

# Would you let HAL-320 be your captain today?


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ICAPS'22 Workshop on Reliable  
Data-Driven Planning and Scheduling



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**AIR**  
Airbus AI Research

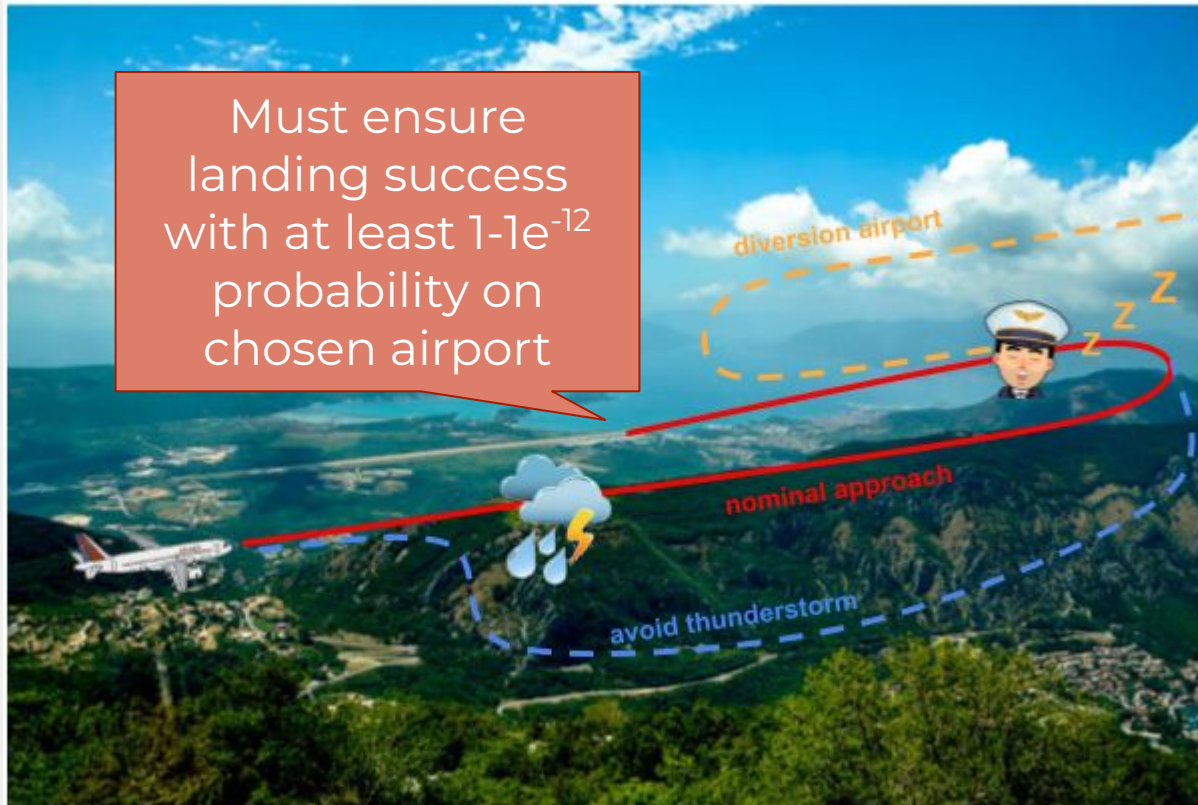


Dear passengers, welcome in 2059.  
I'm HAL-320, your new captain. John fell  
asleep, so I'm just taking over the commands  
to fly you back home.  
Keep calm and enjoy your flight!

Well... Keep calm, we're not still there 😊💧



# A typical use case: airport diversion strategy

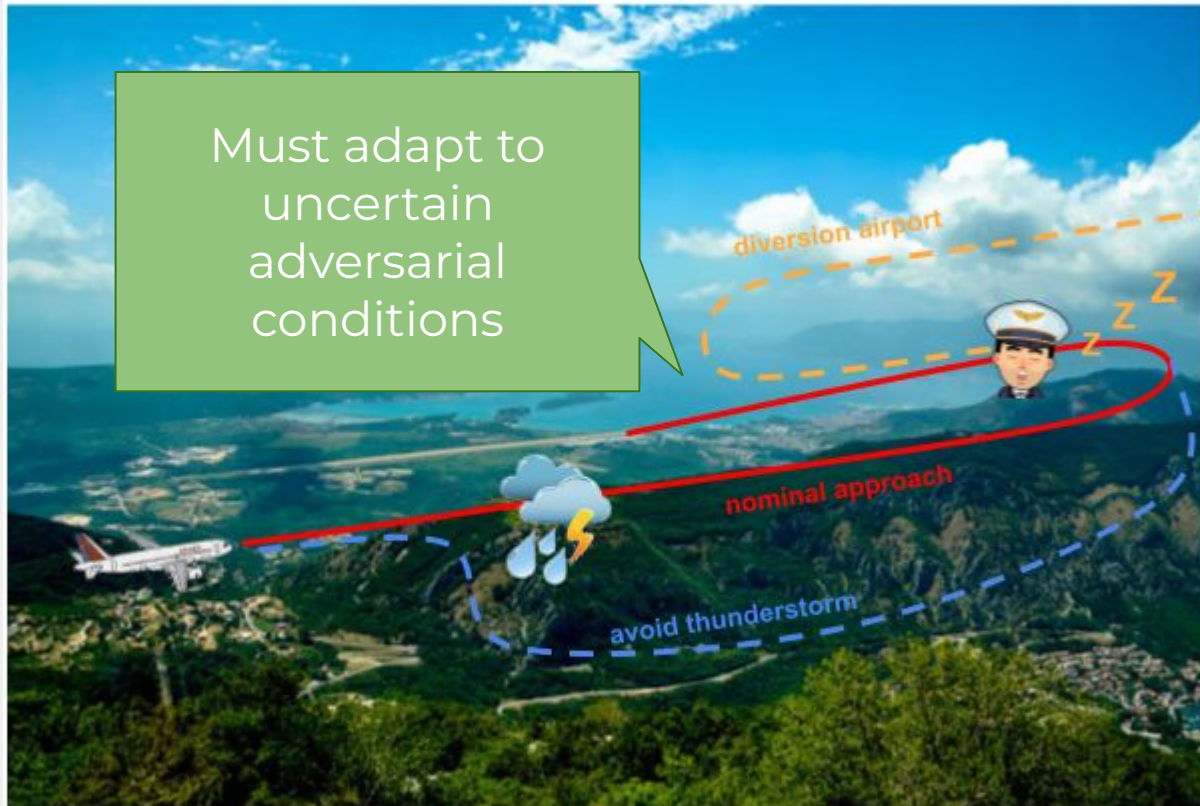


Autonomous system to take over the pilot as a last resort

Must ensure:

✈ Safety

# A typical use case: airport diversion strategy

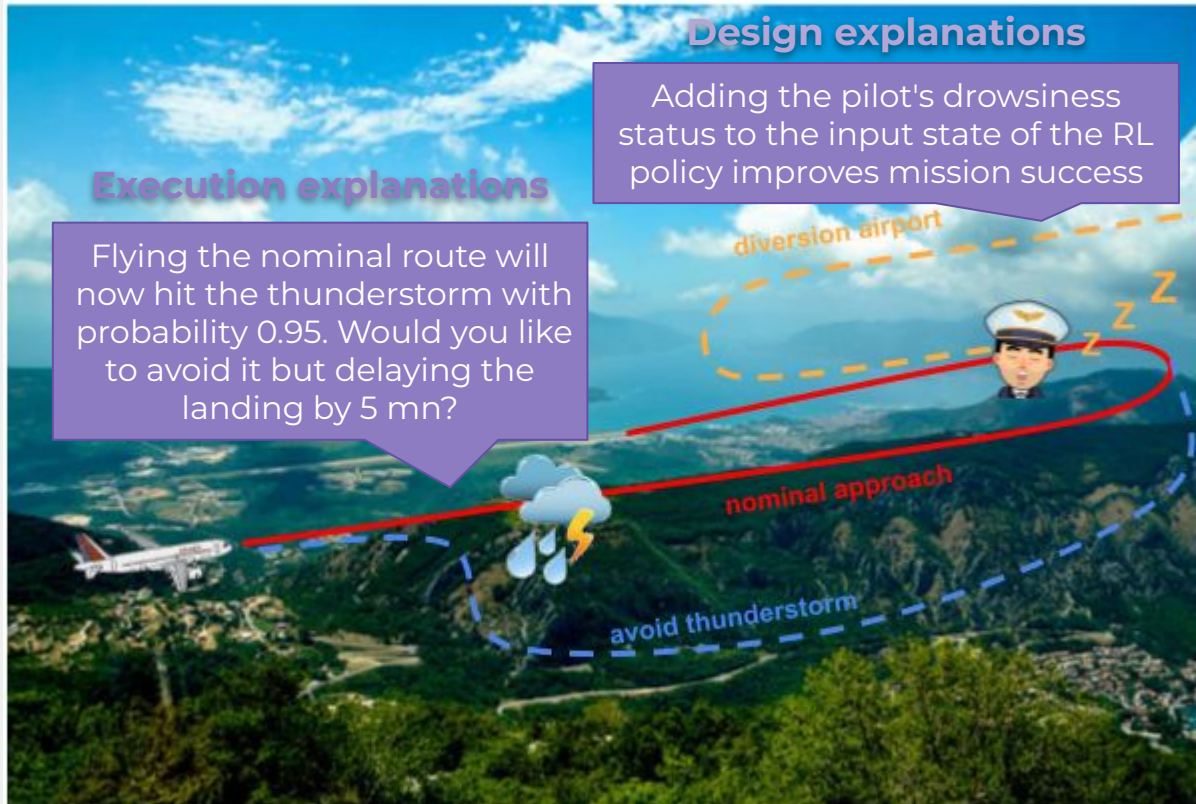


Autonomous system to take over the pilot as a last resort

Must ensure:

