COMBINING AI & OR FOR LARGE-SCALE AIRLINE RECOVERY PROBLEMS

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AGENDA

8’ INTRODUCTION & GENERAL FRAMEWORK

12’ CREW RECOVERY w. AIRCRAFT & PASSENGER CONSIDERATIONS

12’ INTEGRATED AIRCRAFT, CREW AND PASSENGER RECOVERY

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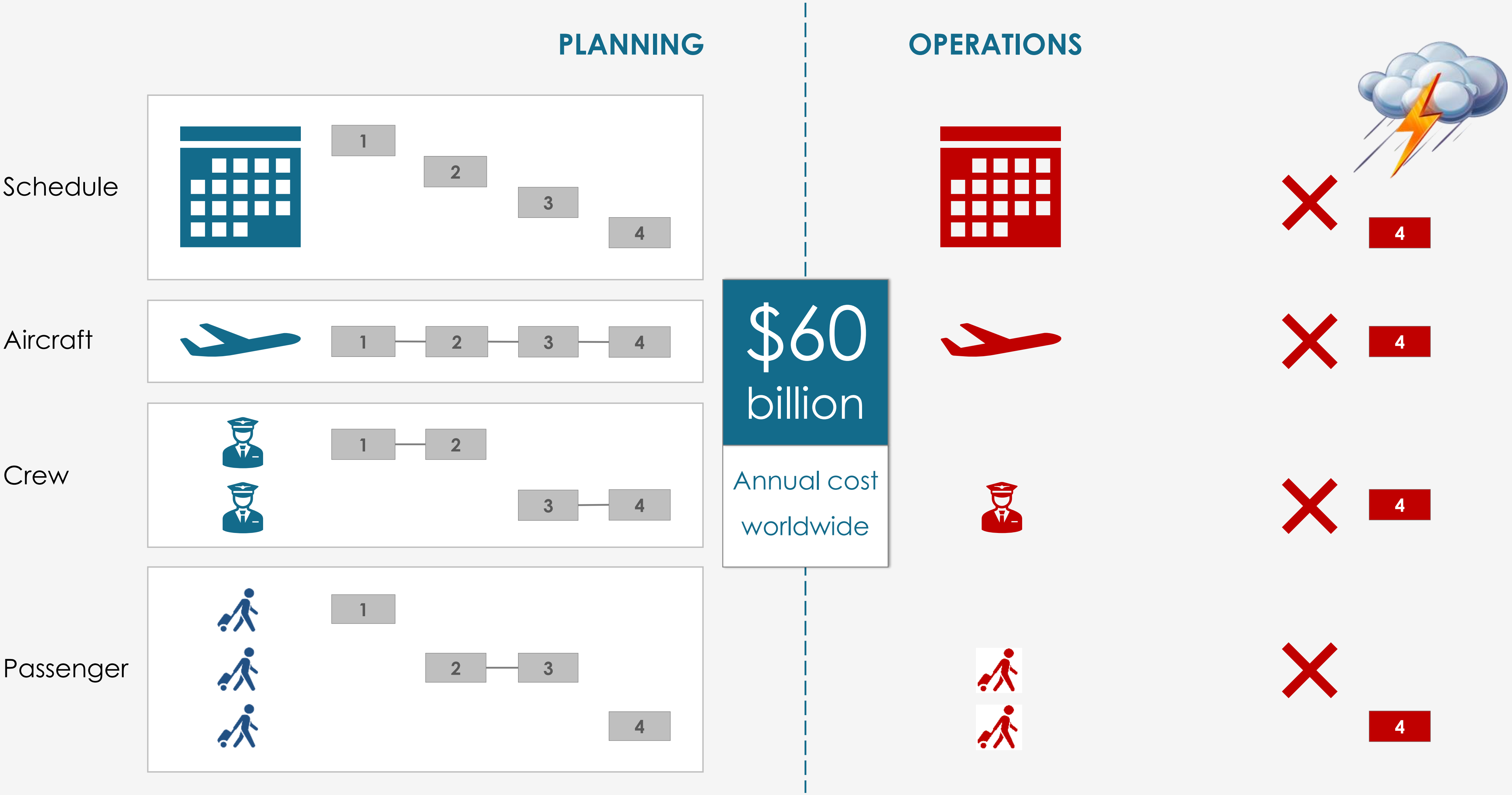
Due to the **irregular nature of flight operations**, planned flight, aircraft, and crew schedules are often disrupted



PLANNING

OPERATIONS

Schedule

Aircraft

Crew

Passenger

$60 billion

Annual cost worldwide

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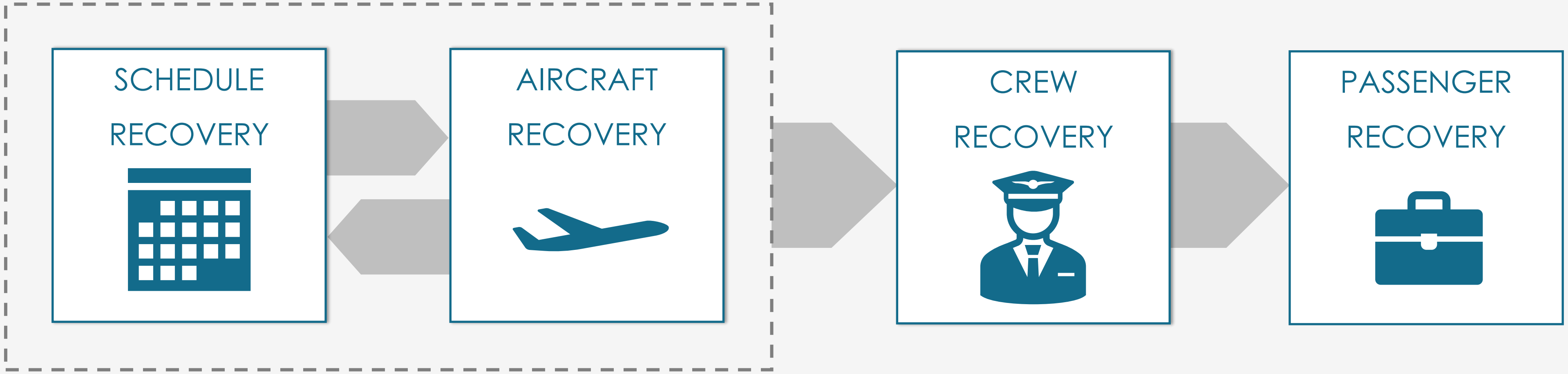
Airline recovery is the process by which airlines recover their aircraft crew schedules and passenger itineraries


SCHEDULE RECOVERY

AIRCRAFT RECOVERY

CREW RECOVERY

PASSENGER RECOVERY

- Rescheduling
- Canceling flights

- Rerouting
- Backup aircraft

- Rescheduling
- Reserve crew

- Re-directing to other itineraries

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Practical requirements for an efficient recovery process

QUALITY

High-quality /
low-cost solutions
are needed

SPEED

The solutions should be
created within limited
time frames

FLEXIBILITY

The method should be
able to adapt to the
available solution time

INTERPRETABILITY

The recovery decisions
should be
interpretable/explainable

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Combining **optimization** and **machine learning** helps build methods that meet the practical requirements.

OPTIMIZATION	Creates a realistic model of the problem, ensures solution feasibility, and maintains solution quality.
MACHINE LEARNING	Accelerates the solution process by predicting some of the recovery decisions in advance.

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Machine Learning for Combinatorial Optimization

