

# SafeOPS

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## Evaluating an AI-based Decision Support for Go-around Handling

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RPAS and AI in Aviation  
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# Efficiency Resilience Trade-Off

## *Efficiency Isn't the Only Economic Virtue*

It often comes at the expense of resilience, as the new coronavirus is making clear.

Reference:

<https://www.wsj.com/articles/efficiency-isnt-the-only-economic-virtue-11583873155>

### **Efficiency:**

- Optimizing a system/process in a known/defined environment.
- No unused resources

### **Resilience:**

- Ability to absorb, adapt or recover from rare or unpredictable events and disturbances.
- Requires 'reserved capacity' / safety margins

CSIS

CENTER FOR STRATEGIC &  
INTERNATIONAL STUDIES

COMMENTARY

## Resilience vs. Efficiency

Reference:

<https://www.csis.org/analysis/resilience-vs-efficiency>



Reference:

[https://upload.wikimedia.org/wikipedia/commons/1/1f/Container\\_Ship\\_%27Ever\\_Given%27\\_stuck\\_in\\_the\\_Suez\\_Canal%2C\\_Egypt\\_-\\_March\\_24th%2C\\_2021\\_%2851070311183%29.jpg](https://upload.wikimedia.org/wikipedia/commons/1/1f/Container_Ship_%27Ever_Given%27_stuck_in_the_Suez_Canal%2C_Egypt_-_March_24th%2C_2021_%2851070311183%29.jpg)

# European ATM Master Plan

## Goals that are hard to combine?

- Increase of capacity
  - + 60% IFR Network throughput
  - + 5-10% IFR movements at congested airports
- Increase ATM related safety by 100%



## What is a good trade-off?


- When should we prioritize safety, when capacity?

## Decision Intelligence:

- Provide ATCOs with real time / predictive risk information
- Use predictive information to support decision-making
- Increase safety and resilience



## PERFORMANCE AMBITIONS FOR 2035 FOR CONTROLLED AIRSPACE

Key performance area	SES high-level goals 2035	Key performance indicator
 Capacity	Enable 3-fold increase in ATM capacity	<b>Departure delay<sup>4</sup></b> , min/dep <b>IFR movements at most congested airports<sup>5</sup></b> , million <b>Network throughput IFR flights<sup>5</sup></b> , million <b>Network throughput IFR flight hours<sup>5</sup></b> , million
 Cost efficiency	Reduced ATM services unit costs by 50% or more	<b>Gate-to-gate direct ANS cost per flight<sup>1</sup></b> , EUR(2012)
 Operational efficiency		<b>Gate-to-gate fuel burn per flight</b> , kg/flight <b>Additional gate-to-gate flight time per flight<sup>2</sup></b> , min/flight Within the: Gate-to-gate flight time per flight <sup>3</sup> , min/flight
 Environment	Enable 10% reduction in the effects flights have on the environment	<b>Gate-to-gate CO<sub>2</sub> emissions</b> , tonnes/flight
 Safety	Improve safety by factor 10	<b>Accidents with direct ATM contribution<sup>6</sup></b> , #/year Includes in-flight accidents as well as accidents during surface movement (during taxi and on the runway)

Reference:

<https://www.atmmasterplan.eu/exec/overview/performance-ambitions>

# SafeOPS Concept

## Approach and Departure Handling:

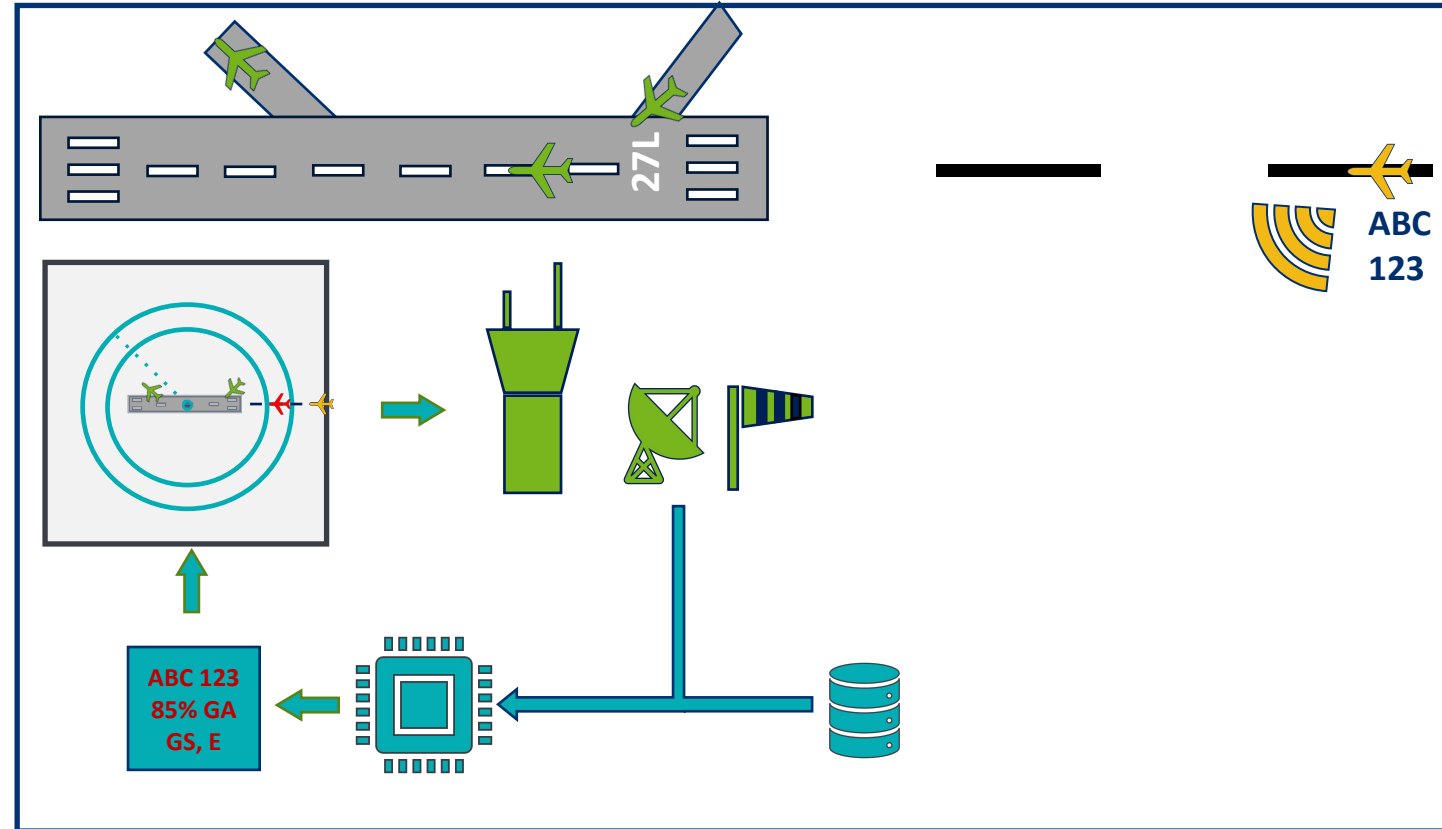
- Tower Controller realizes go-around through
  - Flight Crew's communication
  - Observation of flight (via radar)
- ☐ Reactive tactics to ensure safety

## Predictive Analytics:

- Train an AI/ML model with historical performance and weather data
- Predict go-arounds ahead of time, using radar and weather data

## Real Time Risk Information

- Provide the predictive information to ATCOs



How does the predictive information impact decision-making, safety and resilience in the go-around scenario?