- ✈ Safety
- ✈ Robustness

# A typical use case: airport diversion strategy

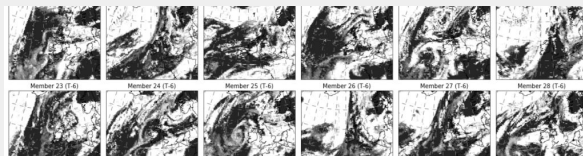


Autonomous system to take over the pilot as a last resort

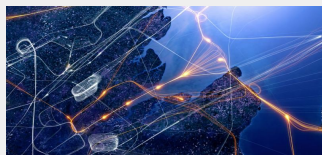
Must ensure:

- ✈ Safety
- ✈ Robustness
- ✈ Explainability

# Diversion management based on Probabilistic Flight Planning



Ensemble Weather Forecast



Traffic Data

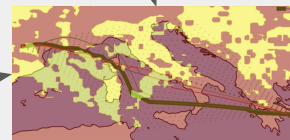


Other Events



Probabilistic Model of Events Impacting the Flight

Pre-Flight



**controlled risk of violating safety constraints**

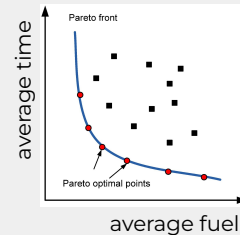


Continuous update (dynamic mode)

In-Flight



Live observations



- Dynamic Flight Plan:**
- Event-based trajectory
  - Proactively modifies the trajectory to mitigate upcoming risks

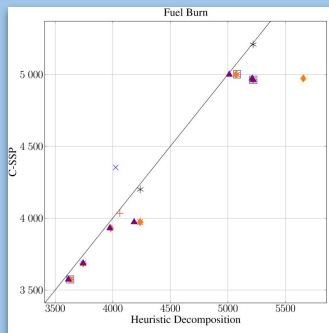
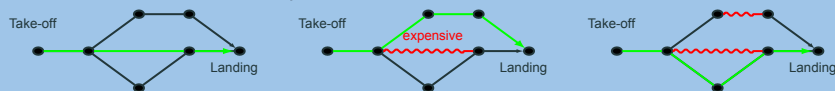
# DONUT project: benchmarking of two complementary flight planning algorithms

## CSSP - Constrained Stochastic Shortest Path

*Optimal and Heuristic Approaches for Constrained Flight Planning under Weather Uncertainty.* F. Geißer, G. Povéda, F. Trevizan, M. Bondouy, F. Teichteil-Königsbuch, S. Thiébaux. ICAPS 2020

Iterative algorithm based on **LP** and **column generation**

**No use of heuristics** due to simulation-based aircraft performance model

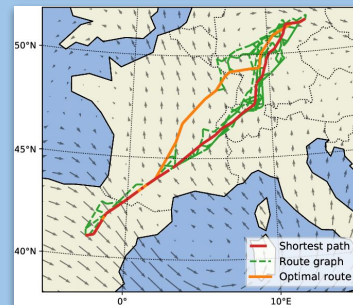
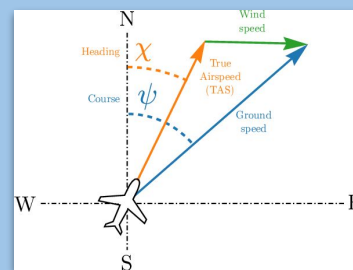


- + Satisfy constraints by construction
- + Robust by construction
- + Handle waypoint graph

- Computationally expensive
- Simplified weather and transition model
- Cannot handle continuous variables

## Parallel Robust Optimal Control

*Probabilistic 4D Flight Planning in Structured Airspaces through Parallelized Simulation on GPUs.* D. Arribas, E. Andrés-Enderiz, M. Soler, A. Jardines, J. García-Heras. Computer Science, 2020



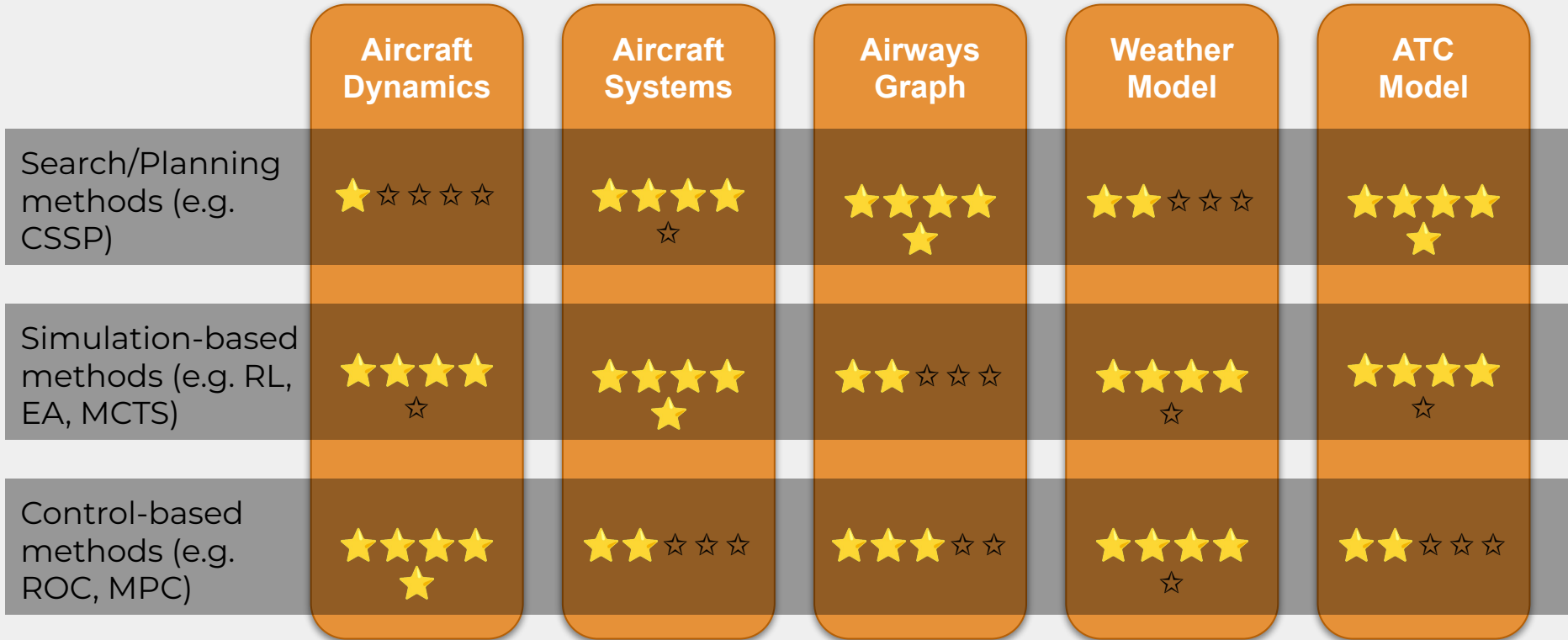
Uses **Augmented Random Search** and **Optimal Control** to produce waypoint-constrained continuous trajectories evaluated on a set of **probabilistic weather scenarios**

- + Use continuous aircraft performance model
- + Robust by construction

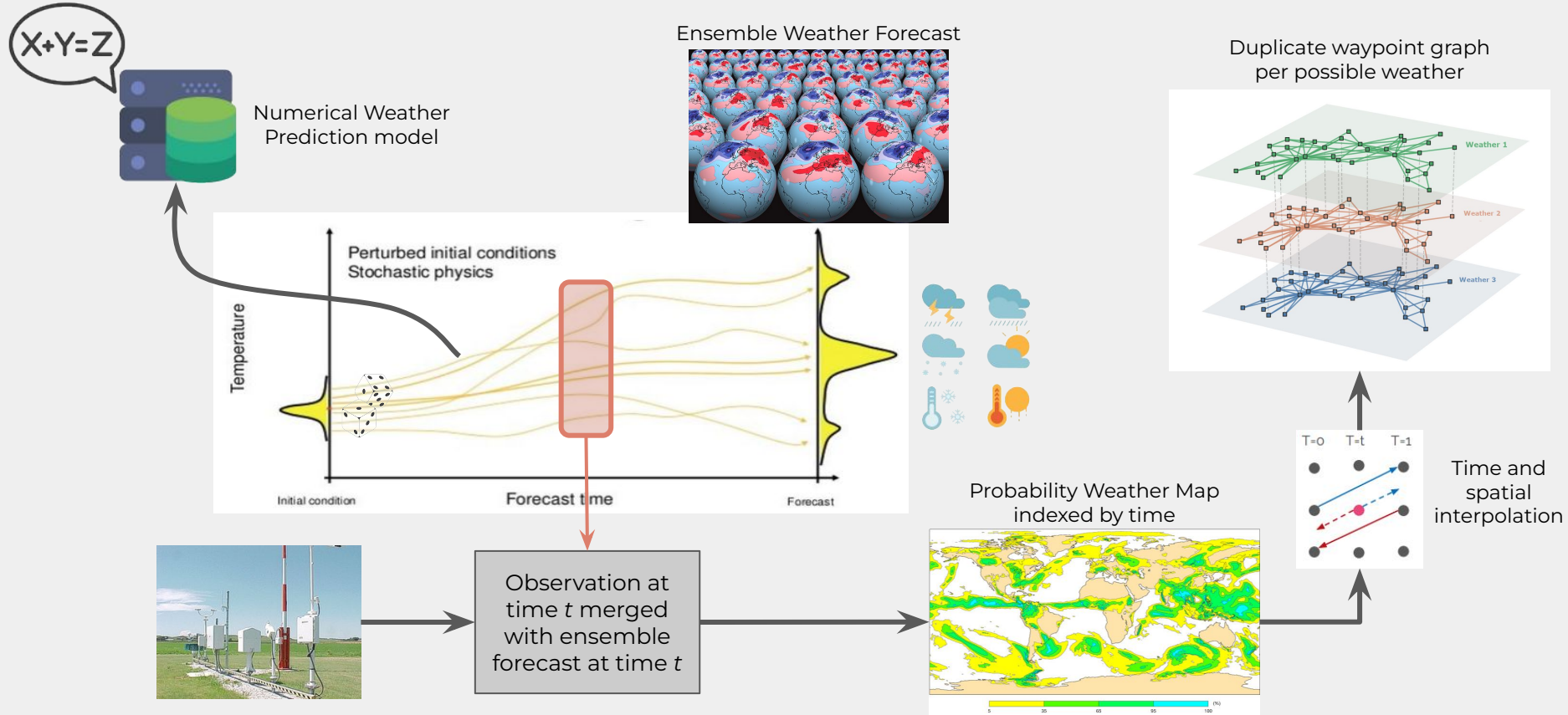
- Not optimal
- A posteriori projection on discrete waypoints



