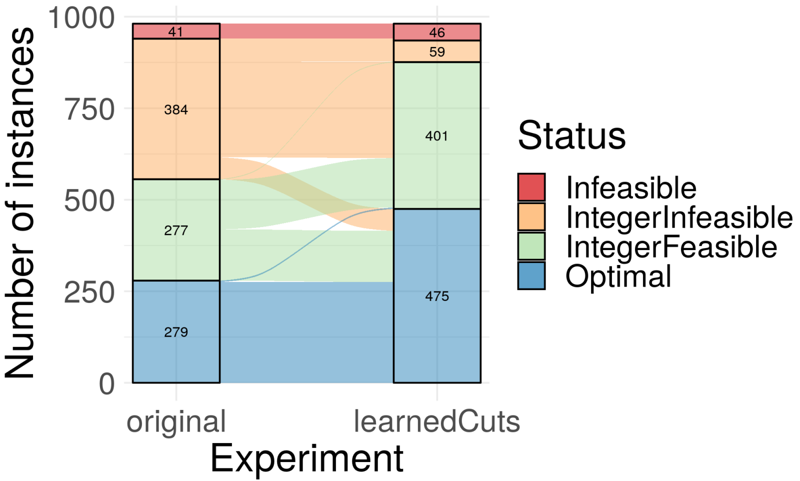
Experiments

- Number of instances: medium (1000), large (1000) and very large (1000).
- We seeded instance generation for better comparison.
- CPLEX running 1 thread and limited to 1 hour.

Largest instances have 60 aircraft, 90 periods.

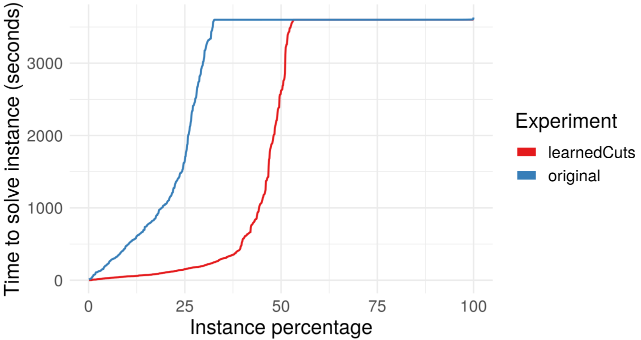
Results: performance

- More solutions.



Results: performance

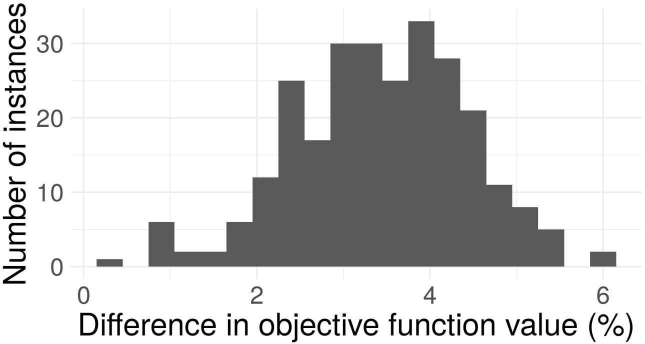
- More solutions.
- Faster solutions.



Results: optimality

We compare instances where the two models returned “optimal”.

- A 82.1% average reduction in solution time for these instances.



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We compare instances where the two models returned "optimal".

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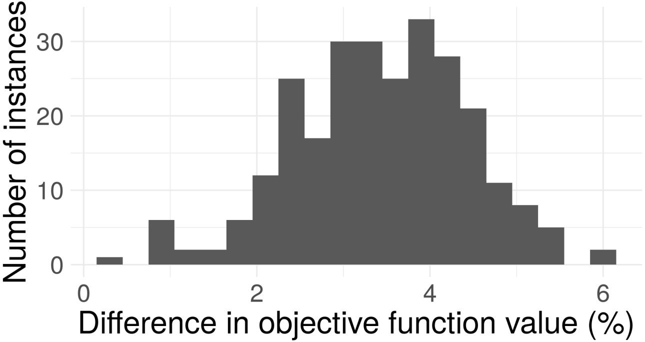
- Less than 7% loss of optimality for $\geq$ 95% of these instances. Most below 4%.