# SafeOPS Structure

## Operational Layer

Systems Engineering approach:

- Understand available procedures and technologies
- Define initial ConOps & requirements
- Evaluate impact of concept on safety and resilience

## Risk Framework

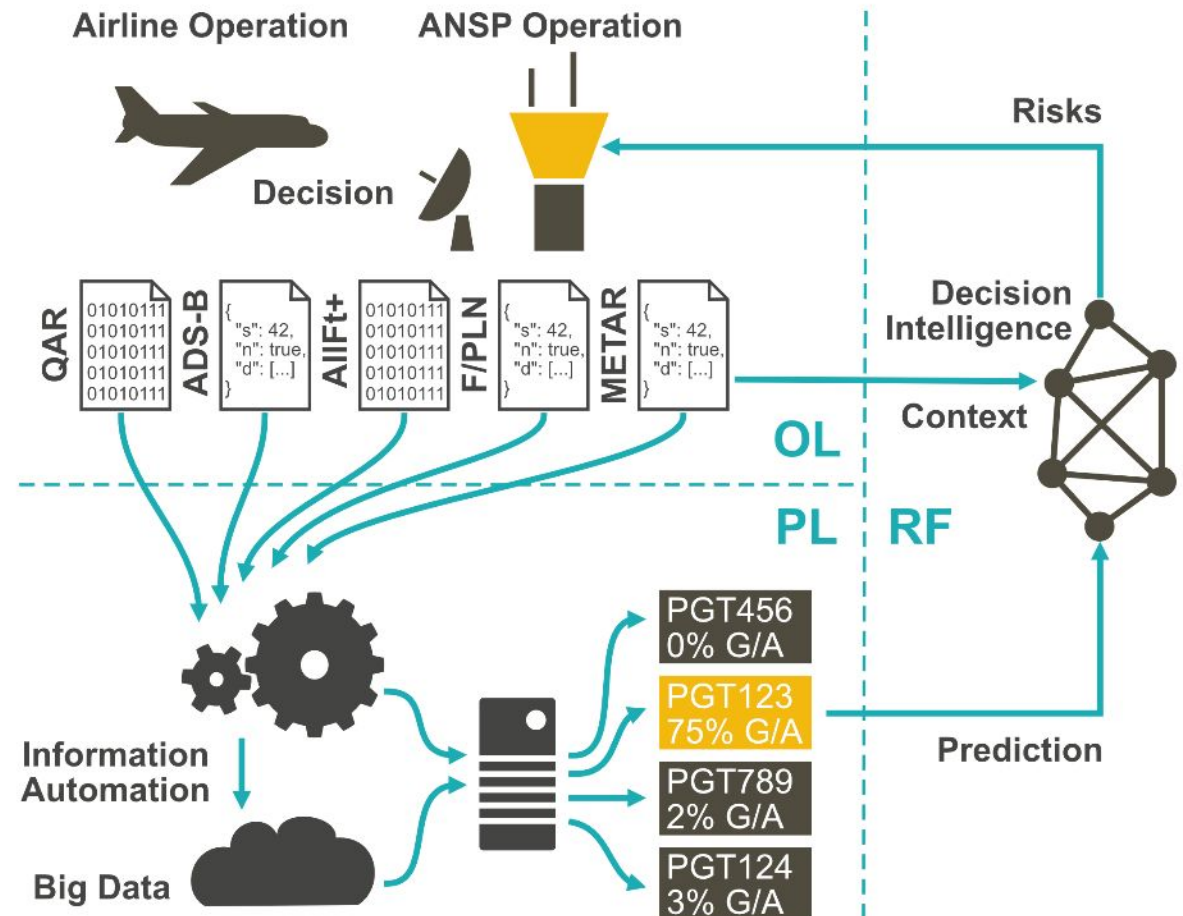
Addresses the operational risks of the concept:

- Investigate provision of probabilistic information
- Human Performance/Integration of concept
- Initial safety assessment concept

## Predictive Layer

Addresses big data related tasks:

- Data acquisition and pre-processing
- AI solution identification
- AI training



# Investigated Scenario

## Go-Arounds:

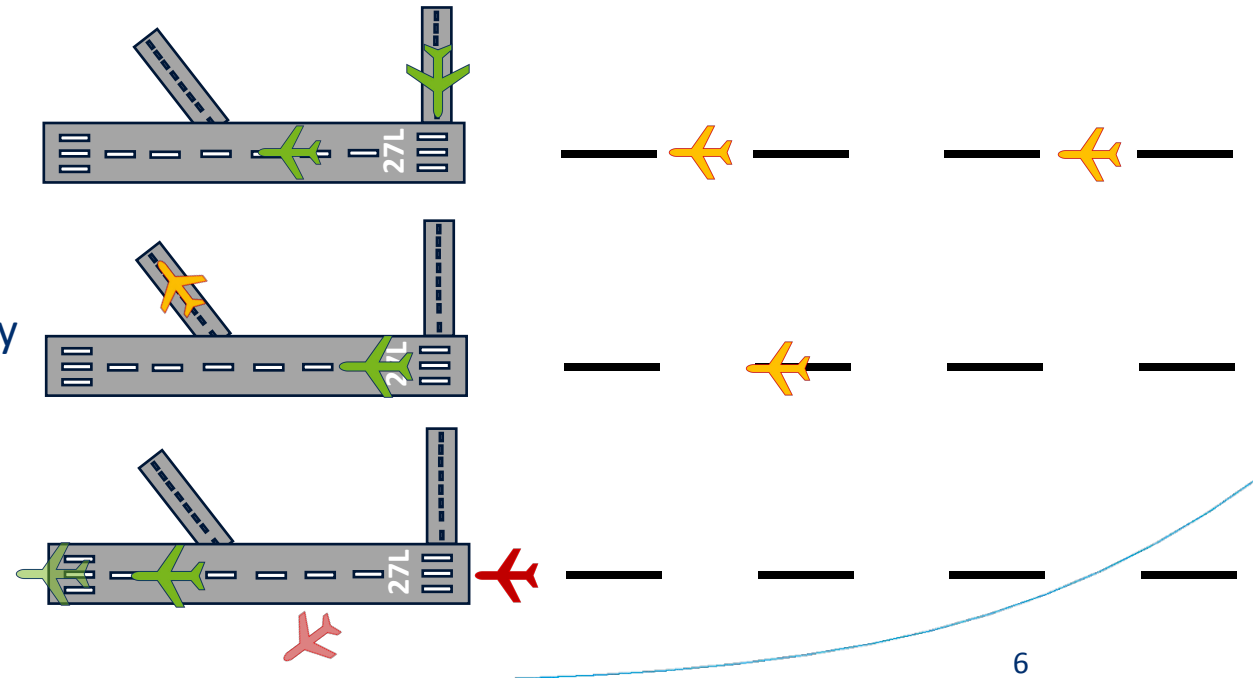
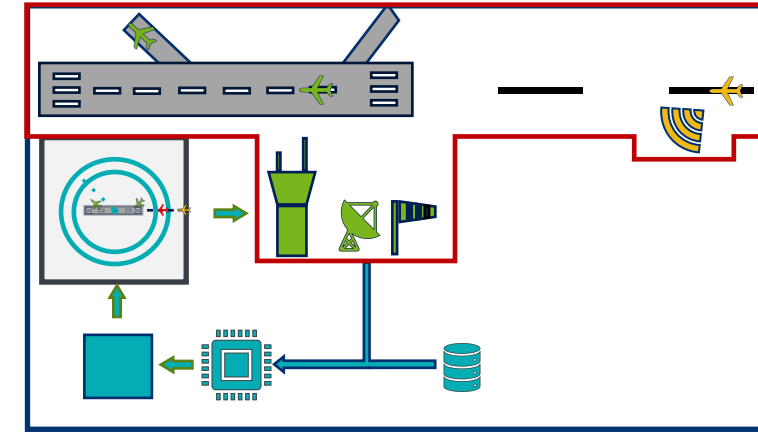
- Go-arounds are standard procedures for ATCOs and Pilots
- On average 3 out of 1000 approaches result in a go-around