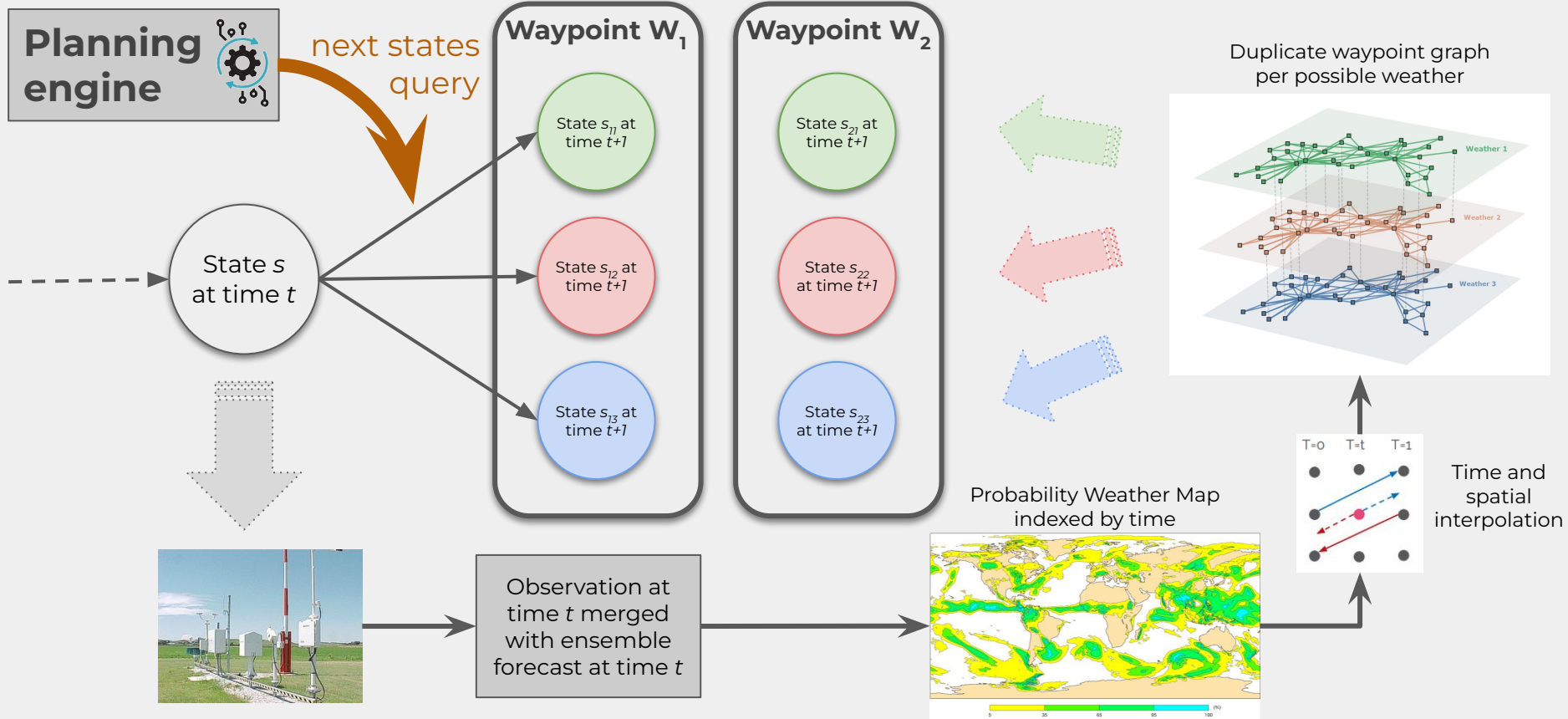
# No approach ruling all the others out

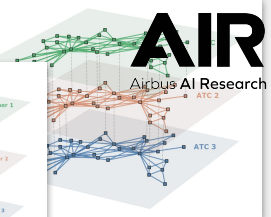


# A complex probabilistic weather model

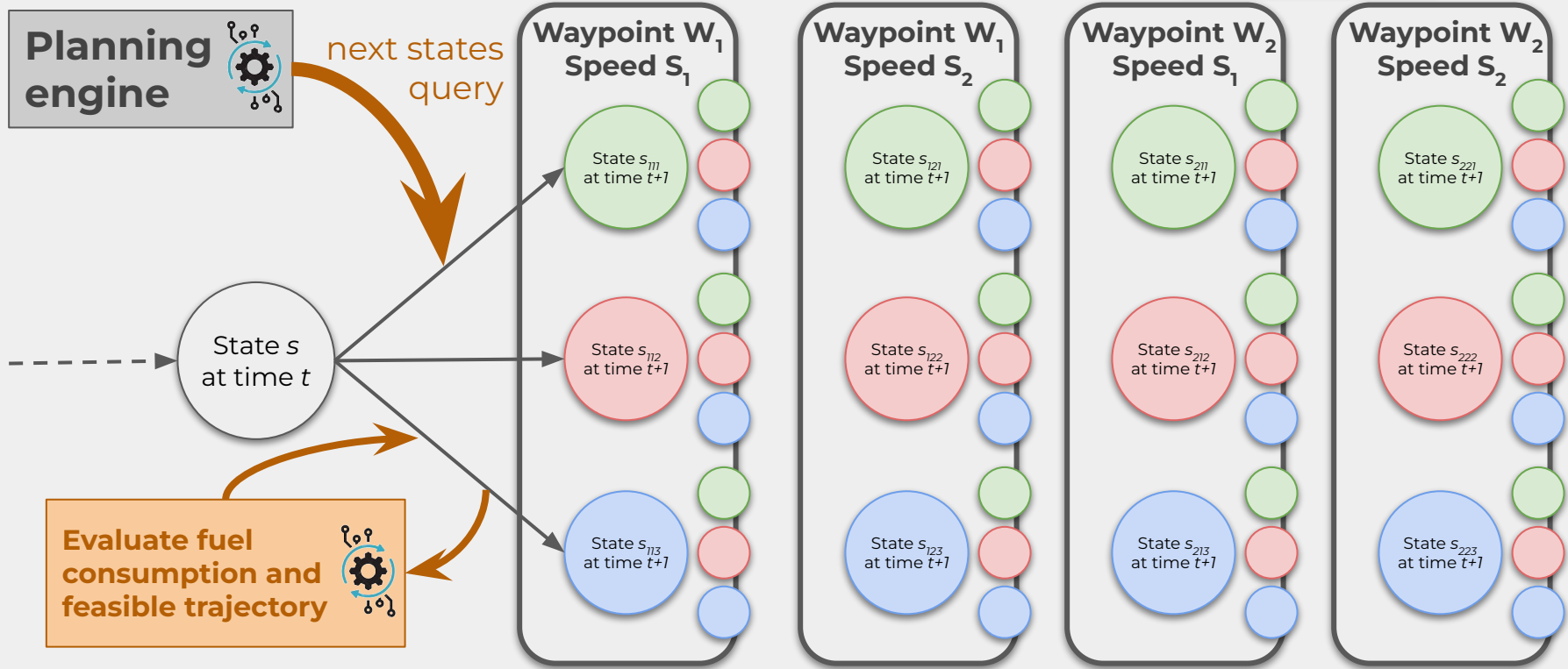


# A complex probabilistic weather model





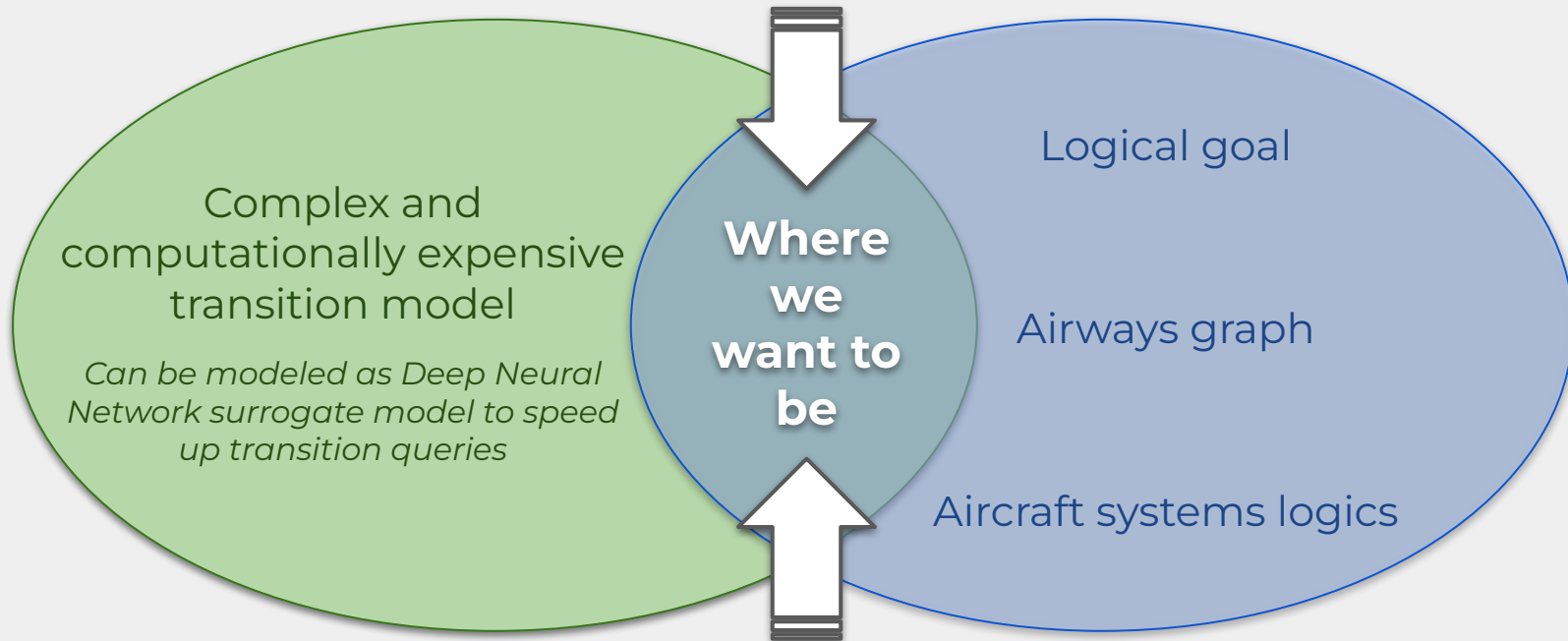
# The full transition model story



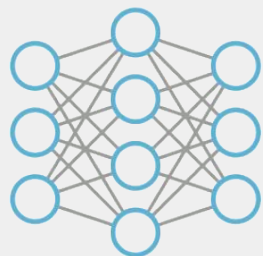
# No free lunch: need for hybrid planning method

## Simulation-based methods

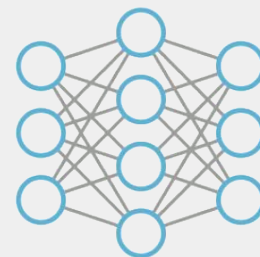
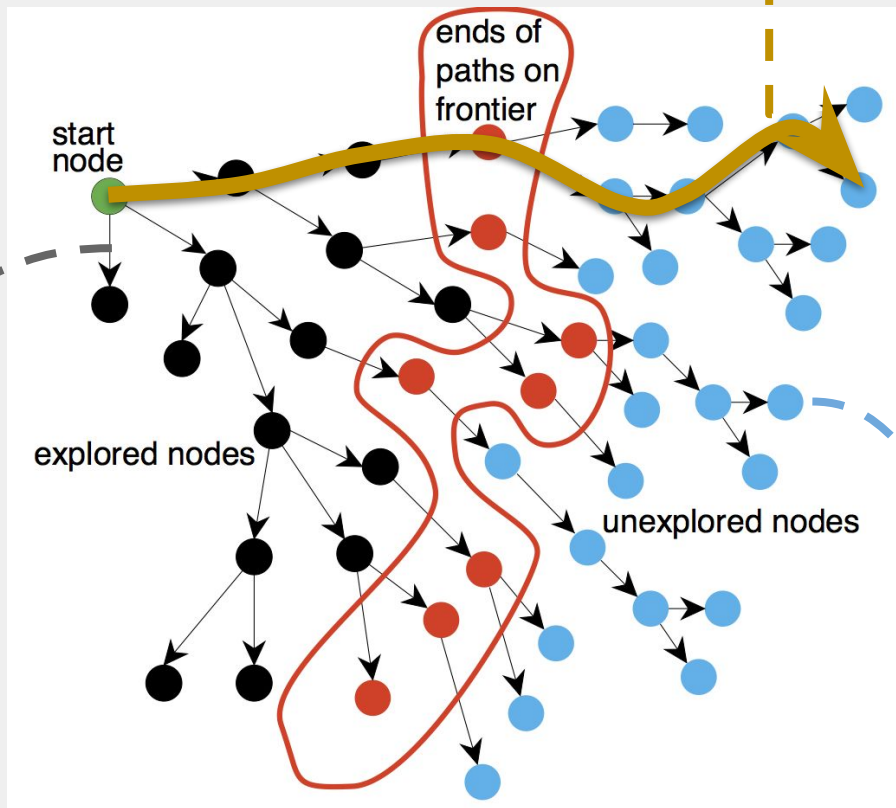
## Search-based methods



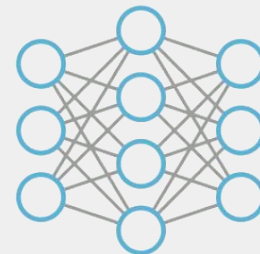
# Possible hybridizations of deep learning with a typical search algorithm



Surrogate model of transitions  
*(aircraft performance evaluation, weather & ATC prediction)*



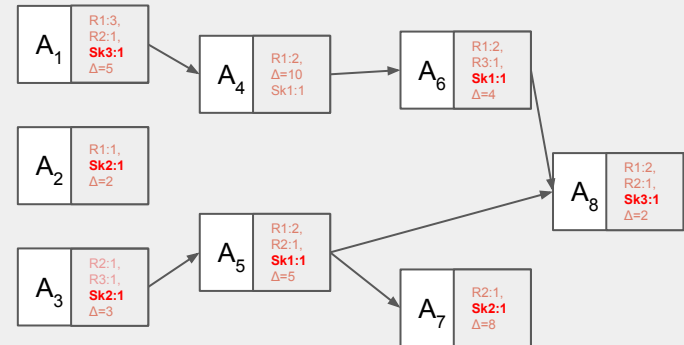
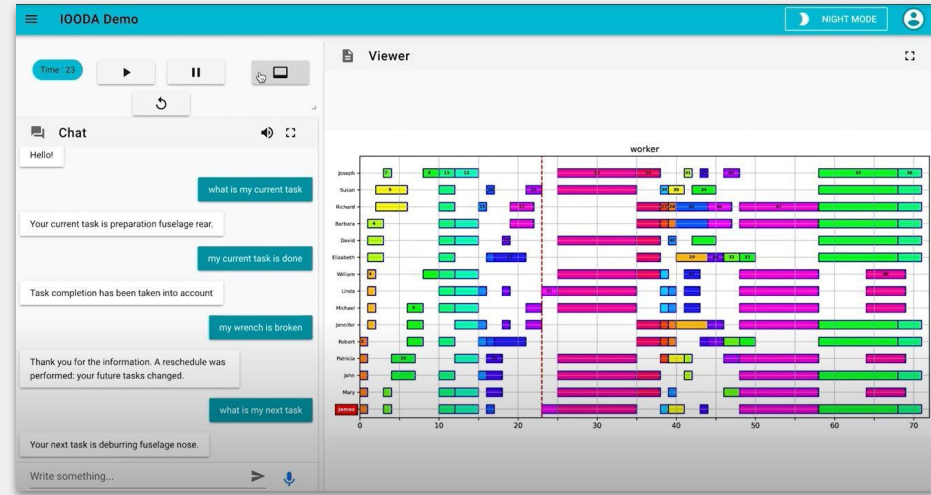
Surrogate model of the solver



Heuristic function  