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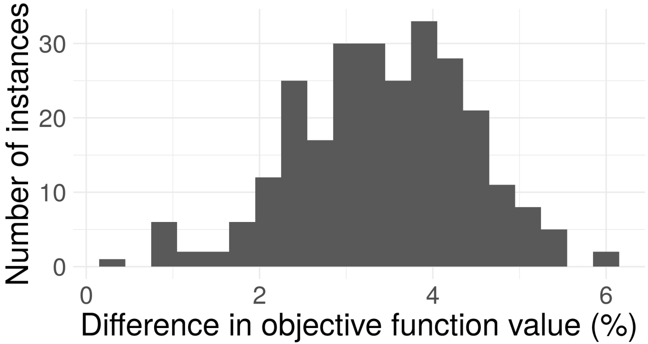
- Better predictions can reduce this loss even further.



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Publication: Peschiera, F., Dell, R., Royset, J. et al. A novel solution approach with ML-based pseudo-cuts for the Flight and Maintenance Planning problem. OR Spectrum, 2020.

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Applying said graphs within a Variable Neighborhood Descent

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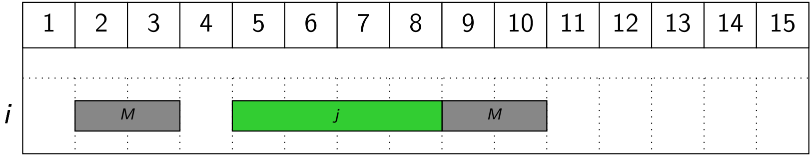
Patterns



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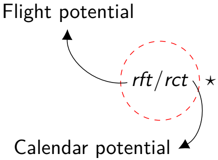

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⋆ Q. Deng, B. F. Santos, and R. Curran. A practical dynamic programming based methodology for aircraft maintenance check scheduling optimization. European Journal of Operational Research, 2020.

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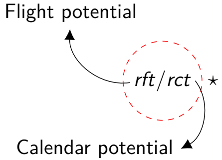

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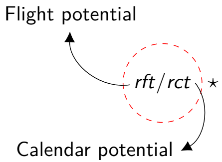

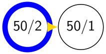

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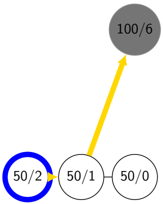

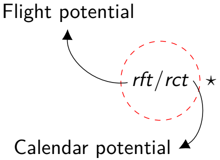

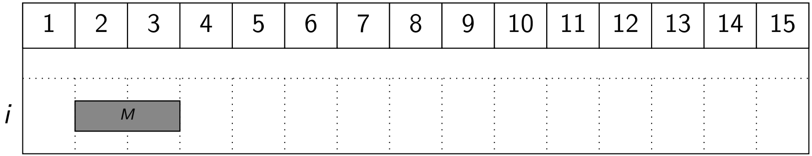

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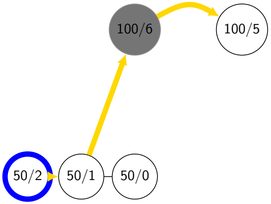