Under certain conditions, go-arounds can become complex:

- High congestion
- Conflicting departure and missed approach procedure

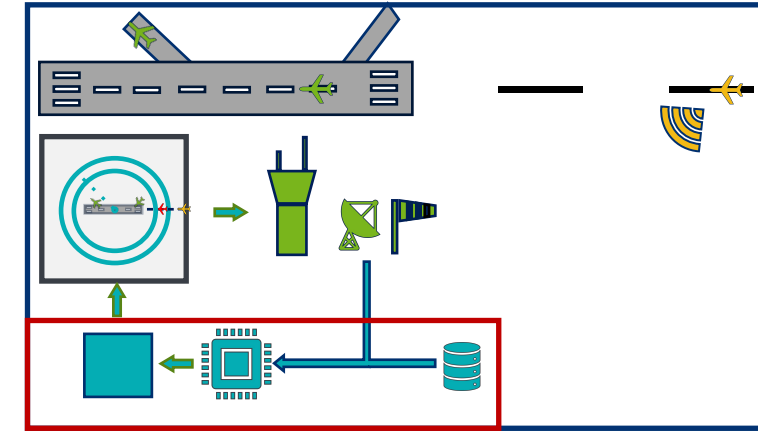
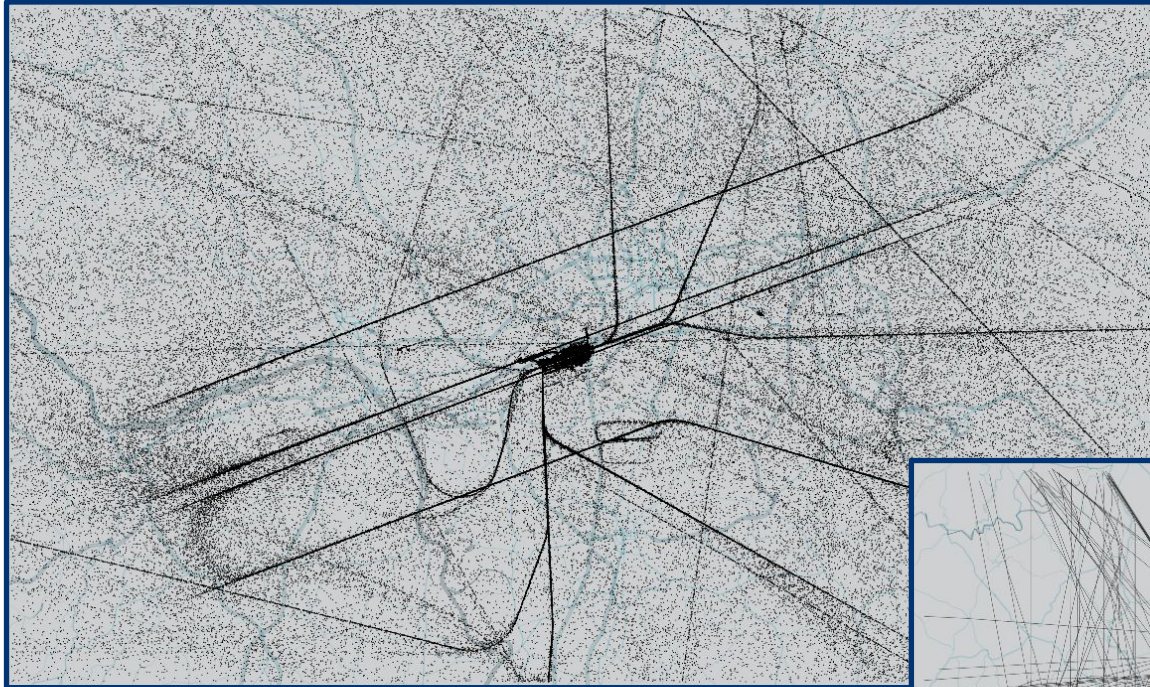
## □ Knock-on effects:

- Separation challenges
- Wake turbulence challenges
- High (peak) workload for ATCO and Pilots to ensure safety