*(learned from previous solved instances of the search problem)*

# Another example of hybridization: stochastic manufacturing task scheduling

Stochastic Multi-Skill Multi-Mode Resource  
Constrained Project Scheduling Problem with  
Time-Constrained Precedence Constraints



# Solving extended RCPSPs with Large Neighborhood Search

## Large Neighborhood Search

- Result Storage :  $results = []$   
- RCPSP Problem :  $problem$   
- Number of iterations  $iteration_{les}$

Init master problem :  
 $MP(problem)$   
-  $i = 0$

Compute initial solution :  
 $results = [greedy(problem)]$

$i > iteration_{les}$

Yes

Return results

No

$RMP \leftarrow add_{constraints}(MP(problem), results)$

$results_i = solve(RMP)$

$results_i = postprocess(results_i)$

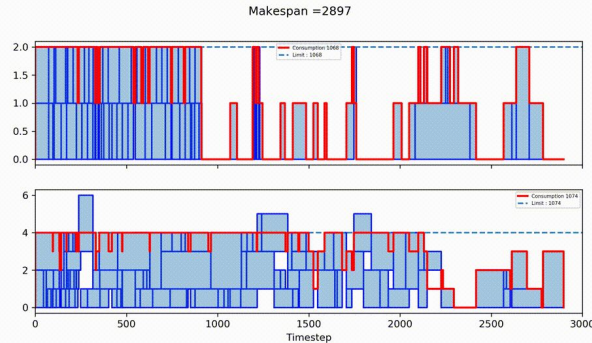
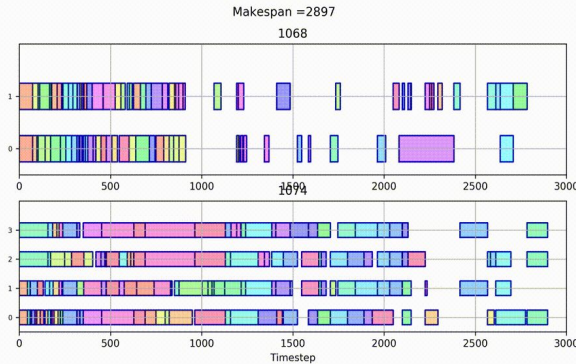
$results = results + results_i$   
 $i = i + 1$