Bengio et. al. (2020), European Journal of OR

LEARNING METHOD

✓ Demonstration *

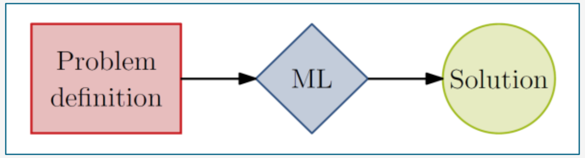
- Supervised learning

○ Experience

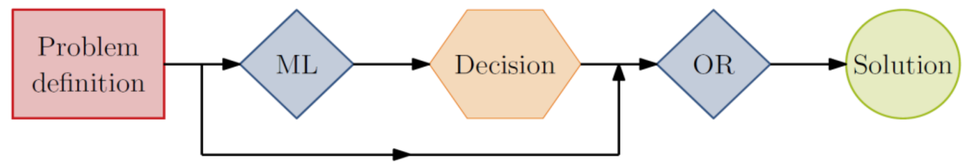
- Reinforcement learning

ALGORITHMIC STRUCTURE

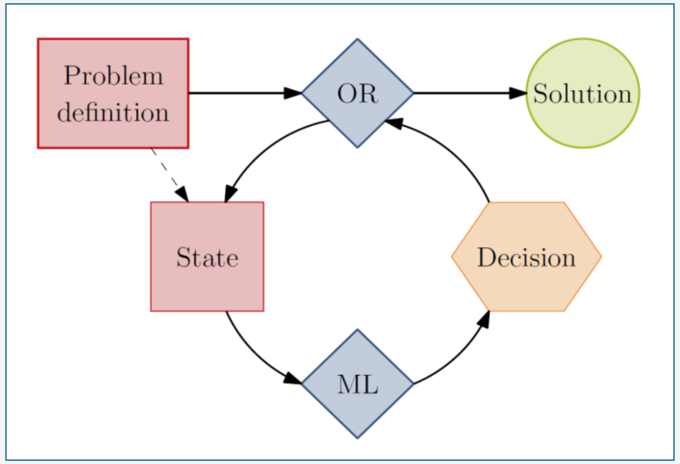
○ End to end learning



✓ Learning to configure



○ ML alongside optimization



*If based on expert input, the performance is limited

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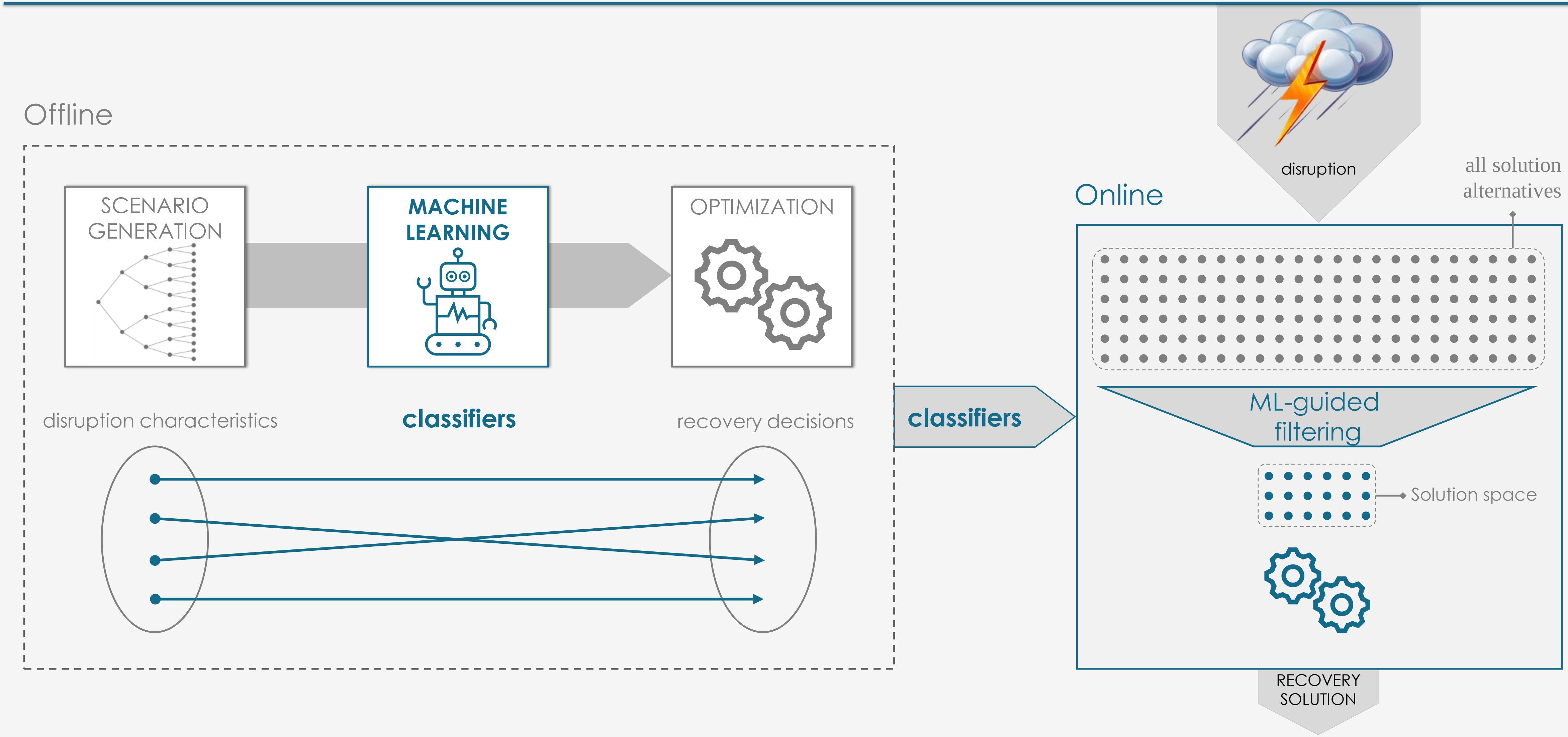
Tailoring a **solution space** for each disruption and solution time limit with **supervised learning**



Offline

SCENARIO GENERATION

MACHINE LEARNING

OPTIMIZATION

disruption characteristics

classifiers

recovery decisions

classifiers

Online

disruption

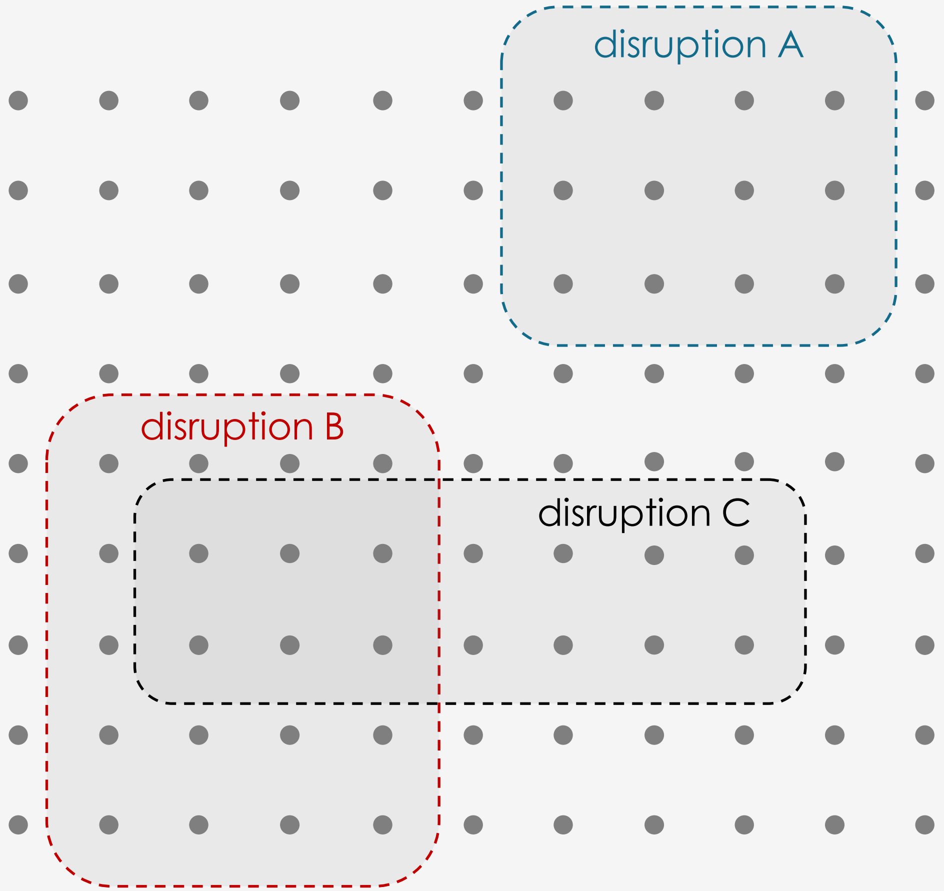
all solution alternatives

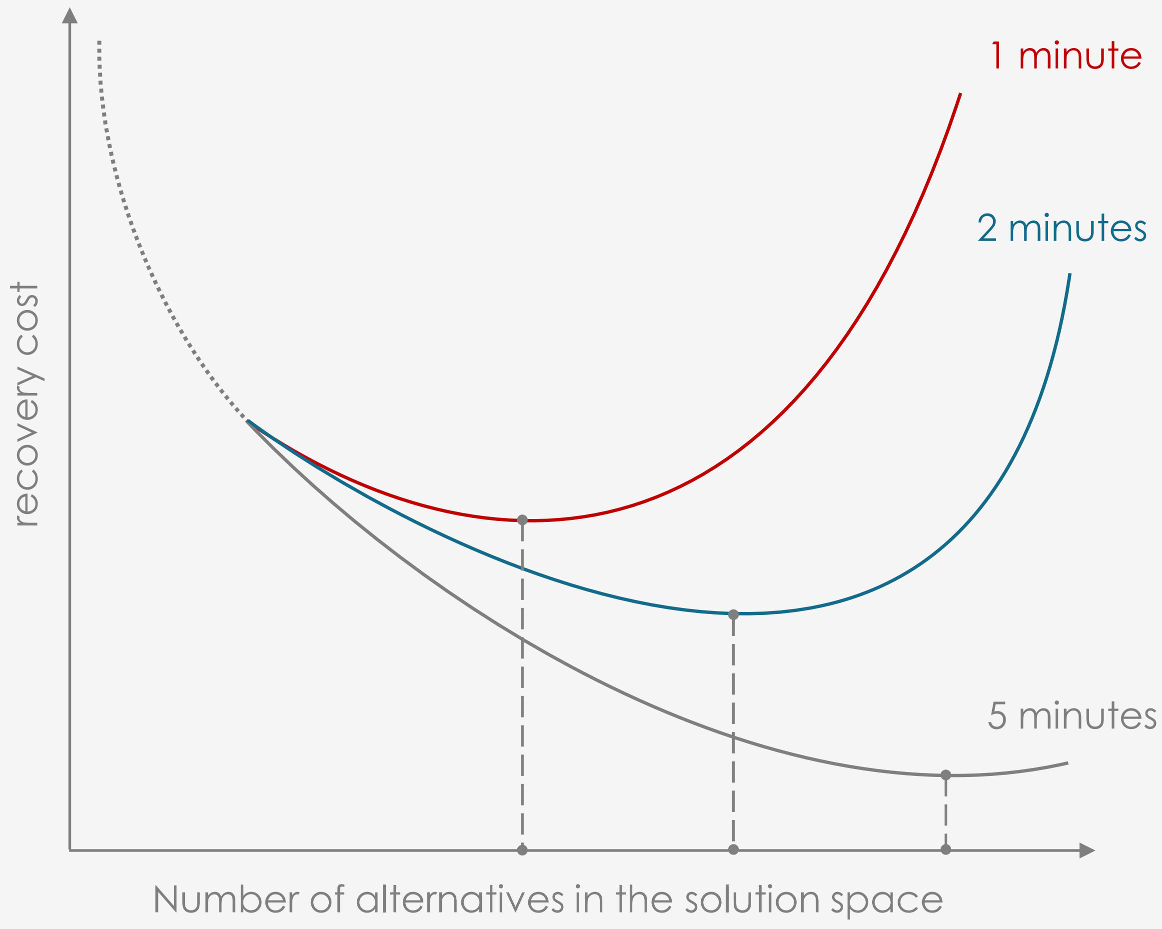
ML-guided filtering

Solution space

RECOVERY SOLUTION

The most effective solution space depends on the **disruption characteristics** and the **available solution time**