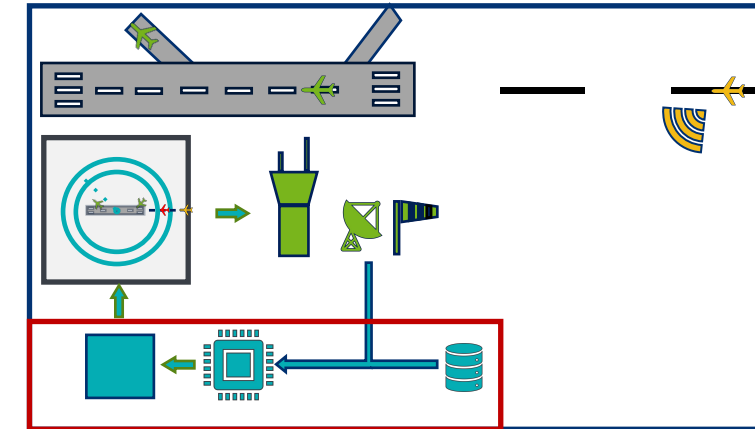
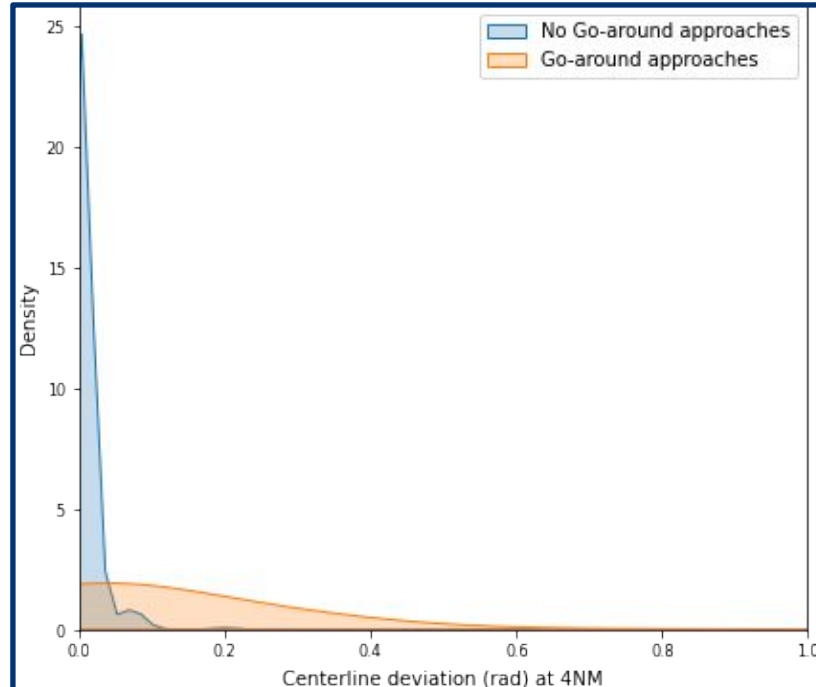
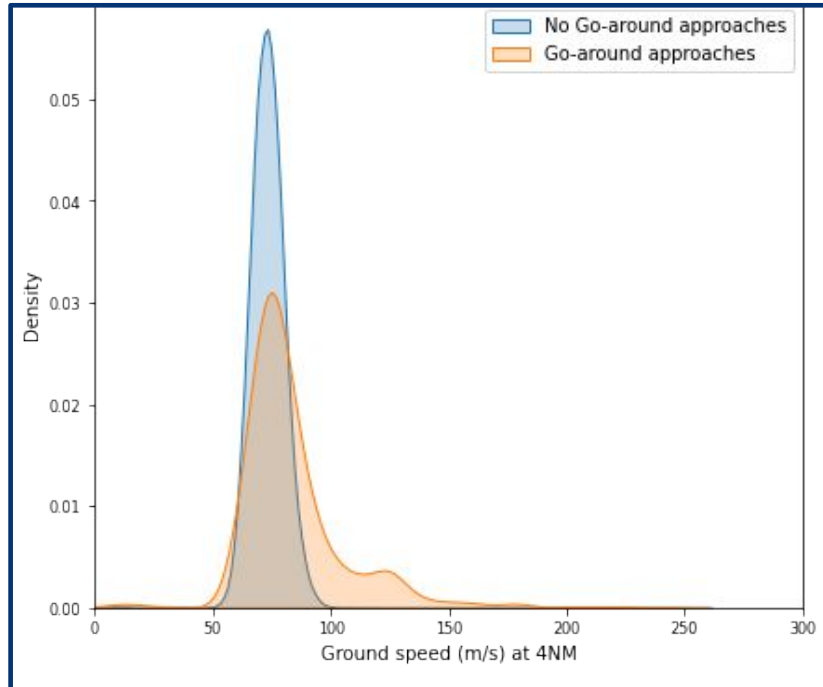




# Ai/ML Prototype – Data Pipeline (1)



# Ai/ML Prototype – Data Pipeline (2)



Training Data (D4.1/D4.2)

Nr. approaches	Nr. Go-arounds	GA/1000 approaches
227044	646	2.85

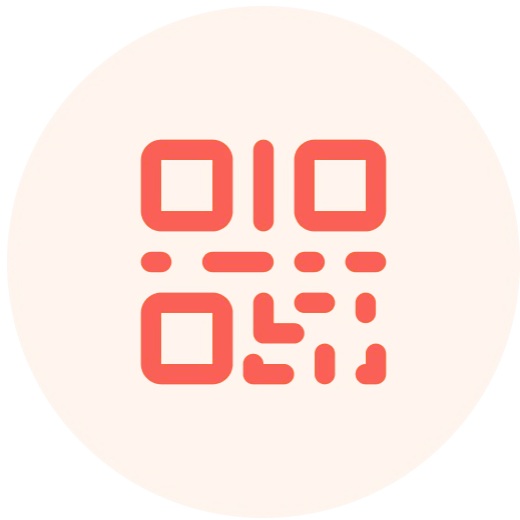


# Ai/ML Prototype - Features

Feature type	Feature name
Flight information	Callsign
	ICAO24
	WTC
	Approach attempt
	Hour
	Day
	Week
Weather data	Wind speed
	Wind direction
	Temperature
	Visibility
	Approach type
	Dew point temperature
	Ceiling height
	Cross-wind
	Head/Tail-wind

Feature type	Feature name
Approach performance	Runway ID
	Specific energy level
	Ground speed
	Vertical speed
	Vertical speed variance
	Track
	Track variance
	Altitude
	Track/Runway Bearing deviation
	Centerline deviation
	Localizer ddm dev
	Glideslope ddm dev
	Total go-arounds
Airport information	Runway go-arounds
	Departures
	Arrivals
	Last departure time
	Last arrival time
	Last departure WTC
	Last arrival WTC
	Aircraft in front
	Closing time