Scales to large industrial problems (thousands of multi-mode tasks with multi-skilled workers and temporal precedence constraints)

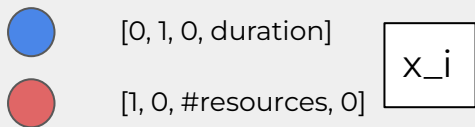
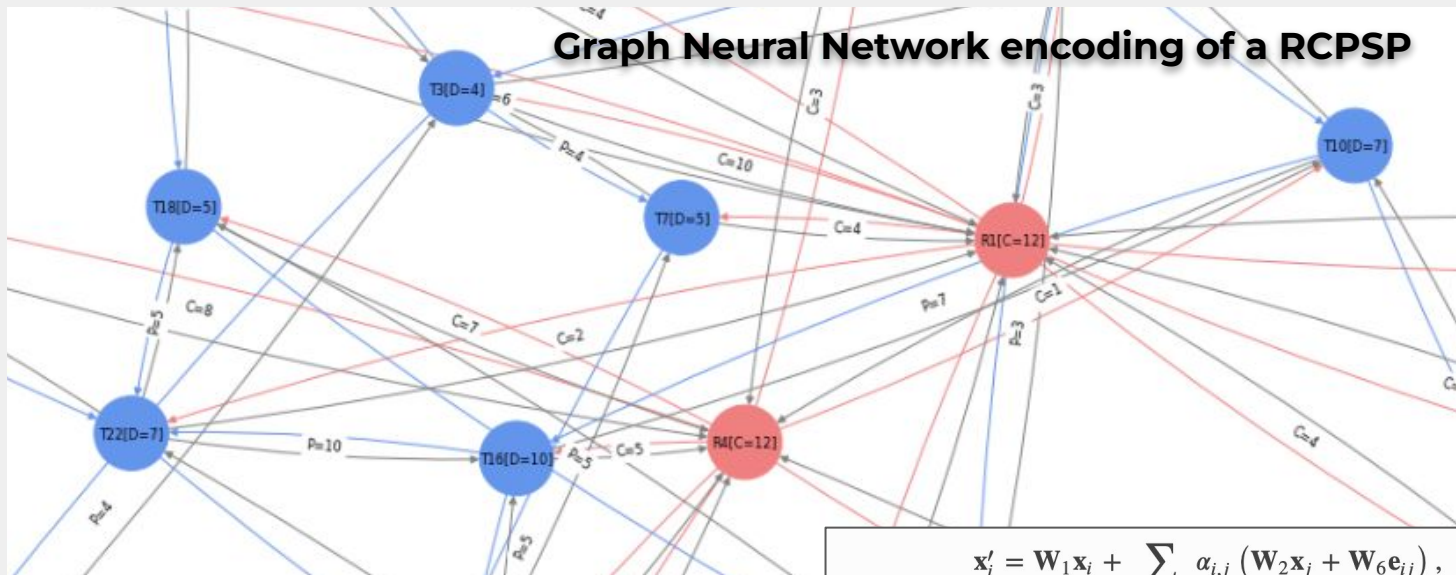


But does not handle uncertainty





# Towards uncertainty and adaptivity handling with Graph Neural Networks

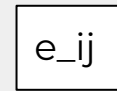


Currently using [TransformerConv](#) as NN layers:

$$\mathbf{x}'_i = \mathbf{W}_1 \mathbf{x}_i + \sum_{j \in \mathcal{N}(i)} \alpha_{i,j} (\mathbf{W}_2 \mathbf{x}_j + \mathbf{W}_6 \mathbf{e}_{ij}),$$

where the attention coefficients  $\alpha_{i,j}$  are now computed via:

$$\alpha_{i,j} = \text{softmax} \left( \frac{(\mathbf{W}_3 \mathbf{x}_i)^\top (\mathbf{W}_4 \mathbf{x}_j + \mathbf{W}_6 \mathbf{e}_{ij})}{\sqrt{d}} \right)$$



precedence  
[0, 1, 0, 0, 0]



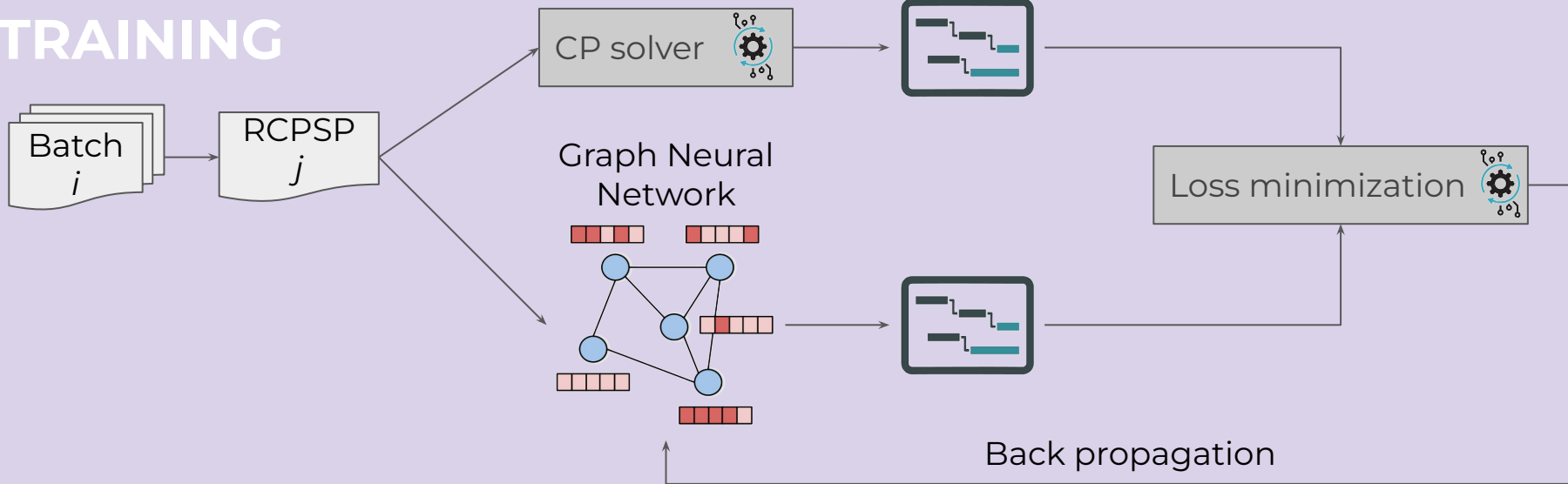
resource  
[1, 0, 0, 0, #consumed]



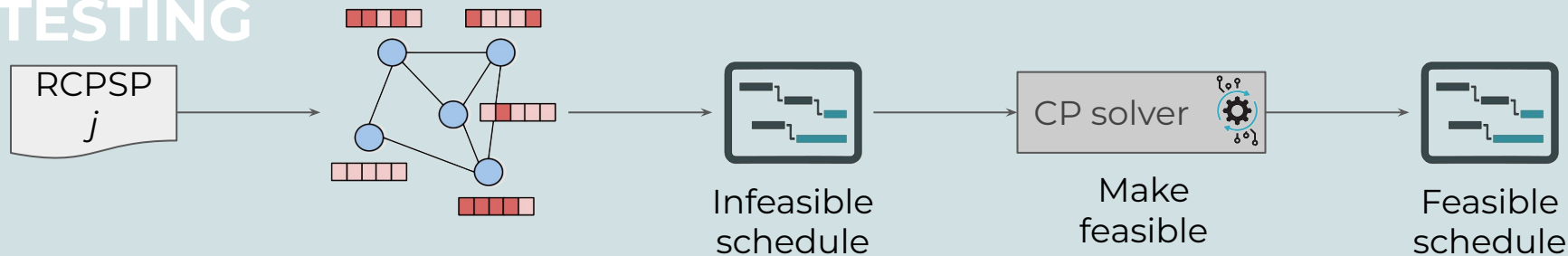
reverse link  
(to propagate information in both ways)  
pre.: [0, 0, 0, 1, 0]  
res.: [0, 0, 1, 0, #consumed]