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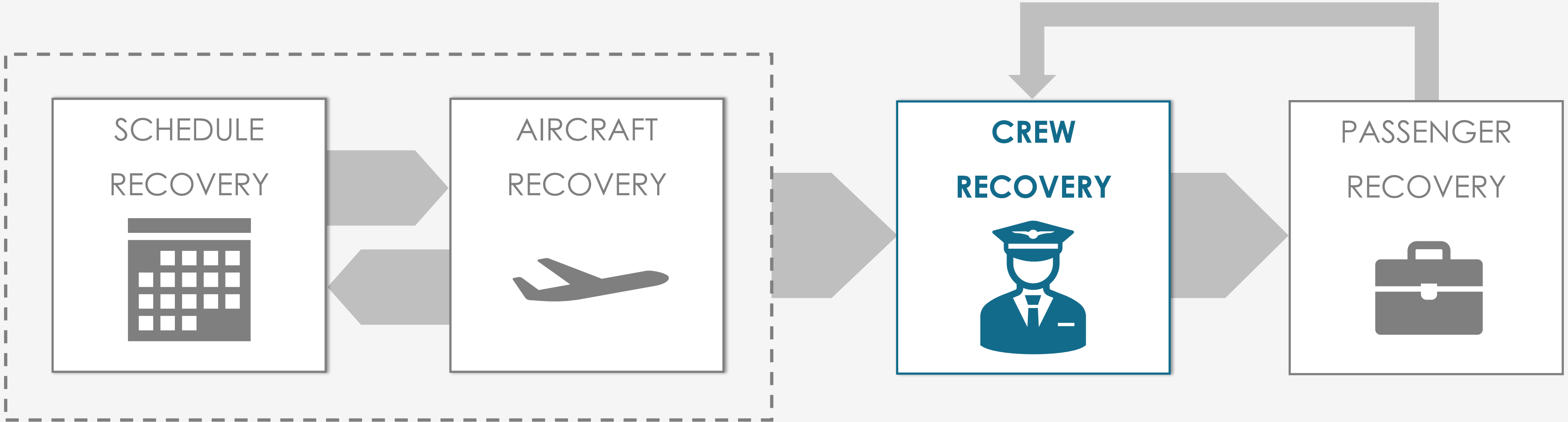
AGENDA

GENERAL FRAMEWORK

CREW RECOVERY w. AIRCRAFT & PASSENGER CONSIDERATIONS

INTEGRATED AIRCRAFT, CREW, AND PASSENGER RECOVERY

The **crew recovery** solution approach maintains the feasibility of the aircraft recovery solution



SCHEDULE RECOVERY

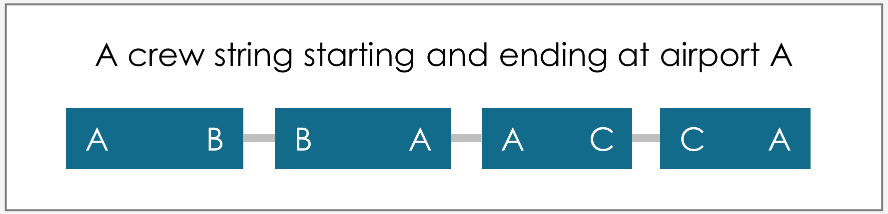
AIRCRAFT RECOVERY

CREW RECOVERY

PASSENGER RECOVERY

String-based modeling

- String is a sequence of flights operated by a crew



A crew string starting and ending at airport A

- Rescheduling
- Reserve crew

Legality Rules

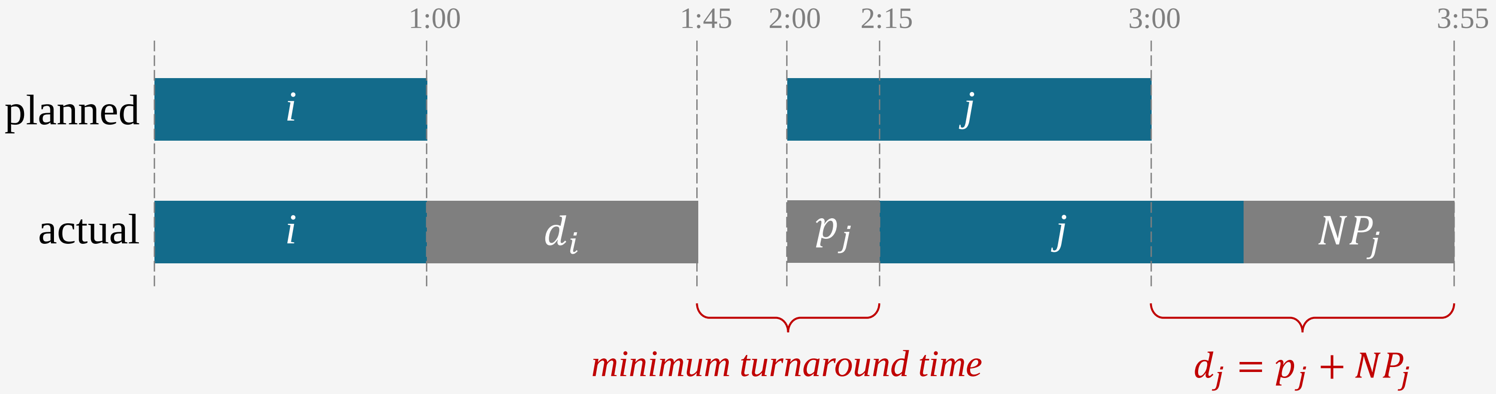
- Maximum flight duty period (FDP)
- Minimum connection time
- Minimum duty rest time
- Weekly, monthly duty time limits
- …

Main Contributions

- A data-driven and ML-guided way for feasible solution space reduction for crew recovery optimization.
- Fast and tunable solution methods to find better solutions for the crew recovery problem within the limited timeframes, compared to other practical approaches.
- A string-based set-covering type model for crew recovery problem with aircraft and passenger considerations that accounts for the propagation of delays through the network.
- Interpretable classifiers provide into crew recovery decisions by discovering latent factors determining whether a recovery decision is suitable for a given disruption.

Delay propagation mechanism & Disruption definition

- Delay of a flight has two components
  - Propagated delay p_j
  - Non-propagated delay NP_j



- Disruption scenario consists of the *NP* delay values of each flight

$$\boxed{\text{Disruption scenario}_n = \{\, NP_i \mid \forall i \in I \,\}}$$

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Crew Recovery Model (CRM): Objective function

CRM minimizes the total recovery cost, including those due to crew duty modifications, crew delays, high-cost reserve crew use, disrupted passenger costs, and passenger delay costs.

Decision Variables

y_s^k : 1 if crew string $s \in S$ is assigned to crew $k \in K$; 0 otherwise

w_s^k : delay of crew string $s \in S$ when assigned to crew $k \in K$ (in minutes)

z_i : 1 if flight $i \in I$ is assigned to a high-cost crew; 0 otherwise

d_i : total arrival delay of flight $i \in I$ (in minutes)

p_i : propagated departure delay of flight $i \in I$ (in minutes)

q_p : 1 if the passenger itinerary $p \in P$ becomes broken; 0 otherwise

v_p : delay of the passenger itinerary $p \in P$ (in minutes)

$$\min \overbrace{\sum_{k\in K}\sum_{s\in S_k}(\underbrace{CC_s^k \cdot y_s^k}_{\text{crew salary}} + \underbrace{WC_s^k \cdot w_s^k}_{\text{crew delay}}) + \underbrace{\sum_{i\in I} ZC_i \cdot z_i}_{\text{high-cost reserve}}}^{\text{total crew cost}} + \overbrace{\sum_{p\in P}(\underbrace{QC_p \cdot q_p}_{\text{stranded pax}} + \underbrace{VC_p \cdot v_p}_{\text{pax delay}})}^{\text{total passenger cost}}$$

Crew Recovery Model (CRM): Constraints

$$\text{s.t.} \quad z_i + \sum_{k \in K} \sum_{s \in S_k} a_{i,s} \cdot y_s^k \geq 1 \qquad \forall i \in I \tag{2.2}$$

$$\sum_{s \in S_k} y_s^k = 1 \qquad \forall k \in K \tag{2.3}$$

$$\sum_{k \in K_s} y_s^k \leq 1 \qquad \forall s \in S \setminus S^D \tag{2.4}$$

Crew coverage

$$NP_i + p_i \leq d_i \qquad \forall i \in I \tag{2.5}$$

$$d_i - SC_{ij} - M \cdot (1 - \sum_{k \in K_s} y_s^k) \leq p_j \qquad \forall (i,j) \in F_s, \forall s \in S \tag{2.6}$$

$$d_i - SR_{ij} \leq p_j \qquad \forall (i,j) \in F_r, \forall r \in R \tag{2.7}$$

$$d_i - SP_{ij} - M \cdot q_p \leq p_j \qquad \forall (i,j) \in F_p, \forall p \in P \tag{2.8}$$

Delay propagation

$$d_{LF_r} \leq LD_r \qquad \forall r \in R \tag{2.9}$$

Aircraft rotation feasibility

$$d_{LF_s} - M \cdot (1 - y_s^k) \leq w_s^k \qquad \forall s \in S_k, \forall k \in K \tag{2.10}$$

$$w_s^k \leq LD_s^k \qquad \forall s \in S_k, \forall k \in K \tag{2.11}$$

Crew duty feasibility

$$d_{LF_p} - M \cdot q_p \leq v_p \qquad \forall s \in S_k, \forall k \in K \tag{2.12}$$