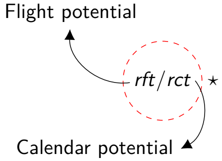

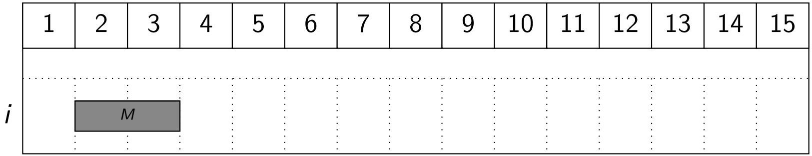

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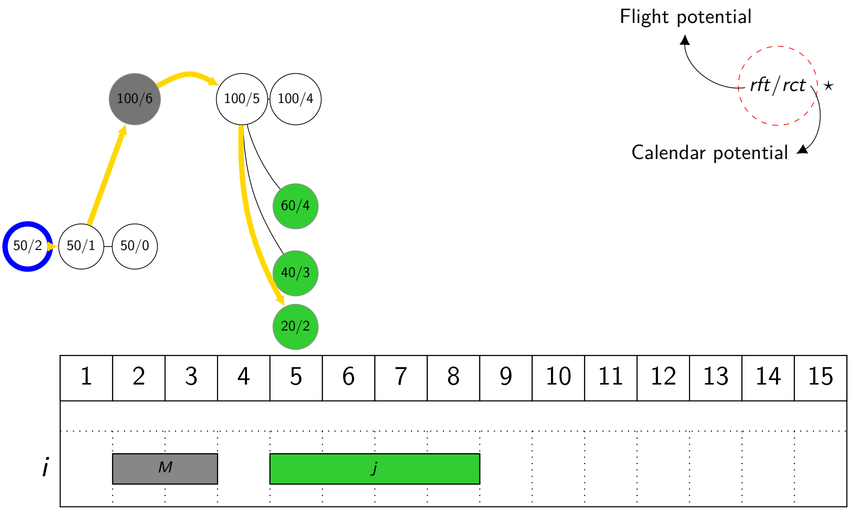

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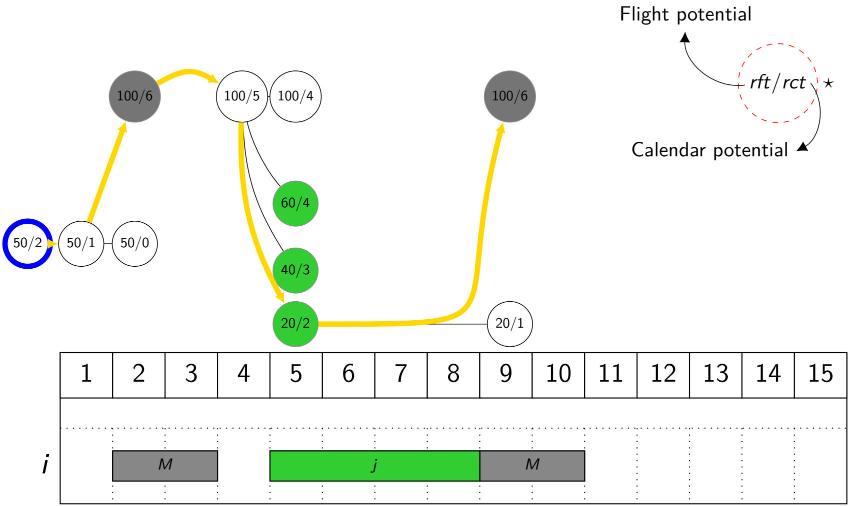

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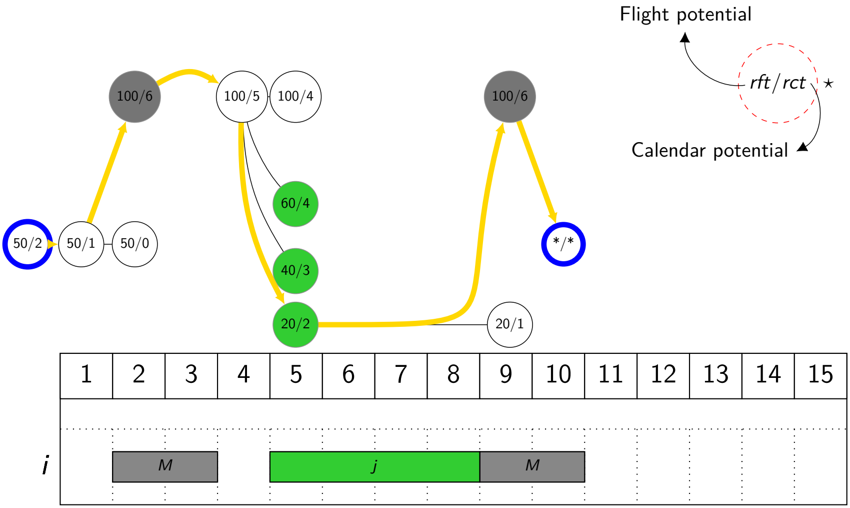