# Hybridizing CP+GNN (supervised learning from CP solution examples)

## TRAINING

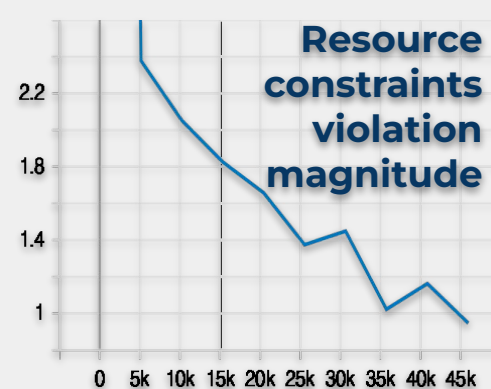
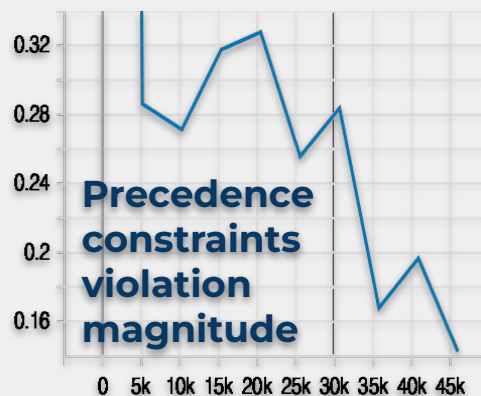
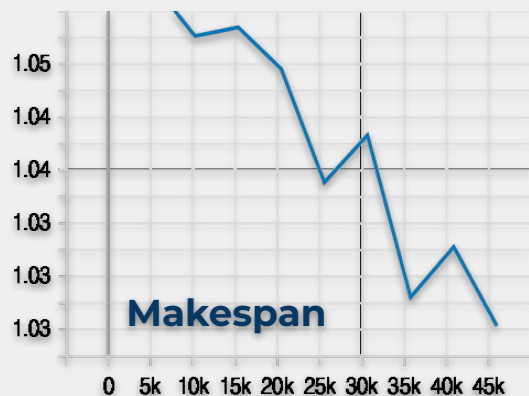
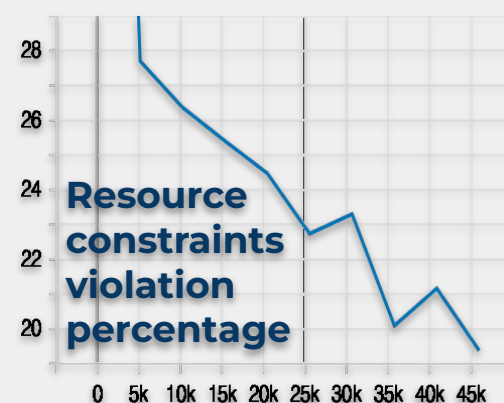
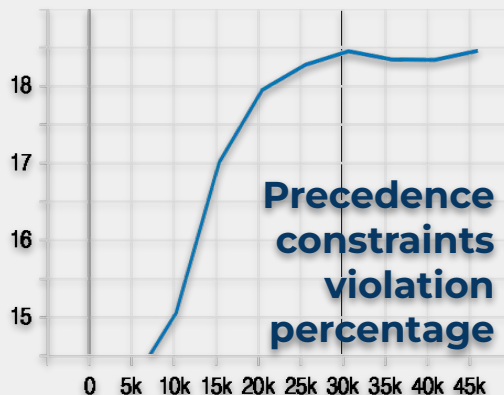
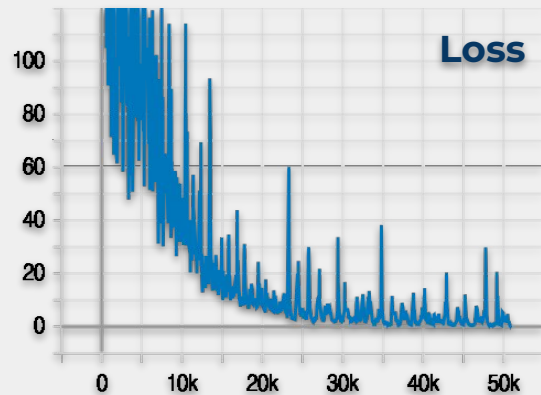


## TESTING



# CP + GNN : *training* statistics

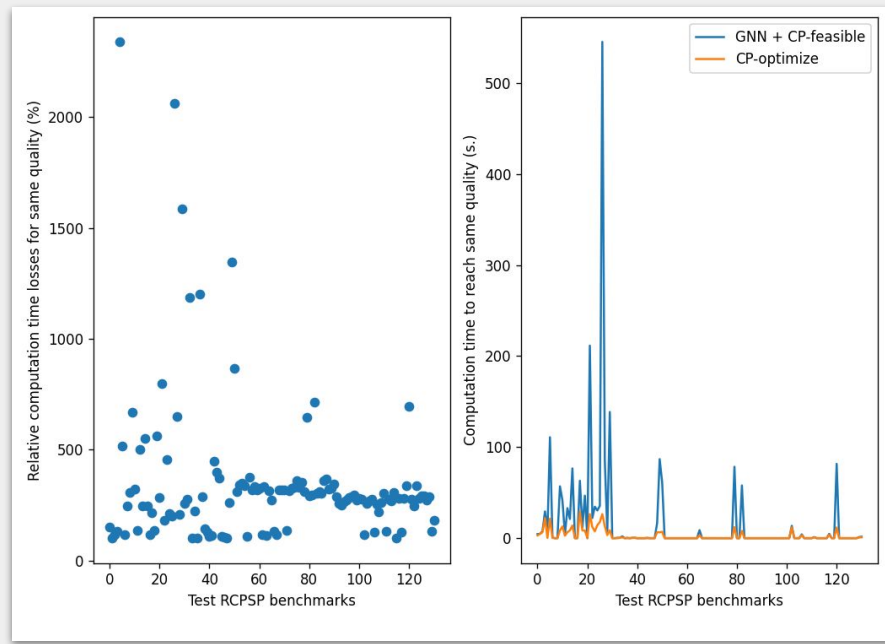
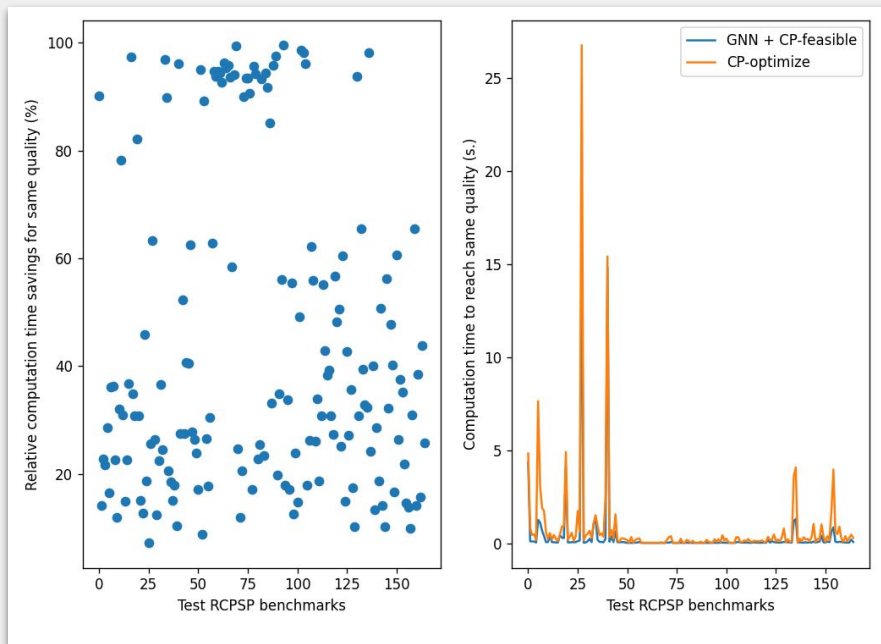
(80% of 2040 RCPSP instances)



# CP + GNN : *testing statistics*

(20% of 2040 RCPSP instances)

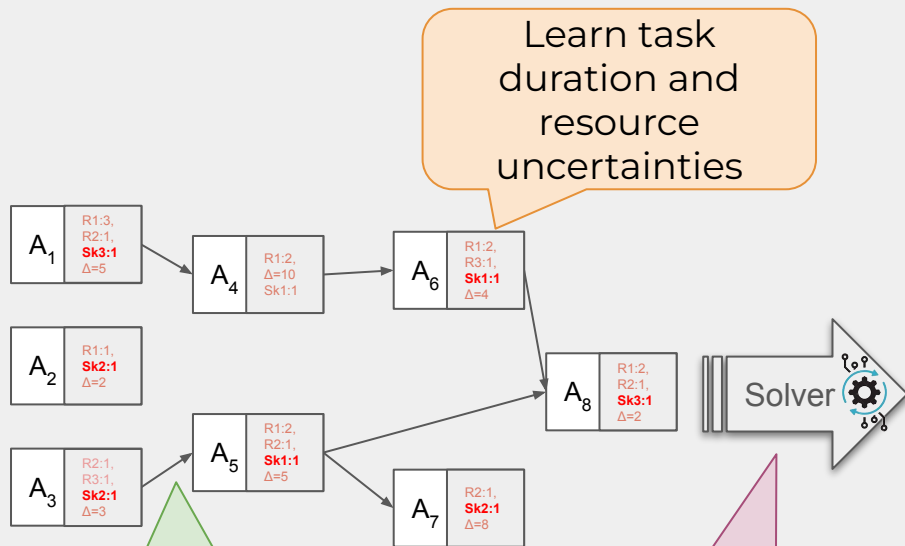
Protocol: evaluate vanilla CP solver time to get same quality solution as GNN+CP solver, then compare with GNN+CP solver time  $\Rightarrow$  **Does warm-starting CP with GNN solution help?**



👍 Benchmarks where warm-starting the CP solver with the GNN inferred solution **helps**

👎 Benchmarks where warm-starting the CP solver with the GNN inferred solution **harms**