Passenger delay

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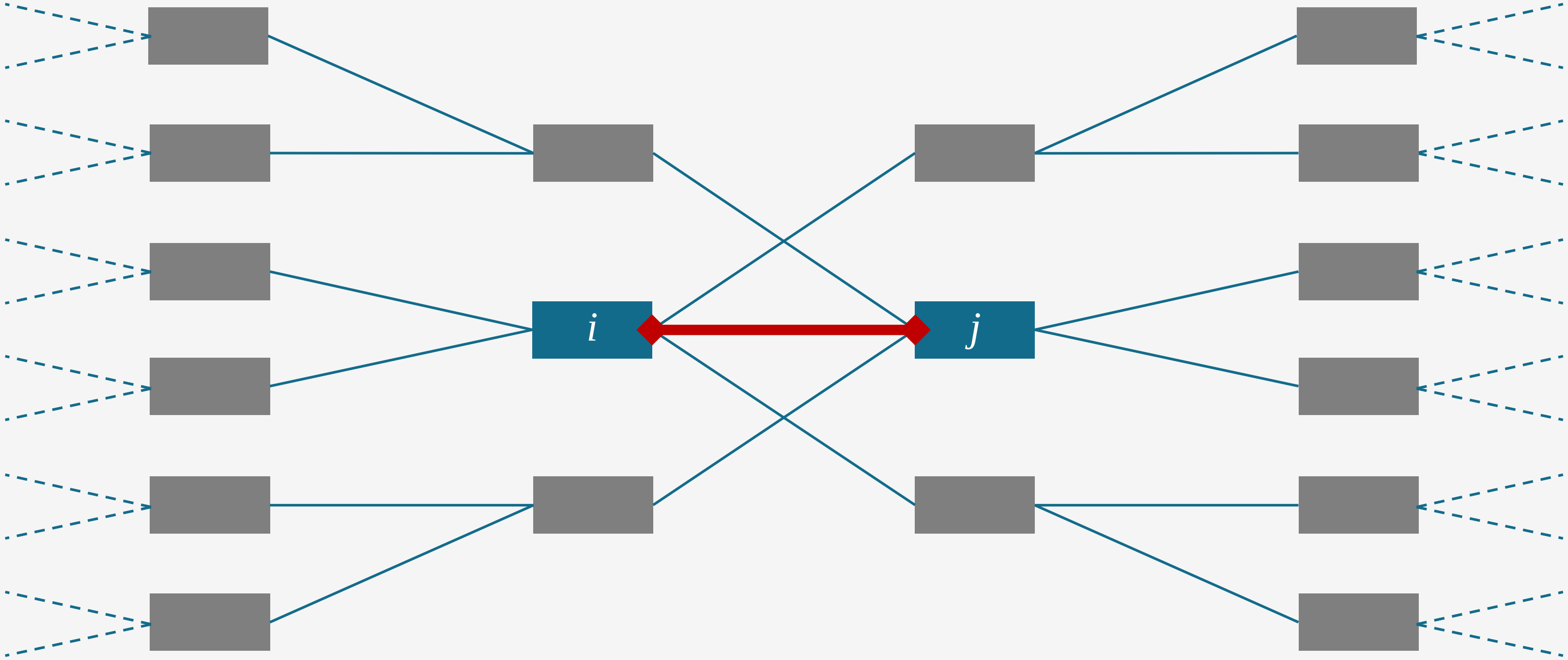
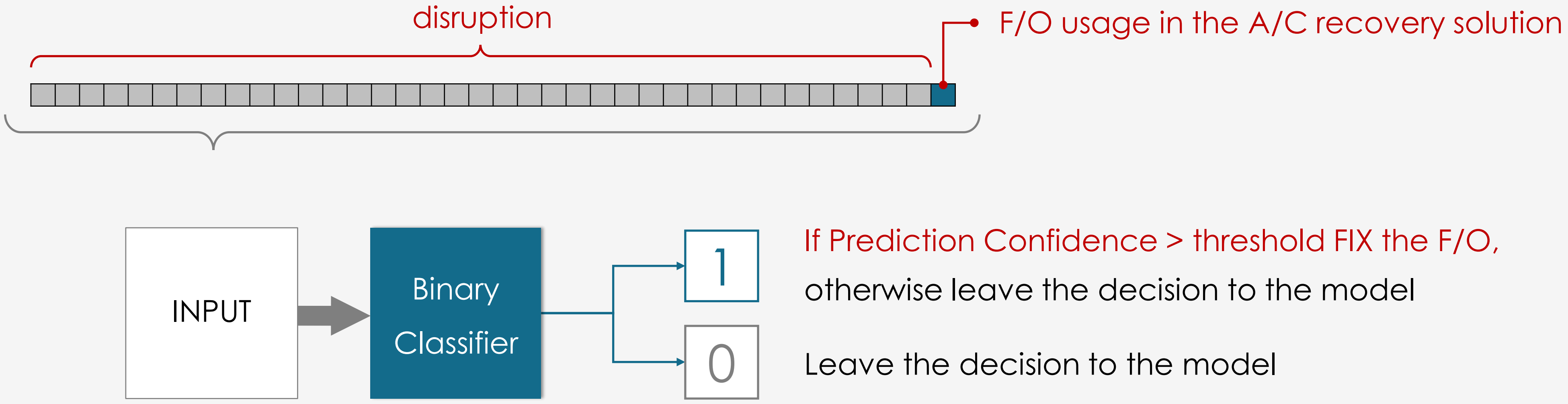
Fixing a set of **follow-on** pairs in advance provides significant reduction in the solution space

- A follow-on (F/O) is the consecutive assignment of two flights in a crew schedule.



Binary classifiers are trained to predict whether the F/O is likely to be in the crew recovery solution for a given disruption



If Prediction Confidence > threshold FIX the F/O, otherwise leave the decision to the model

Leave the decision to the model

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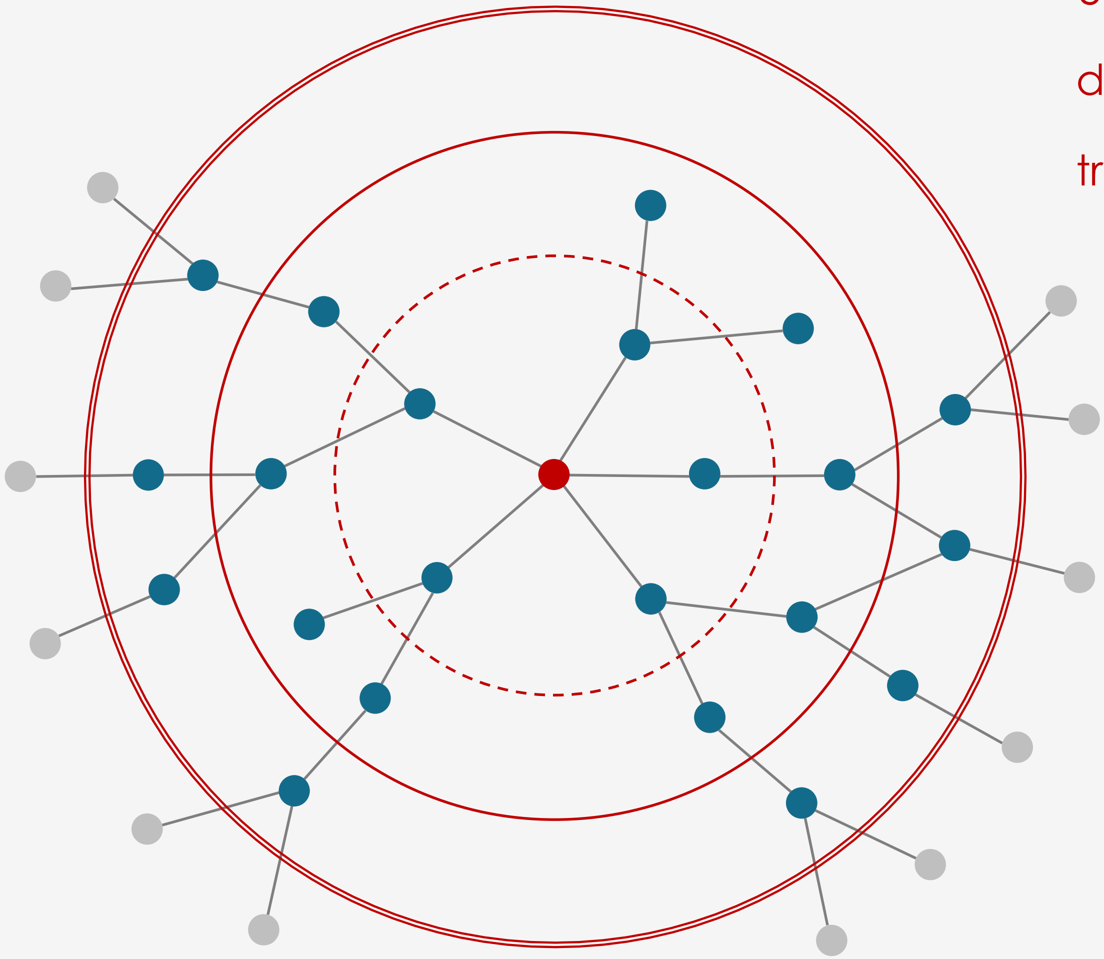
Local disruptions include NP delay information from only temporally and spatially close flights for each follow-on (F/O)

Neighborhood network for an F/O

- Nodes are F/O pairs
- Edges are feasible connections to other F/O pairs.
- N-hop neighborhood includes flights that can be connected to current F/O with < N edges.

Using 2-hop neighborhood disruptions decreases the training input size by ~95%.

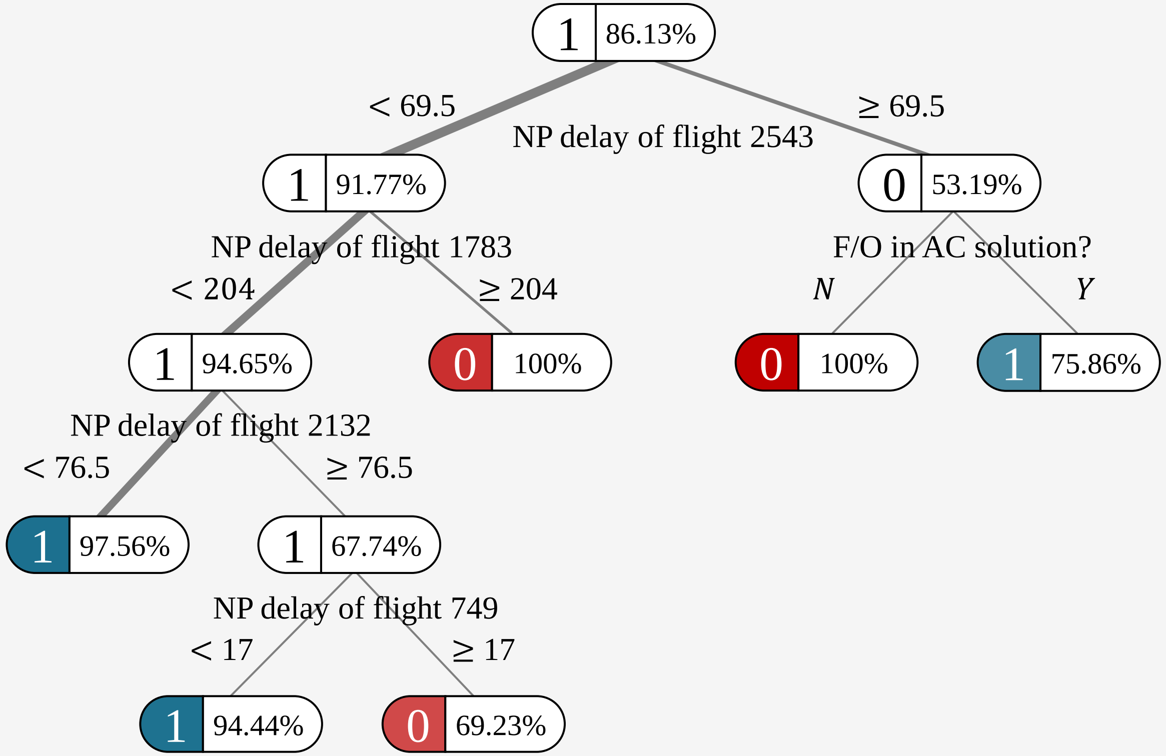


The **interpretable structure** of the trained tree-based classifiers help discover insights into recovery decisions