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#1131280**



**How many % of actual go-arounds are predicted by the AI prototype on average?**

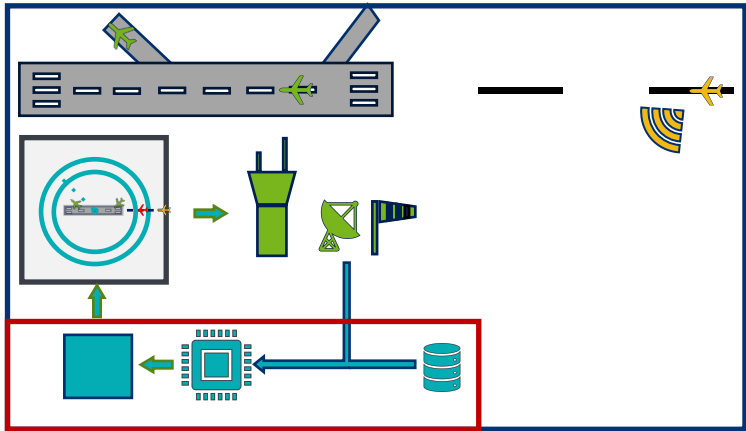
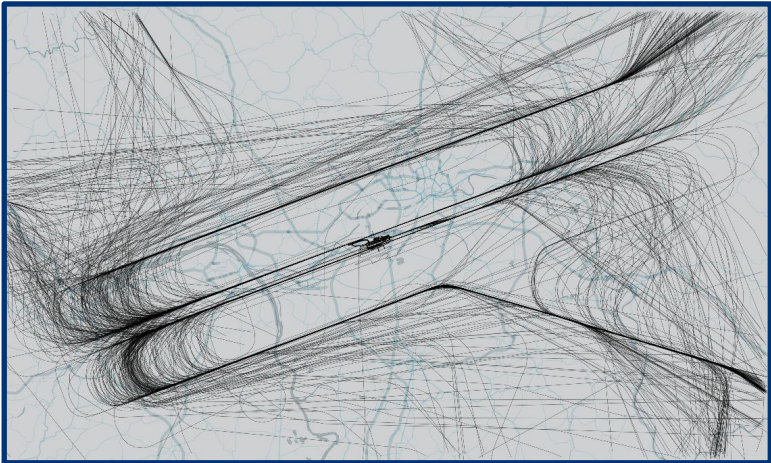
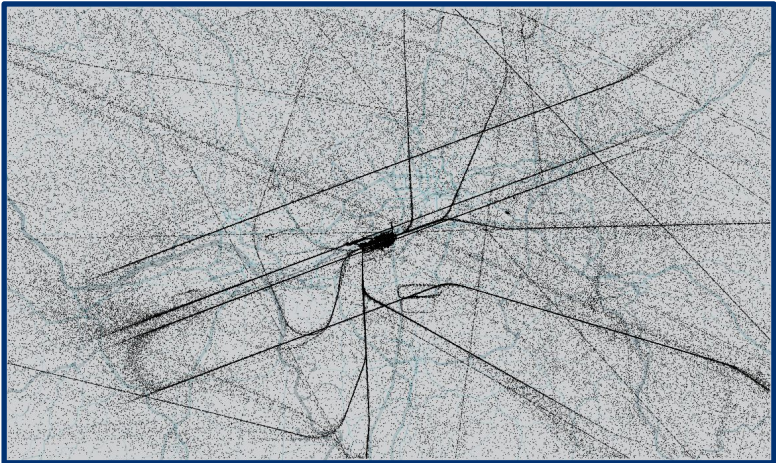


**How many % of approaches that are predicted to become go-arounds, will on average perform a go-around?**

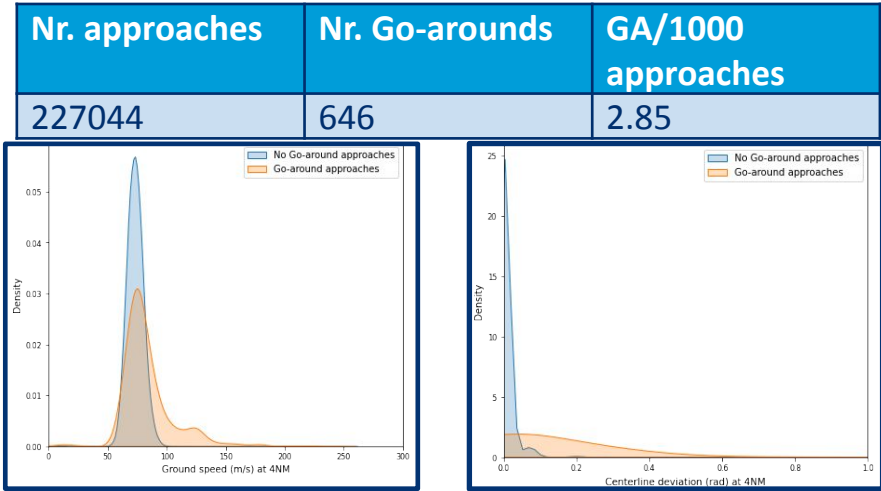
① Start presenting to display the poll results on this slide.



# Ai/ML Prototype



Training Data (D4.1/D4.2)



ML Results (D4.1/D4.2)

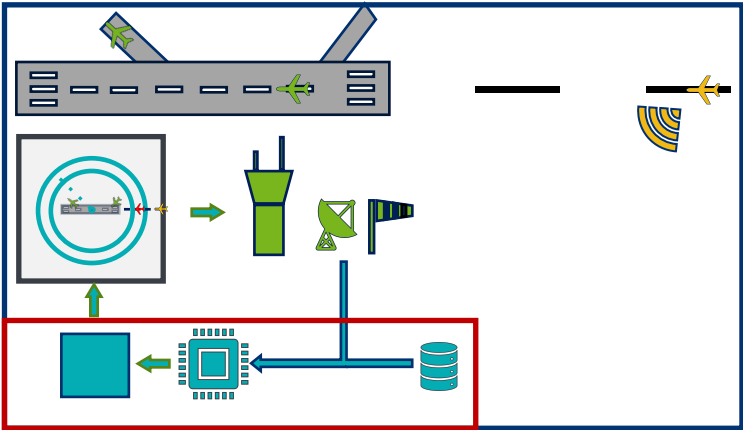
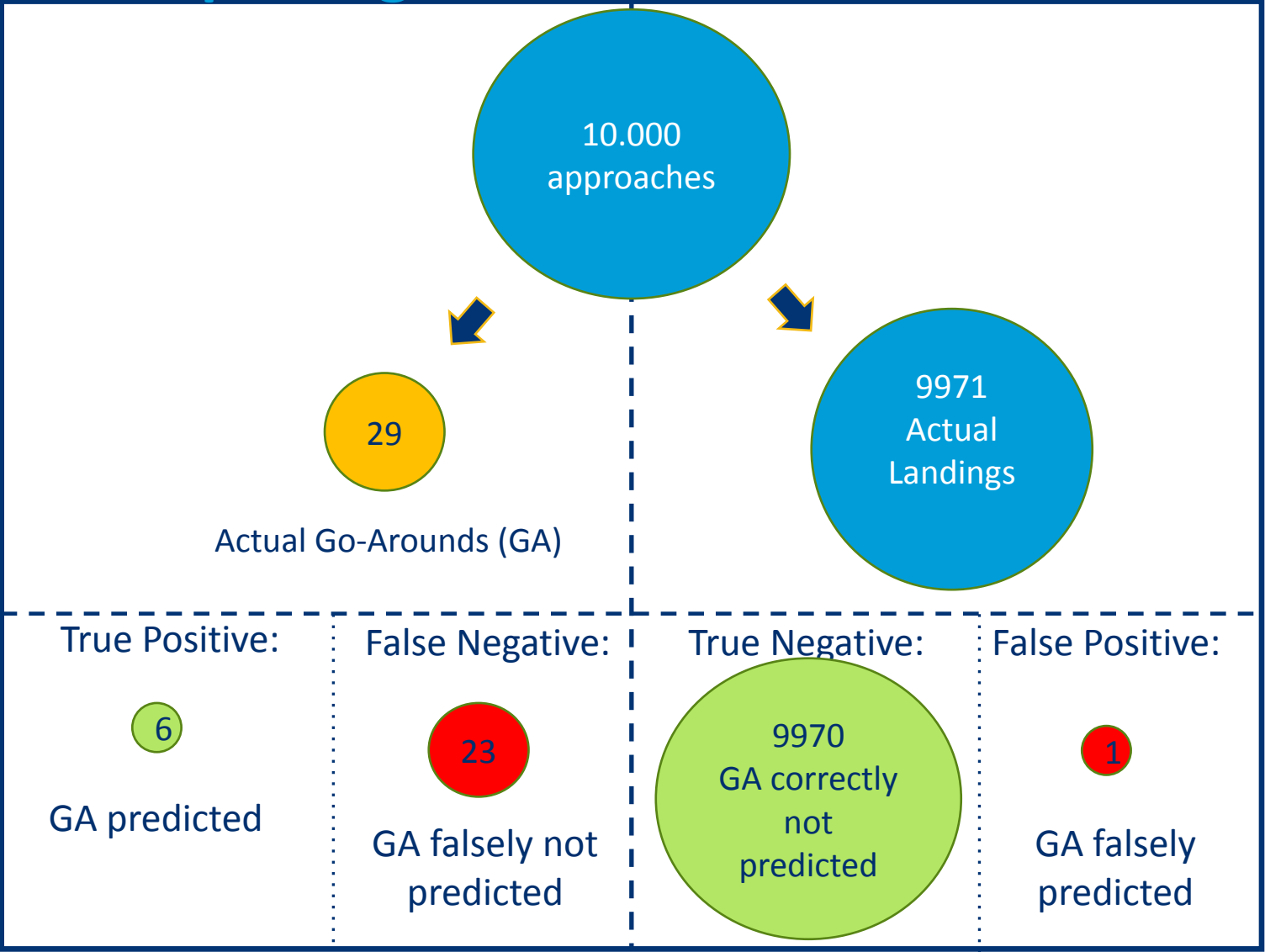
Prediction point	Go-around	Precision	Recall
2NM	True	0.8800	0.3411
	False	0.9981	0.9999
4NM	True	0.8710	0.2093
	False	0.9977	0.9999
6NM	True	0.9091	0.0775
	False	0.9974	0.9999