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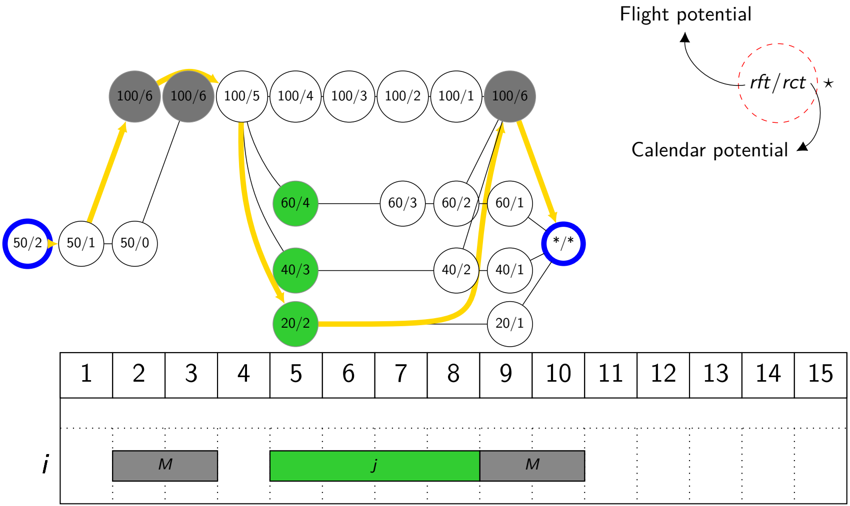
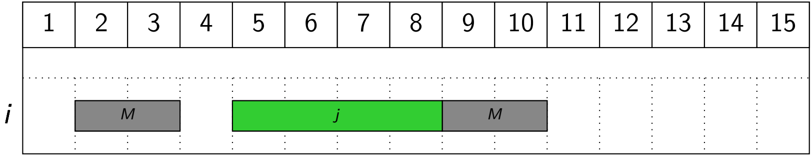


Pattern extraction



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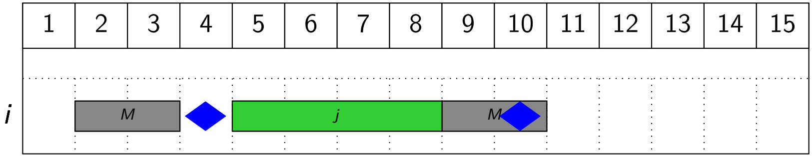

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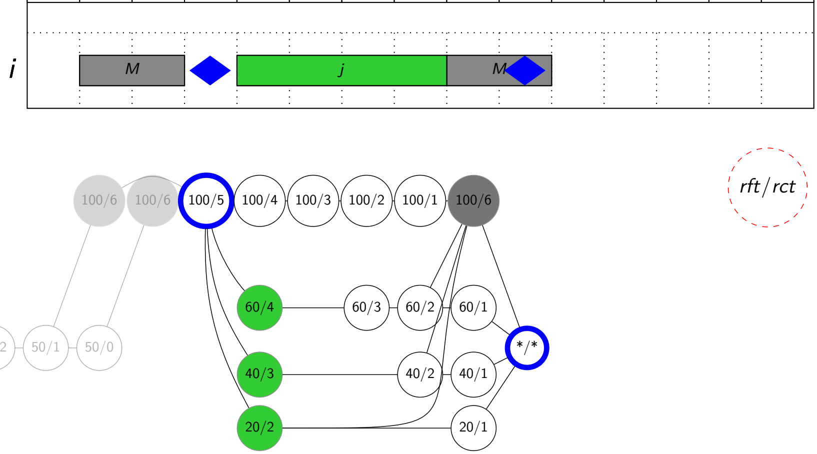