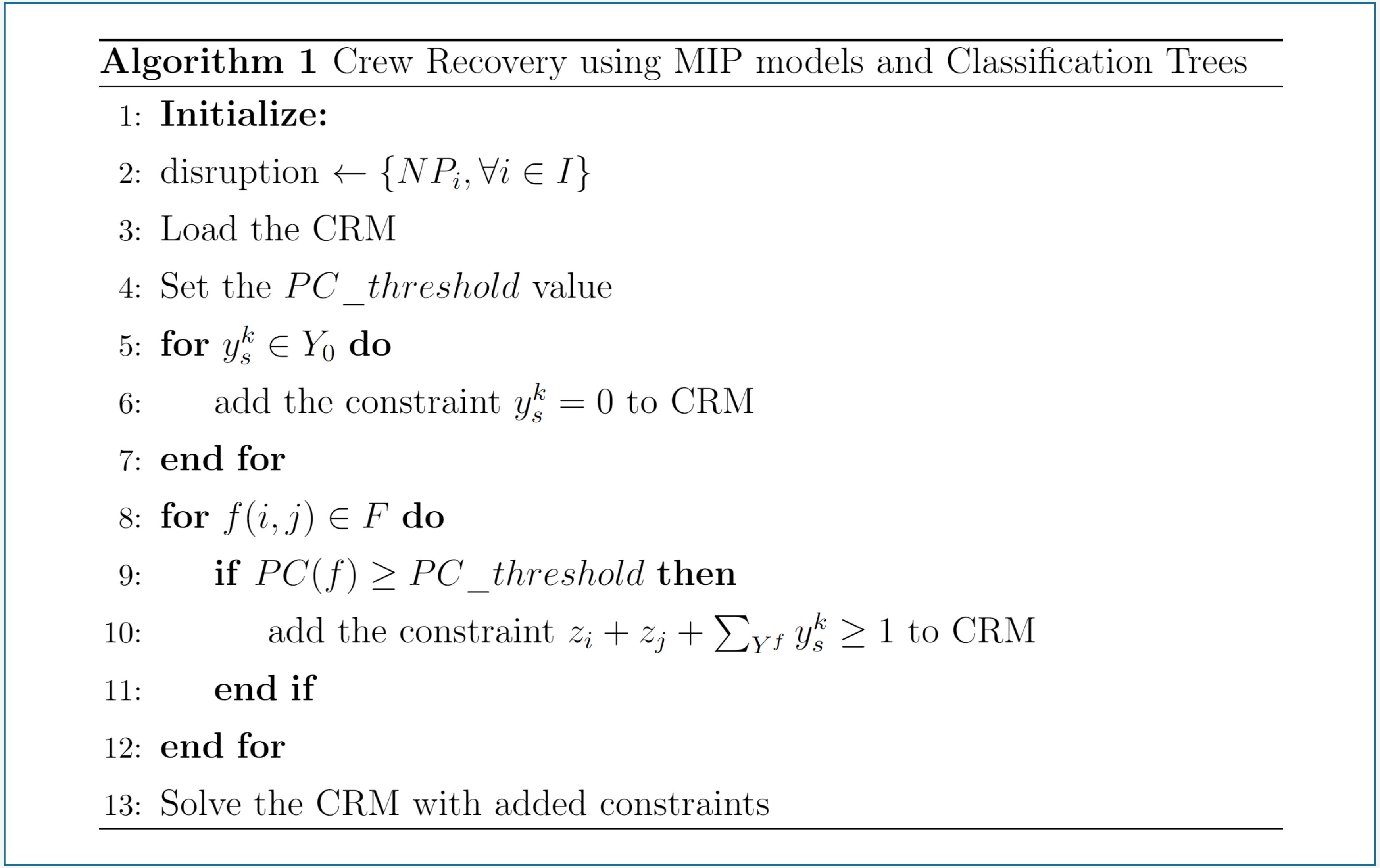
F/O: 1783-2543 (DAL-LGA-MDW)

Classifier precision: 92.31%

Flight id	Departure station	Arrival station	Departure Time (in UTC minutes)	Arrival Time (in UTC minutes)
1783	DAL	LGA	1260	1455
2543	LGA	MDW	1495	1655
2132	LGA	MDW	1360	1515
749	DTW	MDW	950	1020



Crew Recovery using MIP & Classification Trees Algorithm



Algorithm 1 Crew Recovery using MIP models and Classification Trees

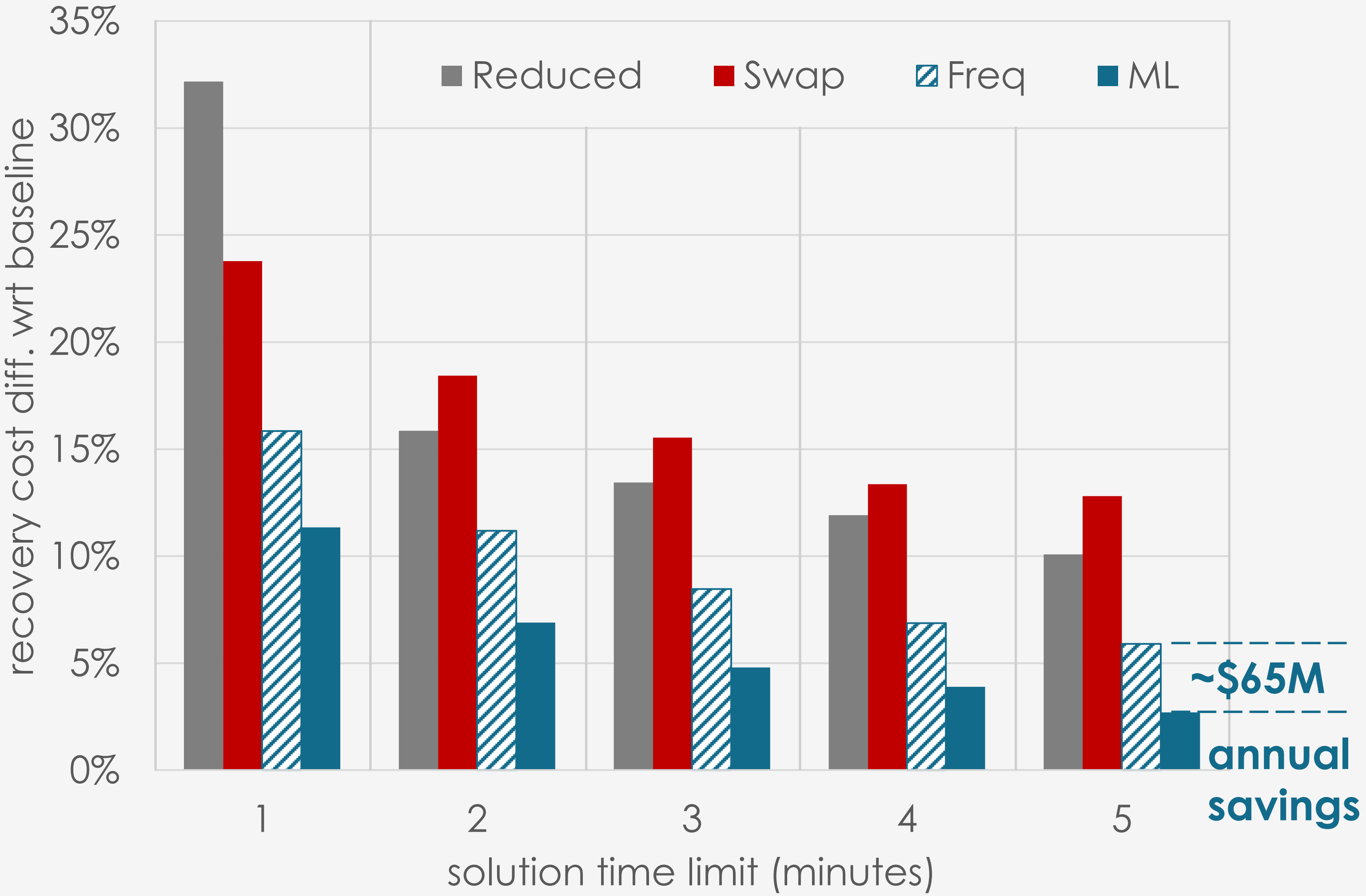
```
**Initialize:**
disruption $\leftarrow \{NP_i, \forall i \in I\}$
Load the CRM
Set the $PC\_threshold$ value
**for** $y_s^k \in Y_0$ **do**
    add the constraint $y_s^k = 0$ to CRM
**end for**
**for** $f(i,j) \in F$ **do**
    **if** $PC(f) \geq PC\_threshold$ **then**
        add the constraint $z_i + z_j + \sum_{Y^f} y_s^k \geq 1$ to CRM
    **end if**
**end for**
Solve the CRM with added constraints
```

Benchmark solution methods

- Default: The crew recovery model is sent to the optimizer with the specified solution time limit.
- Reduced: 0-frequency assignments are removed from the solution space before initiating the optimization run.
- Swap: Fix & dive type of heuristic in which for each broken crew schedule, a number of planned crew schedules with swap opportunities are included in the solution space while the remaining are left untouched.
- Freq: Solution space reduction is performed based on F/O frequencies in the database.
- ML: Starts with a reduced solution space, same as the reduced method. Further solution space reduction is performed based on prediction confidence values calculated by the trained classifiers.

ML-method outperforms others in all solution time limits

Default method cannot generate integer solutions in 5 minutes



~$65M annual savings

- Underlying network has
  - 2,870 flights
  - ten crew bases,
  - 1,200 daily crew members,
  - single fleet regarding crew requirements.
- The baseline solutions are generated using the default approach, where the average run time and optimality gap are 2 hours and ~1%, respectively.