# slido



**Do you think this Ai tool should be used as landing prediction, to enhance capacity?**

# Interpreting Results 4NM



ML Results (D4.1/D4.2)

Prediction point	Go-around	Precision	Recall
2NM	True	0.8800	0.3411
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6NM	True	0.9091	0.0775
	False	0.9974	0.9999

# Low Fidelity Simulation Environment

## Radar Screen Imitation

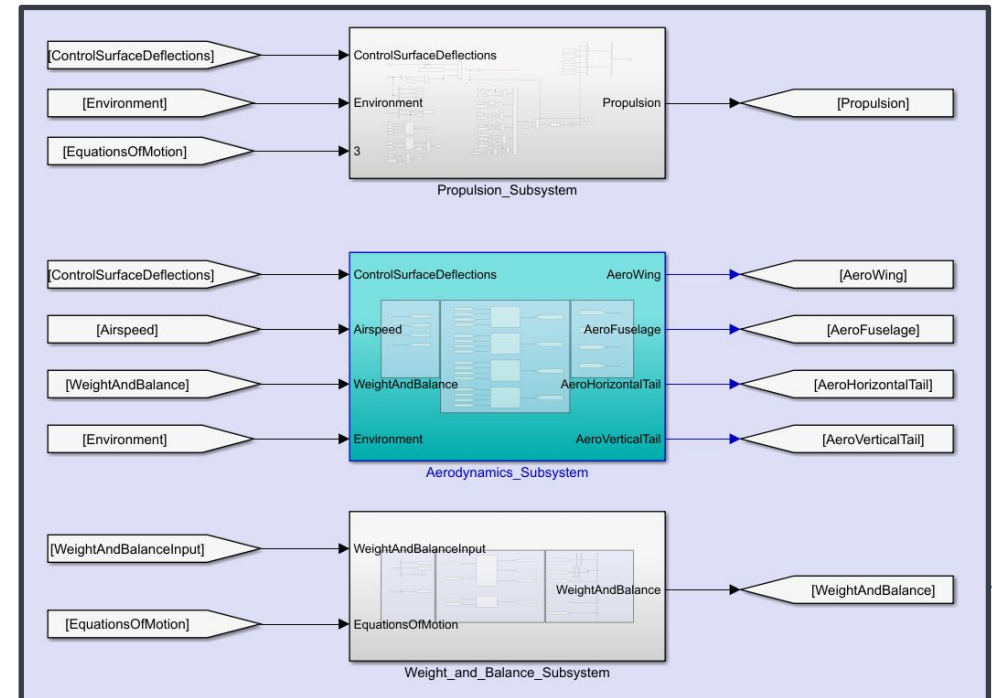
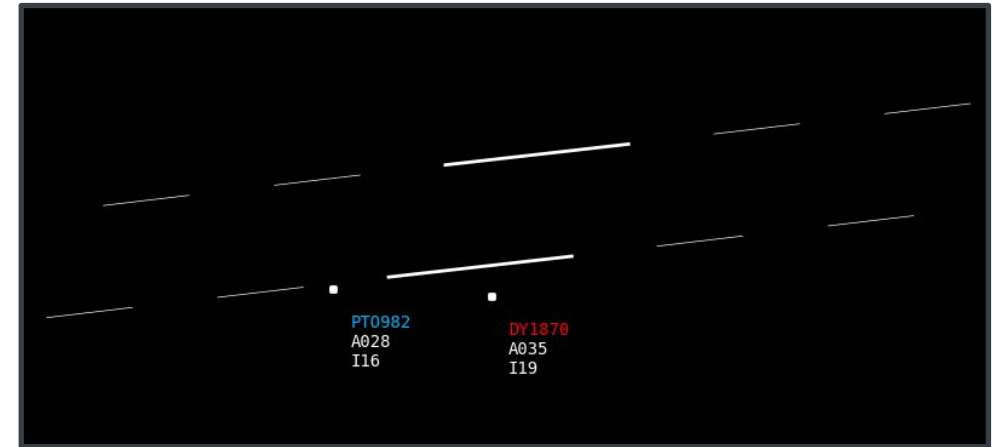
- Implemented in Python
- Easy manipulation of colors and information

## Approach aircraft model

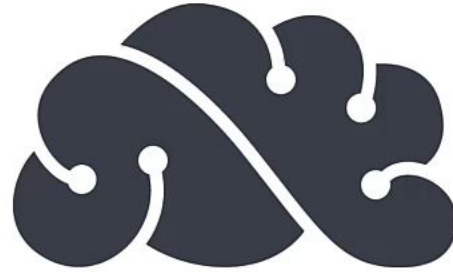
- Medium type, two-engine aircraft
- Performs approach automatically
- Performs standard missed approach procedure upon command
- Can be controlled according to ATCO's commands