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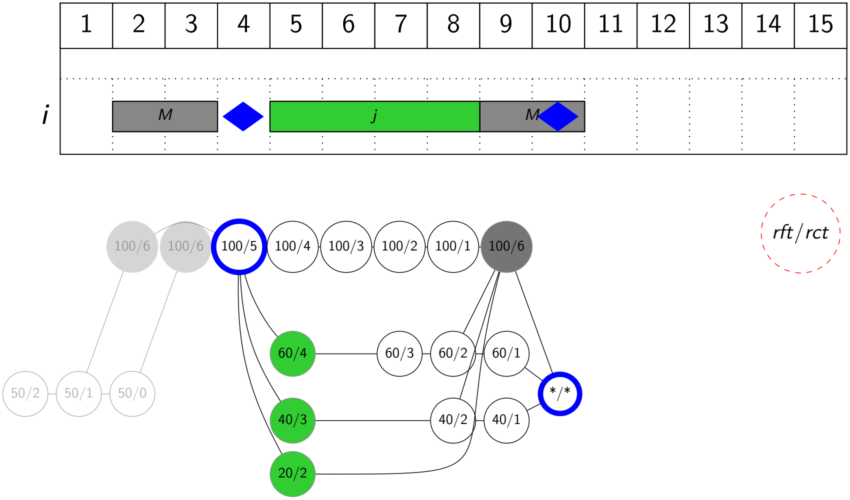

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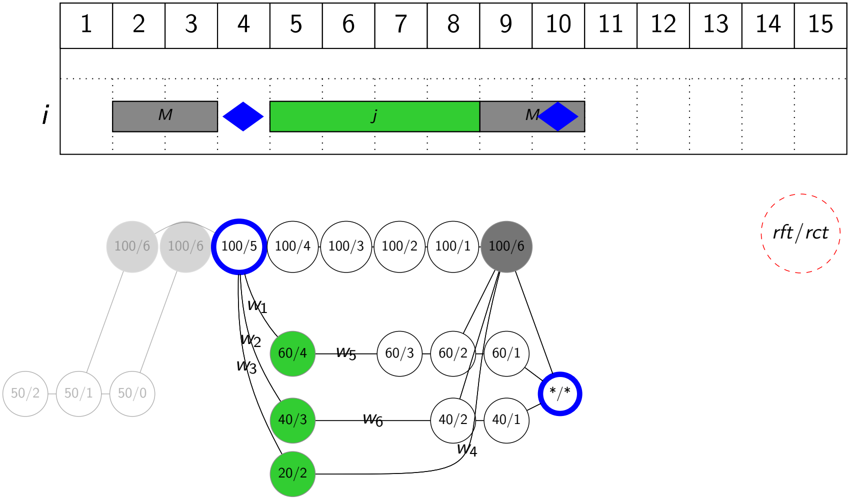

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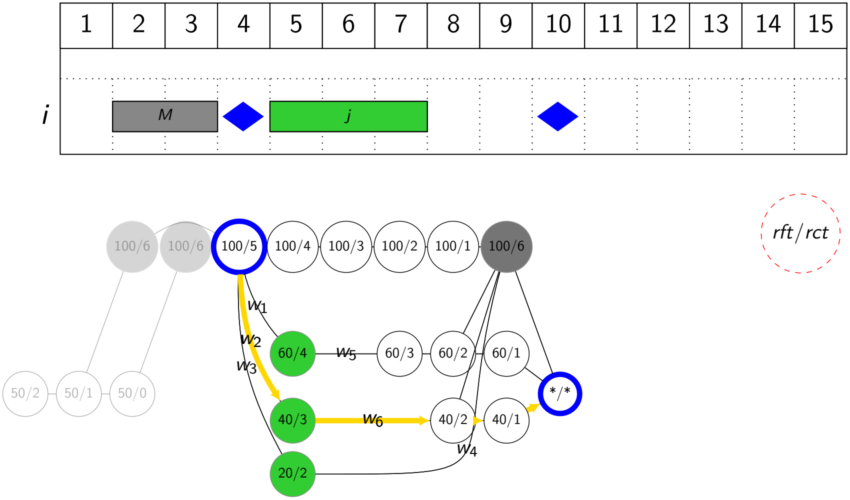