AGENDA

GENERAL FRAMEWORK

CREW RECOVERY w. AIRCRAFT & PASSENGER CONSIDERATIONS

INTEGRATED AIRCRAFT, CREW, AND PASSENGER RECOVERY

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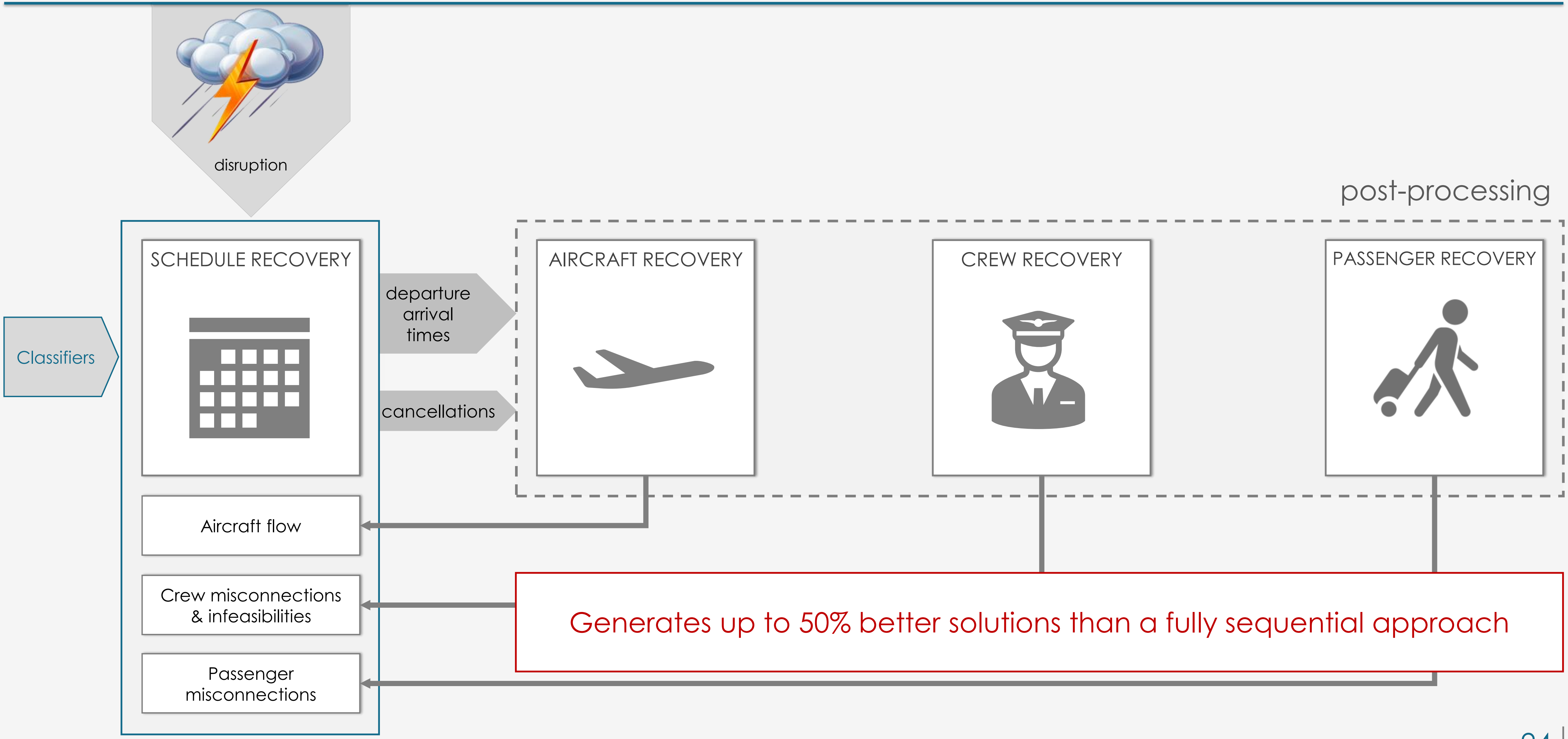
The **integrated recovery** solution approach focuses on solving the most crucial aspects of the recovery steps.



disruption

post-processing

Classifiers

SCHEDULE RECOVERY

departure
arrival
times

cancellations

AIRCRAFT RECOVERY

CREW RECOVERY

PASSENGER RECOVERY

Aircraft flow

Crew misconnections & infeasibilities

Passenger misconnections

Generates up to 50% better solutions than a fully sequential approach

Main Contributions

- Fast and tunable methods for the integrated recovery problem combining optimization and ML.
- A tractable integrated recovery model which considers the major aspects of the schedule, aircraft, crew, and passenger recovery steps. It generates solutions up to 50% better than a fully sequential approach.
- The developed methodology accelerates both the offline and online phases due to the solution space reduction approach and the definition of the feature set.
- Interpretable classifiers provide insights into recovery decisions.

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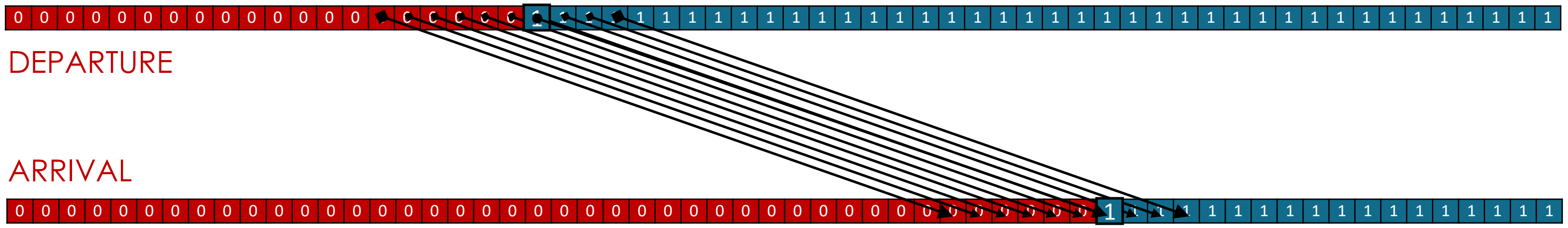
Strong Formulation:
Some constraints are facets of the convex hull

- Based on “Bertsimas, D., & Patterson, S. S. (1998). The air traffic flow management problem with enroute capacities. *Operations research*, *46*(3), 406-422.”

- Binary flight departure and arrival variables for each time increment t

$d_i^{a,t}$: 1 if flight $i \in I$, assigned to aircraft group $a \in A$, has departed by time $t \in T$, 0 otherwise

$r_i^{a,t}$: 1 if flight $i \in I$, assigned to aircraft group $a \in A$, has arrived by time $t \in T$, 0 otherwise



- Some constraints are facets of the convex hull of feasible integer solutions, leading to a strong formulation.

Integrated Recovery Model (IRM): Objective function

Decision Variables

$d_i^{a,t}$: 1 if flight $i \in I$, assigned to aircraft group $a \in A$, has departed by time $t \in T$, 0 otherwise

$r_i^{a,t}$: 1 if flight $i \in I$, assigned to aircraft group $a \in A$, has arrived by time $t \in T$, 0 otherwise

q_f: 1 if the passenger itinerary $f \in F$ becomes infeasible, 0 otherwise

u_s: 1 if the planned crew duty $s \in S$ becomes infeasible, 0 otherwise

z_i: 1 if flight $i \in I$ is cancelled, 0 otherwise

Cost Coefficients

dc_f: per time period passenger delay cost for passenger itinerary $f \in F$

pc_f: cost of passenger itinerary $f \in F$ becoming infeasible

cc_s: cost of planned crew duty $s \in S$ becoming infeasible

ec_s: per time period crew delay cost for duty $s \in S$

zs_i: cancellation savings for flight $i \in I$

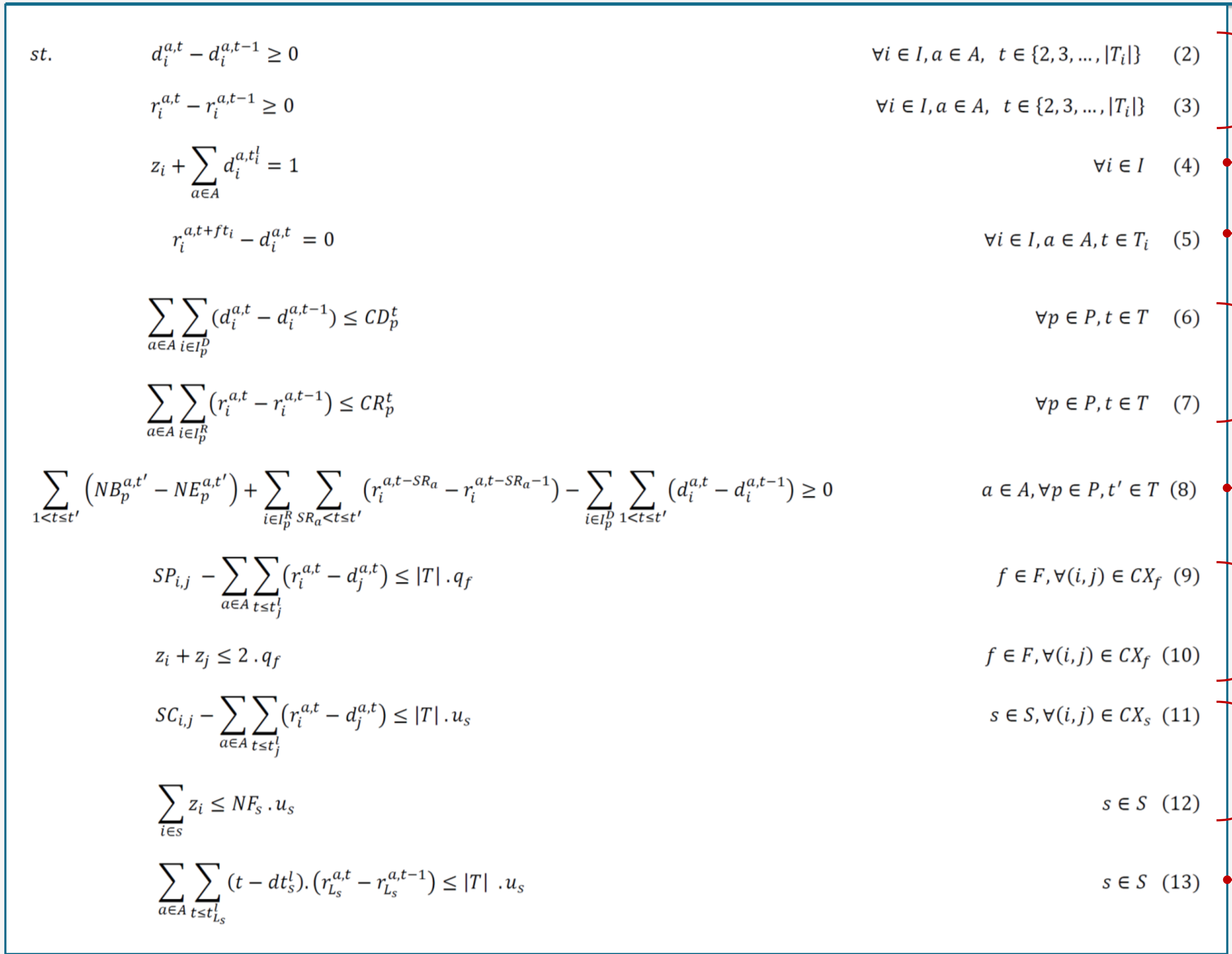
$$\min \overbrace{\sum_{f\in F}(\underbrace{pc_f\cdot q_f}_{\text{pax recovery}} + \underbrace{\sum_{a\in A}\sum_{t^p_{L_f}<t\le t^l_{L_f}} dc_f\cdot(t-t^p_{L_f})\cdot(r^{a,t}_{L_f}-r^{a,t-1}_{L_f}))}_{\text{pax delay}}}^{\text{total pax cost}} + \overbrace{\sum_{s\in S}(\underbrace{cc_s\cdot u_s}_{\text{crew recovery}}+\underbrace{\sum_{a\in A}\sum_{t^p_{L_s}<t\le t^l_{L_s}} ec_s\cdot(t-t^p_{L_s})\cdot(r^{a,t}_{L_s}-r^{a,t-1}_{L_s}))}_{\text{crew delay}}}^{\text{total crew cost}} - \overbrace{\sum_{i\in I} zs_i\cdot z_i}^{\text{cancellation savings}}$$