## Departure aircraft model

- Variable WTC aircraft
- Automatically flies a Standard Instrument Departure Route
- Can be controlled according to ATCO's command







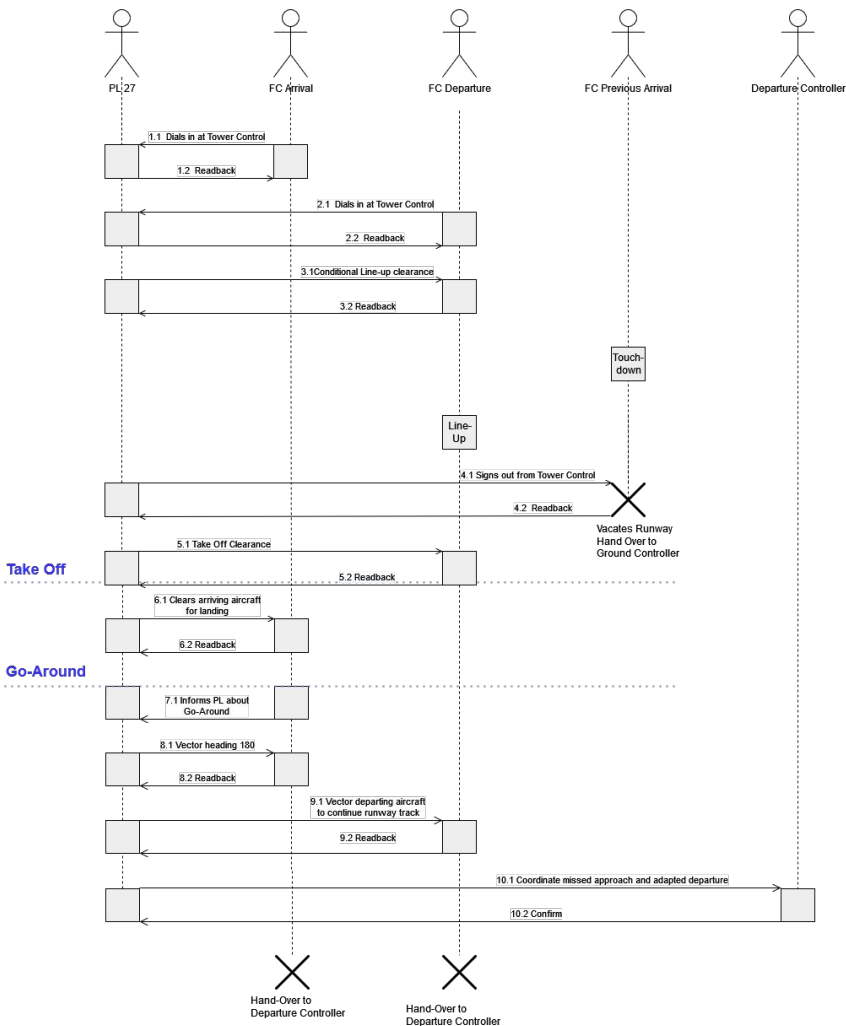
**SafeOPS**

This is an example of the simulation exercises conducted for SafeOPS, where we investigate the effect of go-around forecasts on the approach and go-around handling of Air Traffic Control Officers (ATCOs)

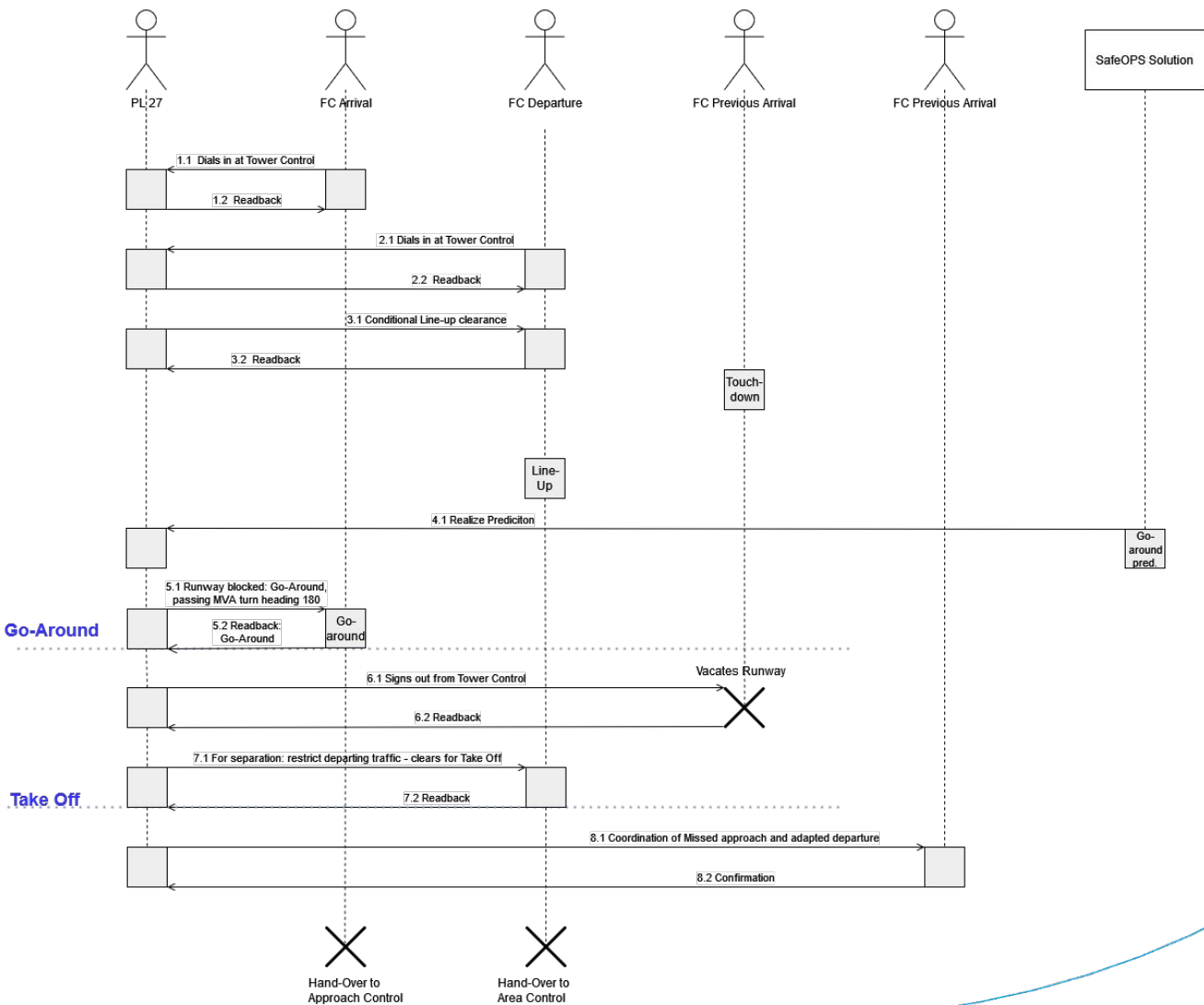


# Simulation Output (1)

## Sequence of Actions w/o Prediction



## Sequence of Actions with Prediction



# Simulation Output (2)

Trajectories of simulated aircraft without prediction



Trajectories of simulated aircraft with prediction





# Simulation Metrics

## 3 (5) Safety Metrics:

### Radar separation:

- Horizontal distance if vertical distance is  $< 1000\text{ft}$
- Vertical distance if horizontal distance is  $< 3\text{NM}$
- Separation infringement (y/n)