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Solution approach: Variable Neighborhod Descent

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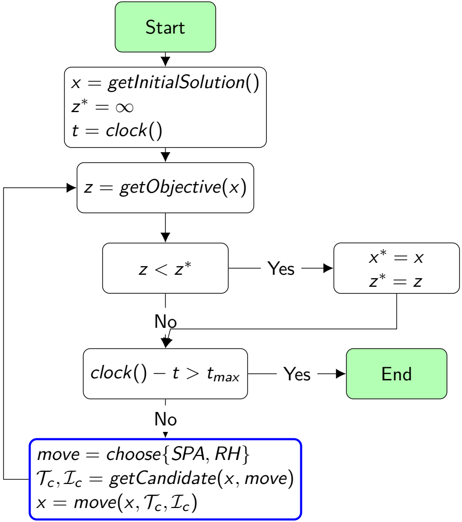

Neighborhood 1: Shortest Path Algorithm (SPA)

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SPA

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Neighborhood 2: Rolling Horizon (RH)

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- Simulated Annealing()

Experiments

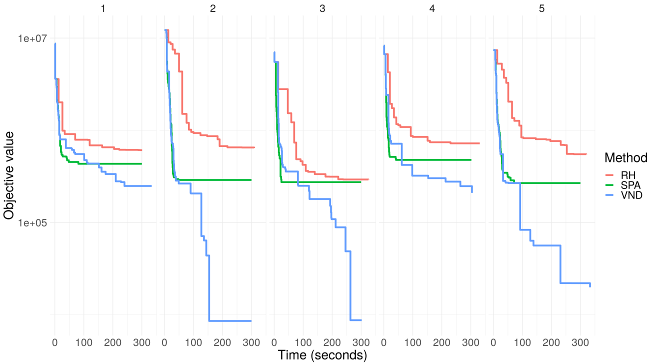
- Instance sizes: large ($|I|$=60), very large ($|I|$=100) and **very** large ($|I|$=255).
- 1 graph per cluster of aircraft and node aggregation with respect to remaining flight time.
- CPLEX running 1 thread for up to 20 minutes.

All instances have 90 periods.

Results: comparing neighborhoods

- SPA: fast but reaches local minima.
- RH: slow but avoids local minima.
- VND=SPA+RH: fast and avoids local minima.

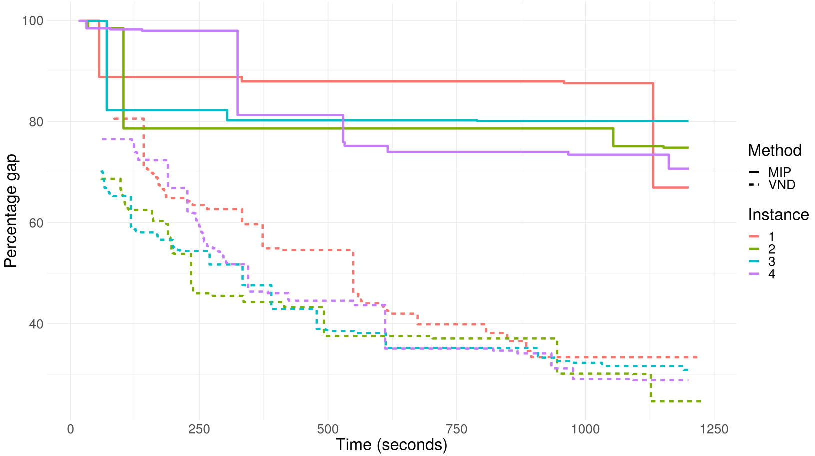
Example of one instance ($|I|$=60) solved 5 times with different random seeds, for 5 minutes.