L_s: the last flight in planned crew duty $s \in S$

L_f: the last flight in passenger itinerary $f \in F$

t_i^p: planned arrival time period of flight $i \in I$

Integrated Recovery Model (IRM): Constraints



$$st. \quad d_i^{a,t} - d_i^{a,t-1} \geq 0 \qquad \forall i \in I, a \in A,\ t \in \{2,3,\dots,|T_i|\} \quad (2)$$

$$r_i^{a,t} - r_i^{a,t-1} \geq 0 \qquad \forall i \in I, a \in A,\ t \in \{2,3,\dots,|T_i|\} \quad (3)$$

departure/arrival time modeling

$$z_i + \sum_{a \in A} d_i^{a,t_i^l} = 1 \qquad \forall i \in I \quad (4)$$

flight coverage

$$r_i^{a,t+ft_i} - d_i^{a,t} = 0 \qquad \forall i \in I, a \in A, t \in T_i \quad (5)$$

flight time consistency

$$\sum_{a \in A} \sum_{i \in I_p^D} \left(d_i^{a,t} - d_i^{a,t-1}\right) \leq CD_p^t \qquad \forall p \in P, t \in T \quad (6)$$

$$\sum_{a \in A} \sum_{i \in I_p^R} \left(r_i^{a,t} - r_i^{a,t-1}\right) \leq CR_p^t \qquad \forall p \in P, t \in T \quad (7)$$

airport capacities

$$\sum_{1<t\leq t'} \left(NB_p^{a,t'} - NE_p^{a,t'}\right) + \sum_{i \in I_p^R} \sum_{SR_a<t\leq t'} \left(r_i^{a,t-SR_a} - r_i^{a,t-SR_a-1}\right) - \sum_{i \in I_p^D} \sum_{1<t\leq t'} \left(d_i^{a,t} - d_i^{a,t-1}\right) \geq 0 \qquad a \in A, \forall p \in P, t' \in T \quad (8)$$

aircraft flow

$$SP_{i,j} - \sum_{a \in A} \sum_{t \leq t_j^l} \left(r_i^{a,t} - d_j^{a,t}\right) \leq |T| \,.\, q_f \qquad f \in F, \forall (i,j) \in CX_f \quad (9)$$

$$z_i + z_j \leq 2 \,.\, q_f \qquad f \in F, \forall (i,j) \in CX_f \quad (10)$$

pax misconnection

$$SC_{i,j} - \sum_{a \in A} \sum_{t \leq t_j^l} \left(r_i^{a,t} - d_j^{a,t}\right) \leq |T| \,.\, u_s \qquad s \in S, \forall (i,j) \in CX_s \quad (11)$$

$$\sum_{i \in s} z_i \leq NF_s \,.\, u_s \qquad s \in S \quad (12)$$

crew misconnection

$$\sum_{a \in A} \sum_{t \leq t_{L_s}^l} \left(t - dt_s^l\right).\left(r_{L_s}^{a,t} - r_{L_s}^{a,t-1}\right) \leq |T| \ .\, u_s \qquad s \in S \quad (13)$$

crew duty duration limit

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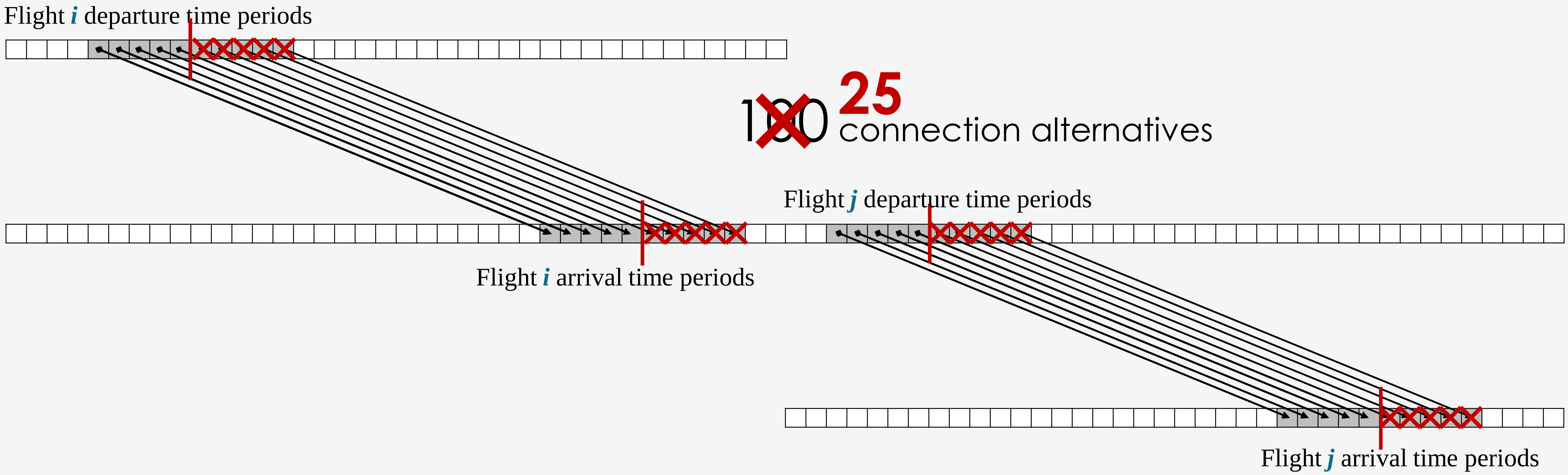
Limiting the number of **flight copies** for individual flights provides significant reduction in the solution space



Flight *i* departure time periods

~~100~~ **25** connection alternatives

Flight *j* departure time periods

Flight *i* arrival time periods

Flight *j* arrival time periods

Binary classifiers are trained to predict whether the delay of a flight will exceed a specific limit (e.g., 1 hour).

Information used in ML model training

Disruption

- Airport departure/arrival capacity,
- Planned departures/arrivals, etc.

Schedule

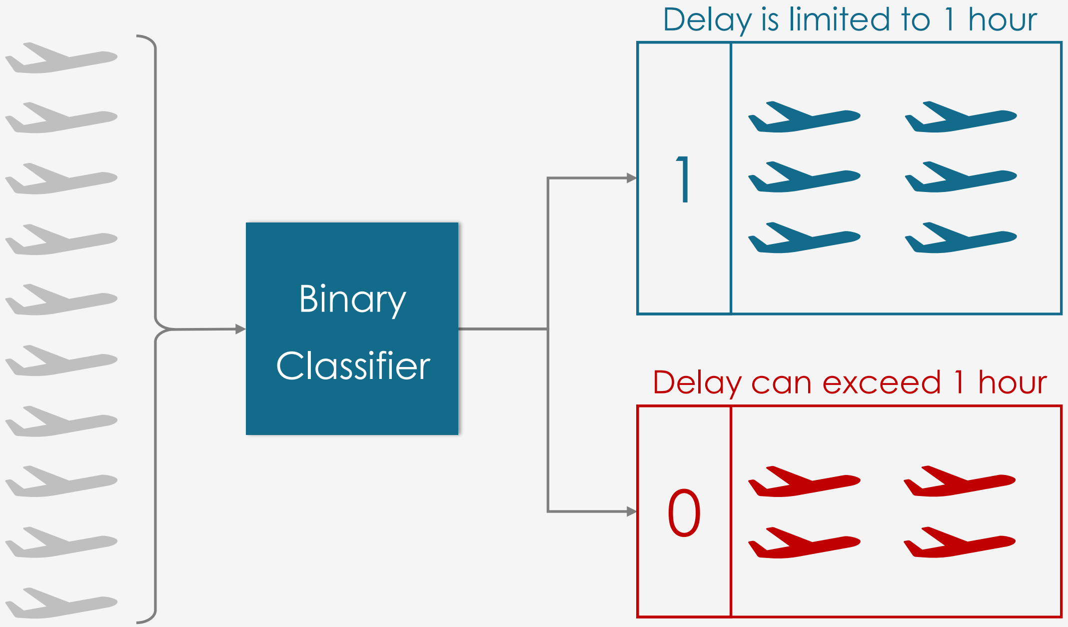
- Frequency of the origin-destination (OD),
- OD frequency order, departure time, etc.