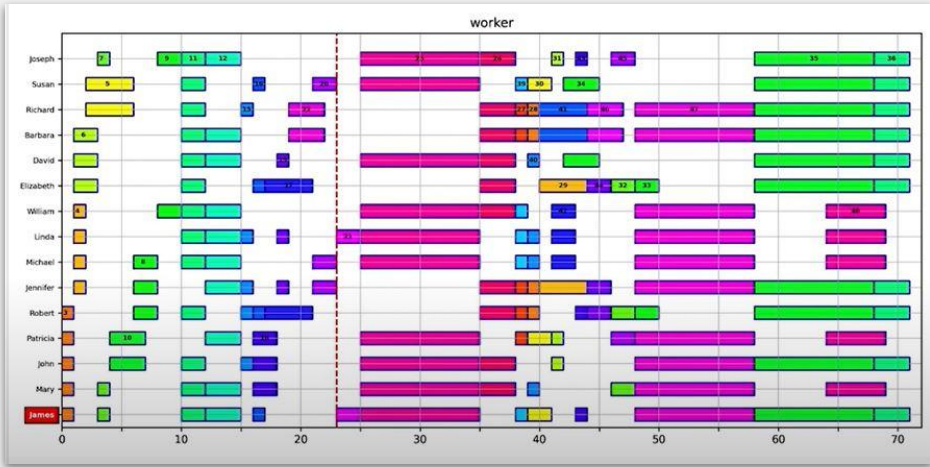
# Possible hybridizations of deep learning with a Constraint Programming solver



Learn task duration and resource uncertainties

Learn constraints from example schedules

Learn surrogate model of the CP solver and warm-start it with the inferred solution



Learn human schedules to warm-start the CP solver

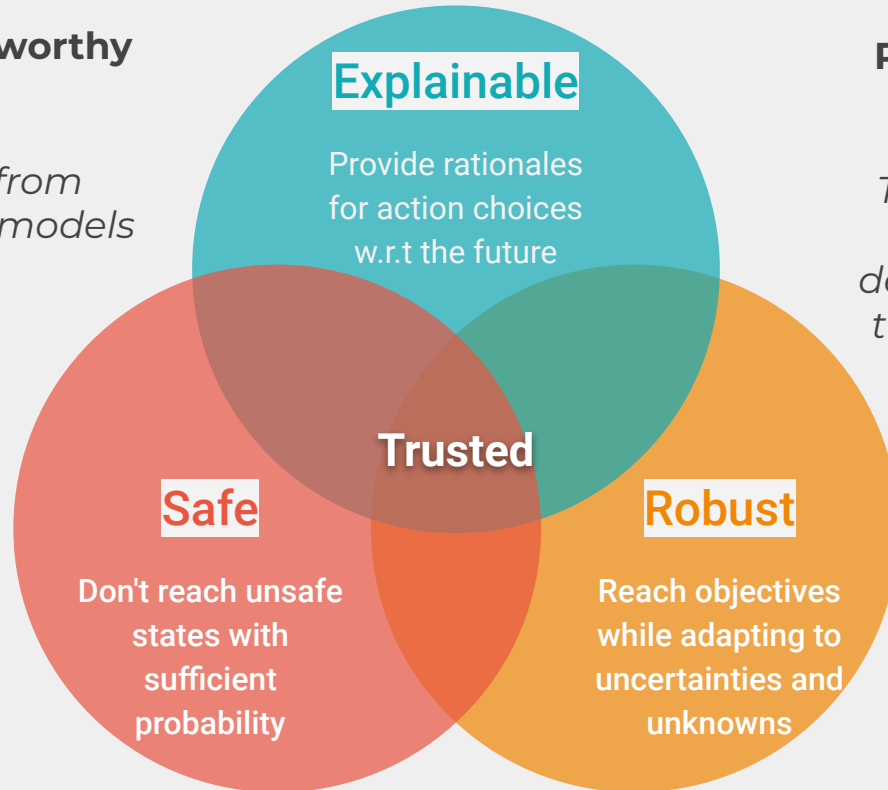
# Trustable decision-making systems

**Different from trustworthy deep learning:**

*valid independently from using deep learning models in decision-making*

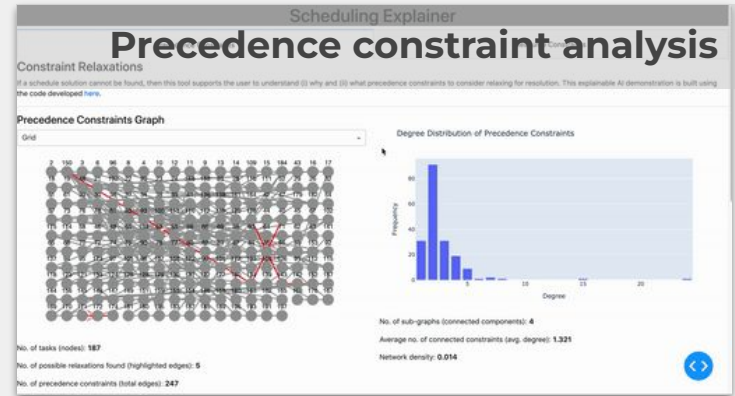
**Relying on deep learning adds to the complexity:**

*Trustworthy properties for deep learning-based decision-making rest upon trustworthy deep learning properties*



# Explaining manufacturing schedules

- ✓ Precedence constraints analysis
- ✓ Resource needs analysis
- ✓ Feature importance analysis of embedded deep learning models
  
- ✗ Runtime task choice explanation



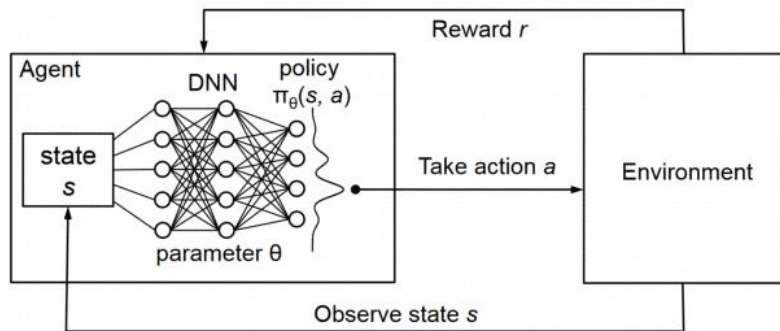




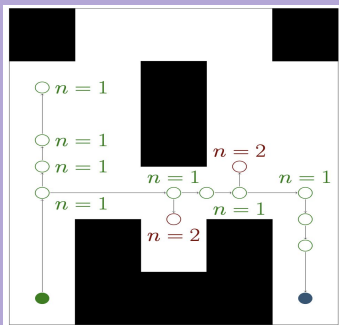
# Robustness: adapt to uncertainties

(and you can't go without a simulator)