Results: large instances

- VND outperforms MIP for very large instances (255 aircraft).

Example comparing the percentage gap to the best known lower bound.



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To be submitted: Franco Peschiera, Alain Haït, Nicolas Dupin, Olga Battaïa. Novel Graph-based matheuristic to solve the Flight and Maintenance Planning problem.

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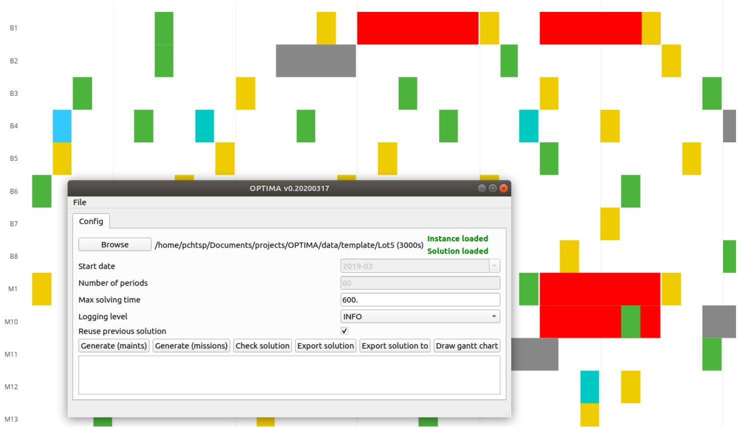
- **A functional desktop application** was developed, deployed and validated successfully by Dassault Aviation on real-life datasets.

Desktop application



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- **Integrate** novel techniques (ML and graph) inside known frameworks (Column Generation, GRASP).
- **Generalize ML methodology** to obtain a probability distribution for patterns, automatize feature extraction.
- **Combine ML and VND**, e.g., by applying learned-cuts during path-sampling to extract promising patterns.

Contributions

Journal articles

- F. Peschiera, R. Dell, J. Royset, A. Haït, N. Dupin, and O. Battaïa. A novel solution approach with ML-based pseudo-cuts for the Flight and Maintenance Planning problem. OR Spectrum, pages 1–30, jun 2020. ISSN 0171-6468. doi: 10.1007/s00291-020-00591-z.
- F. Peschiera, A. Haït, N. Dupin, and O. Battaïa. Long term planning of military aircraft flight and maintenance operations. Technical report, ISAE-SUPAERO, Université de Toulouse, France, 2020 (submitted).
- F. Peschiera, N. Dupin, A. Haït, and O. Battaïa. Novel graph-based matheuristic to solve the flight and maintenance planning problem. Forthcoming (to be submitted).

Conferences

- F. Peschiera, A. Haït, N. Dupin, and O. Battaïa. Maintenance planning on french military aircraft operations. In Congrès annuel de la société Française de Recherche Opérationnelle et d'Aide à la Décision (ROADEF), pages 1–2, Lorient, FR, 2018.
- F. Peschiera, O. Battaïa, A. Haït, and N. Dupin. Bi-objective mip formulation for the optimization of maintenance planning on french military aircraft operations. 2018.
- F. Peschiera, A. Haït, N. Dupin, and O. Battaïa. A novel mip formulation for the optimization problem of maintenance planning of military aircraft. In XIX Latin-Iberoamerican Conference on Operations Research, Lima, PE, 2018
- F. Peschiera, N. Dupin, O. Battaïa, and A. Haït. An alternative mip formulation for the military flight and maintenance planning problem. In Congrès annuel de la société Française de Recherche Opérationnelle et d'Aide à la Décision (ROADEF), Montpellier, FR, 2020.

Thank you for your attention.

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