Crew

- Slack before the next flight on the duty,
- Slack at the end of the duty, etc.

Passenger

- Seat capacity, number of passengers,
- Number of connecting passengers etc.



Binary Classifier

Delay is limited to 1 hour

1

Delay can exceed 1 hour

0

Average classifier precision > 98%

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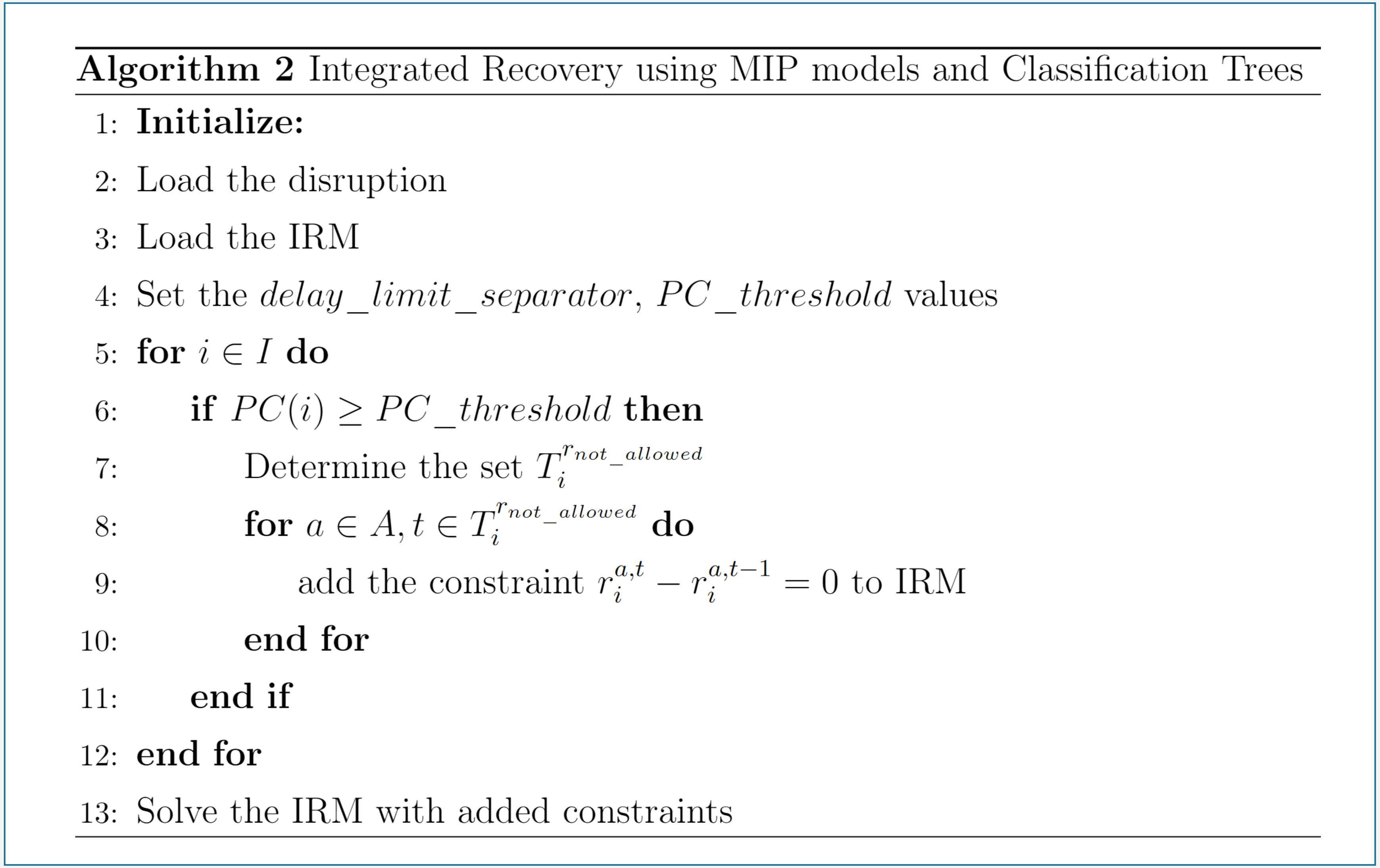
Integrated Recovery using MIP & Classification Trees



Algorithm 2 Integrated Recovery using MIP models and Classification Trees

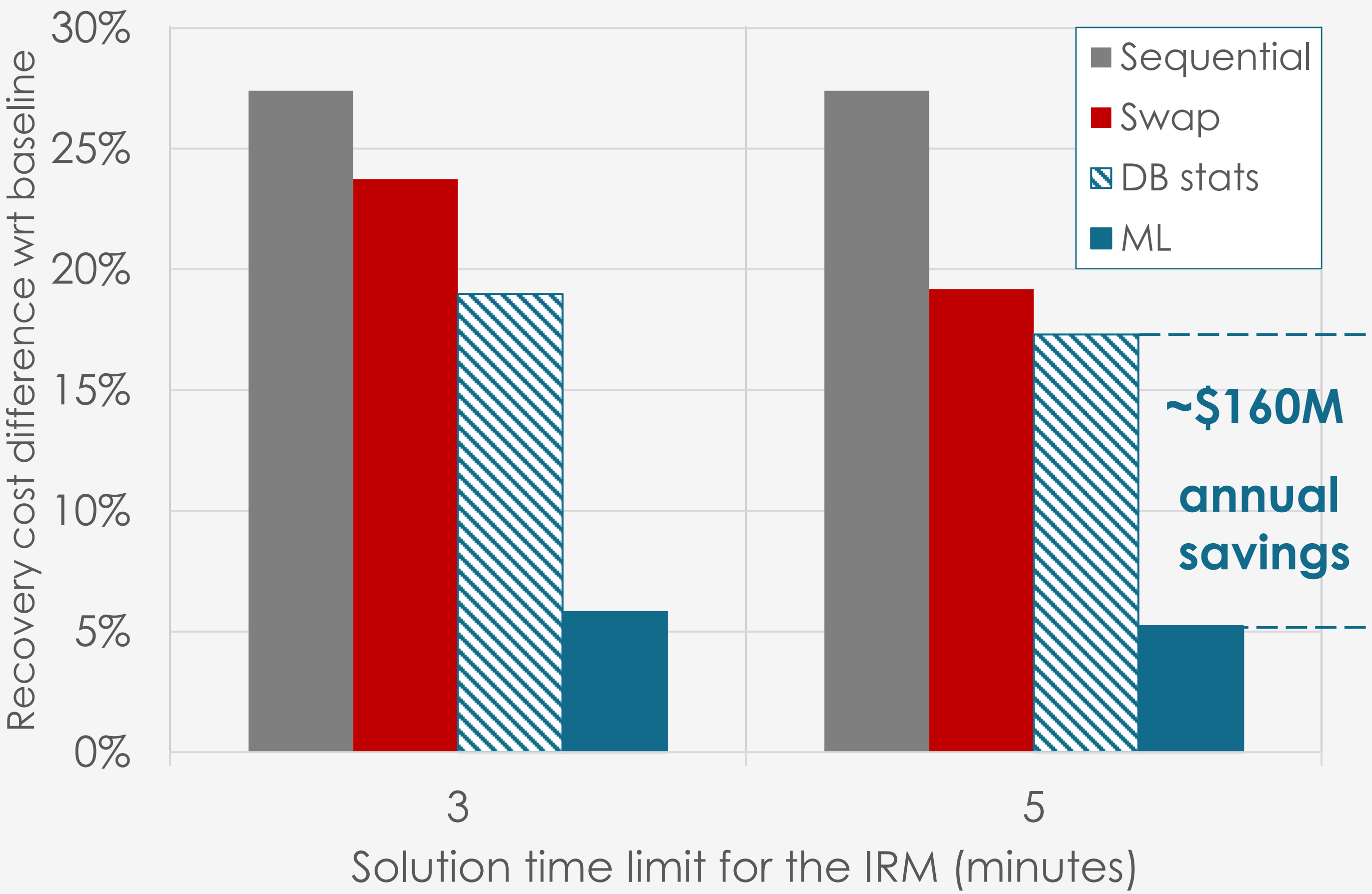
```
Initialize:
Load the disruption
Load the IRM
Set the $delay\_limit\_separator$, $PC\_threshold$ values
for $i \in I$ do
    if $PC(i) \geq PC\_threshold$ then
        Determine the set $T_i^{r_{not\_allowed}}$
        for $a \in A, t \in T_i^{r_{not\_allowed}}$ do
            add the constraint $r_i^{a,t} - r_i^{a,t-1} = 0$ to IRM
        end for
    end if
end for
Solve the IRM with added constraints
```

Benchmark / Solution methods

- Default: The integrated recovery model is sent to the optimizer with the specified solution time limit.
- Sequential: Same as the default method, except that the underlying model does not have crew and passenger considerations.
- Swap: Fix & dive type of heuristic in which for each broken aircraft rotation, a number of planned rotations with swap opportunities are included in the solution space. The remaining planned rotations are left untouched such that the delays of the flights in these rotations are limited to the delays in the fixed solution.
- DB stats: The flight delay limits are determined using the database statistics.
- ML: The delay limits for flights are determined based on ML predictions.

ML-method outperforms others in all solution time limits

Default method cannot generate integer solutions in 5 minutes



- Underlying network has
  - 3,706 flights
  - ten crew bases,
  - 1,600 daily crew members,
  - single fleet regarding crew requirements.
- The baseline solutions are generated using the default approach, where the average run time and optimality gap are 2 hours and ~2%, respectively.

Conclusion

- We developed a framework that can help meet major requirements of a recovery process:

  ☑ Quality ☑ Speed ☑ Flexibility ☑ Interpretability.

- We introduced tractable models for crew and integrated recovery problems.

- We developed methods can generate significantly better-quality solutions than other practical approaches.

Future Research

- Real-life implementation of the proposed methods.
- Generalizable classifiers that do not sacrifice precision performance.
- ML alongside optimization type of algorithms for airline scheduling problems.
- Graph Neural Networks for recovery and scheduling problems

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