## Option 1 : Reinforcement Learning



## Option 2 : Width-Based Planning



**x values:**

$$\frac{ID}{0} \quad ID=1 \quad \frac{IDID}{2} \quad \frac{IDID}{3} \quad ID=4$$

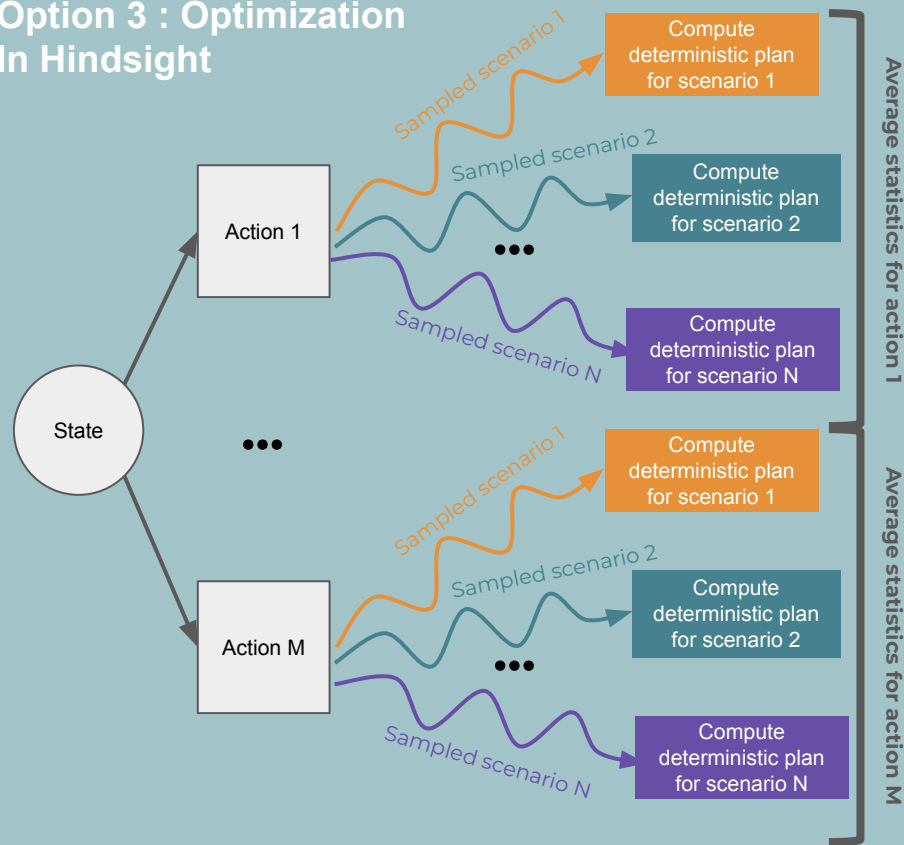
0.5      2.5   3   3.5   4.5

**y values:**

$$\frac{ID}{0} \quad ID=1 \quad \frac{IDID}{2} \quad \frac{IDID}{3} \quad ID=4$$

0.5      2   2.5   3   3.5   4.5

## Option 3 : Optimization In Hindsight

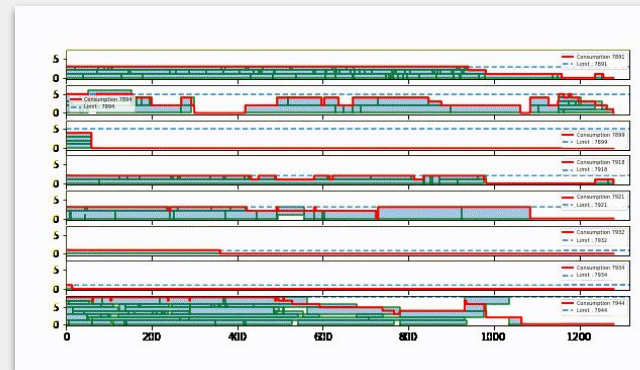
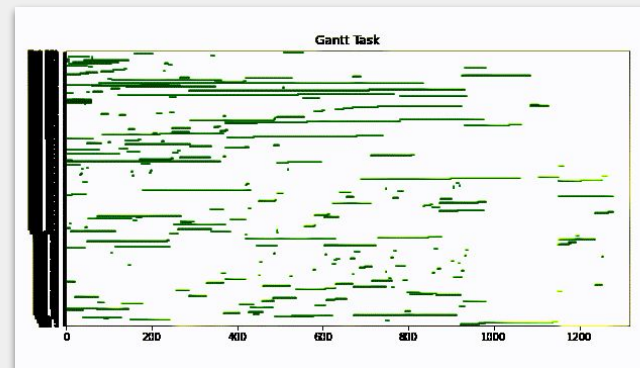


# Robustness: optimization in hindsight showcase

Flight planning under uncertain convective areas

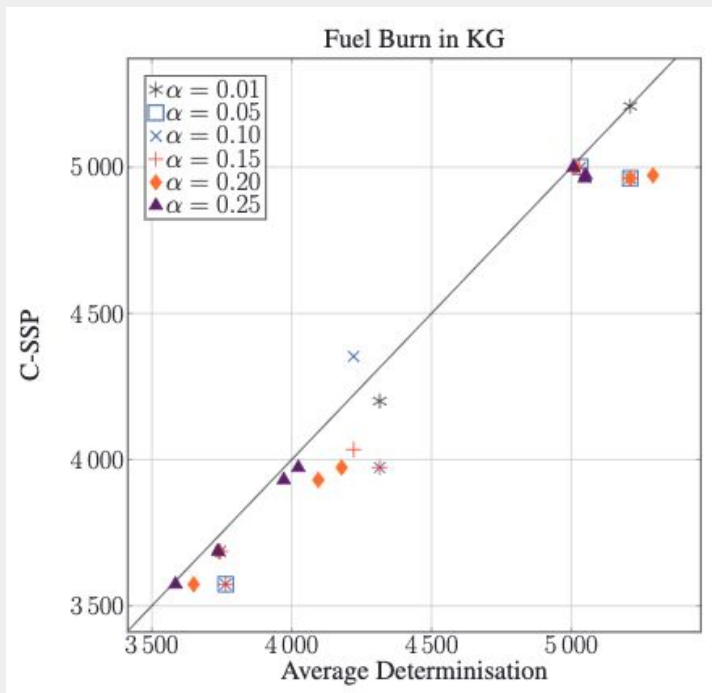


Manufacturing scheduling under uncertain task durations



# Safety: HAL-320, don't crash the plane!

Example: maximum flight time in convective area



$$\begin{aligned} \min_{\vec{p}} \quad & \sum_{p_\pi} E[C_0|\pi]p_\pi && \text{(LP1)} \\ \text{s.t.} \quad & p_\pi \geq 0 && \forall \pi \in \Pi_{det} \text{ (C1)} \\ & \sum_{\pi} p_\pi = 1 && \text{(C2)} \\ & \sum_{p_\pi} E[C_i|\pi]p_\pi \leq u_i \quad \forall i \in \{1, \dots, k\} && \text{(C3)} \end{aligned}$$



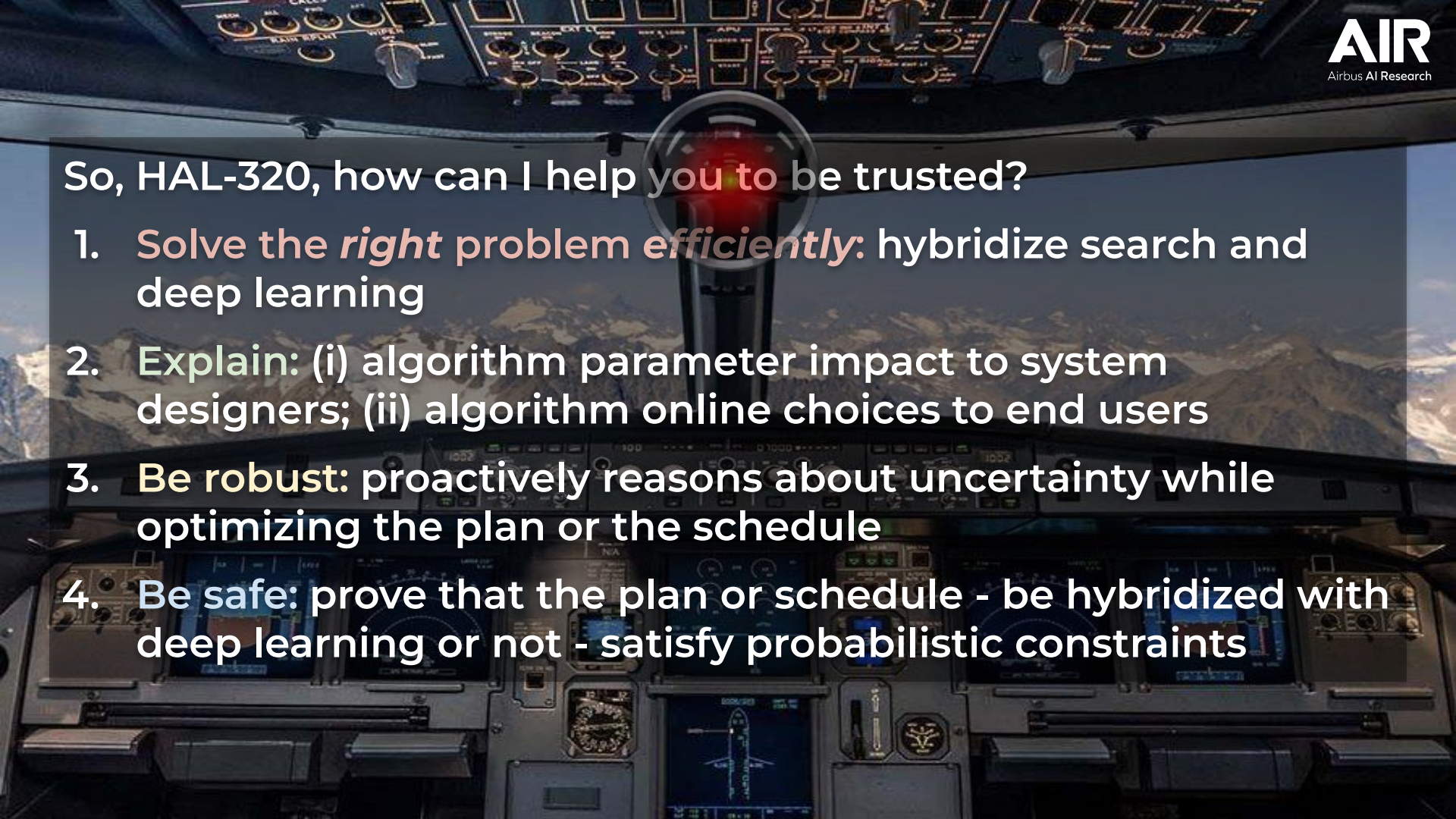
Perfectly deals with flight time constraints that can be modeled in the LP



Unable to capture fuel constraints because aircraft performance model is based on simulation engines

**Optimal and Heuristic Approaches for Constrained Flight Planning under Weather Uncertainty**  
F. Geißer, G. Pováda, F. Trevizan, M. Bondouy, F. Teichteil-Königsbuch, S. Thiébaux. ICAPS 2020

How to solve C-SSPs with simulation-based transitions? With deep-learning surrogate models?



So, HAL-320, how can I help **you** to be trusted?

1. **Solve the *right* problem *efficiently*:** hybridize search and deep learning
2. **Explain:** (i) algorithm parameter impact to system designers; (ii) algorithm online choices to end users
3. **Be robust:** proactively reasons about uncertainty while optimizing the plan or the schedule
4. **Be safe:** prove that the plan or schedule - be hybridized with deep learning or not - satisfy probabilistic constraints

# Acknowledgements



Manon  
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poveda



Charles  
Gretton



Felipe  
Trevizan



Sylvie  
Thi baux



Florian  
Geisser



Daniel  
Gonzalez-Arribas



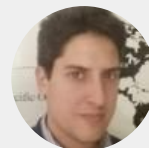
Javier  
Garcia Heras

# AIR

Airbus AI Research



Guillermo  
Gonzalez de  
Garibay



Santiago  
Quintana-Amate



Aniel  
Jardines



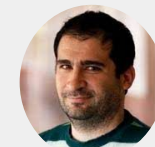
Mark  
Hall



Nahum  
Alvarez



Olivier  
R gnier-Coudert



Manuel  
Soler Arnedo



Eduardo  
Andr s Enderiz