### Wake separation:

- Height difference, when in proximity of preceding aircraft
- Wake separation infringement (y/n)

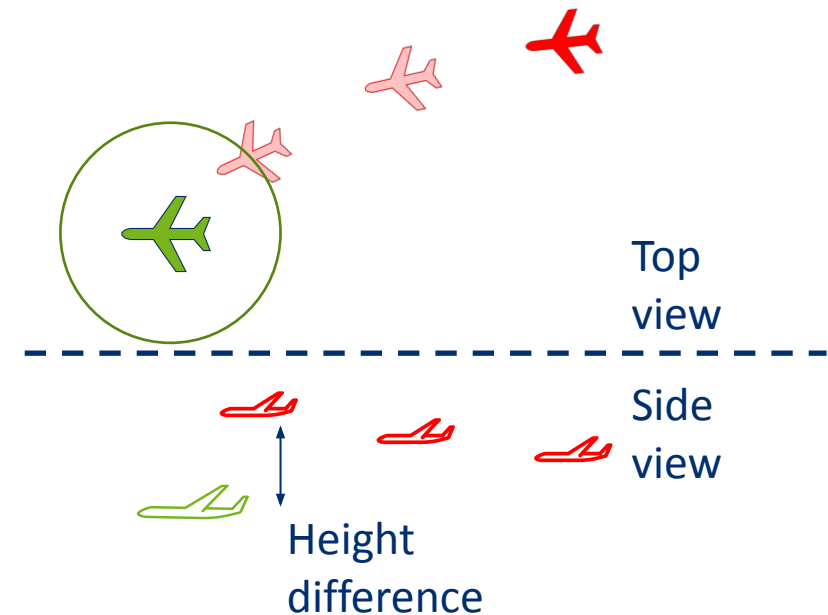
## 3 Resilience Metrics

Workload ☐ overall coordinative tasks in the scenario

Peak workload ☐ coordinative tasks when both A/C are airborne

## 2 Capacity Metrics

- Successful Landing
- Successful Departure





# Simulation Exercises

## True Positive Exercises:

- Compare state-of-the-art go-arounds with go-arounds including predictions

## False Positive Exercises

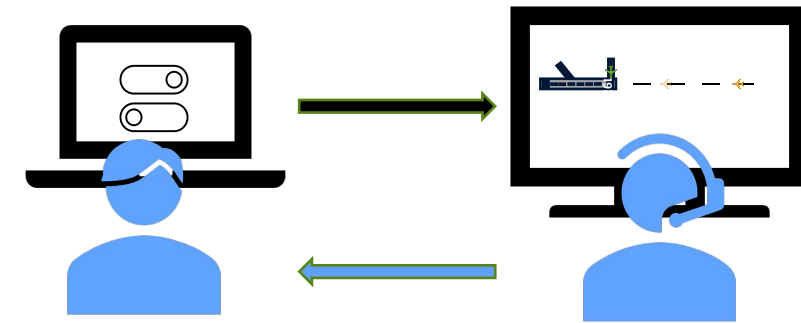
- Compare false positive go-around prediction with landing scenario

## True Negative Exercises

- Compare state-of-the-art landings with correctly, not predicted go-around.

## False Negative Exercises

- Compare state-of-the-art go-arounds with wrongly not predicted go-arounds



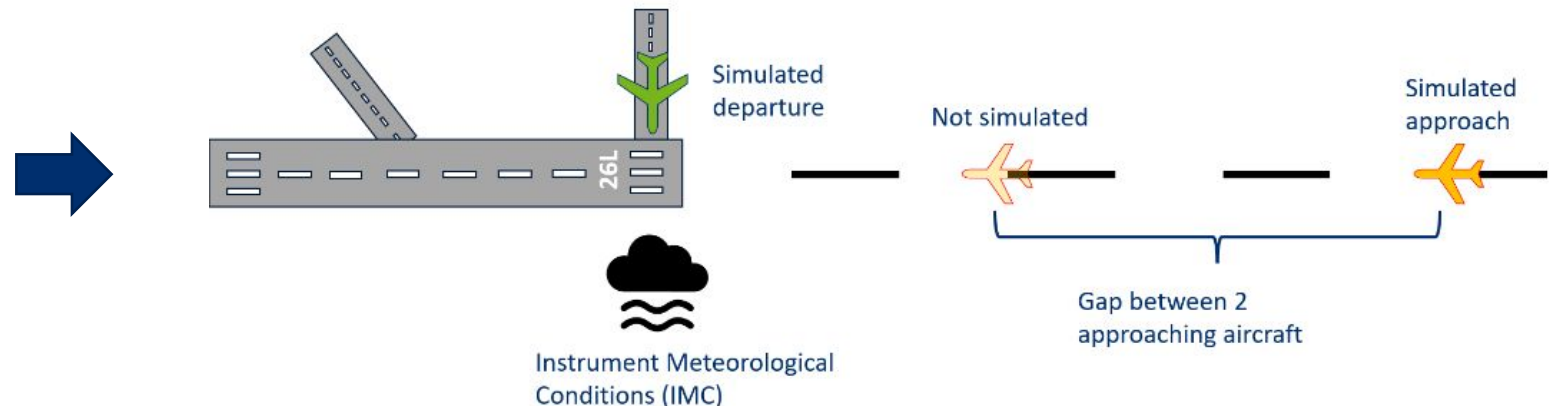
## Simulation Participants:

- 5 ATCOs
- 2 Major European Airports

## Simulation Configurations:

Only a few cases investigated:

- Fixed go-around initialization point
- 2 departure AC types
- Fixed approach performance
- No wind



# Simulation Configuration Example

ID:	Dep.Cfg1			
Airport 2	RWY (take-off)	SID	Gap between approaches	
	26L	S-SID	5NM	
WX	IMC Conditions, no wind, ISA standard			
Aircraft Type	V1		VR	V2
Medium twin engine	142 kt		142 kt	150 kt

ID:	App.Cfg.1			
Airport 2	IAP	Landing, if not commanded otherwise	MA init from RTH, if not requested from ATCO earlier.	Missed approach predicted at xxNM from RWY Threshold
	ILS 26L	Yes	n.a.	n.a.
WX	IMC Conditions, no wind, ISA standard			
Aircraft Type	VAPP			
Medium twin engine	135 kt			

# Simulation Exercises

Exercise ID:	Reference Scenarios			Solution Scenario		
	Scenario ID	Departure Configuration	Approach Configuration	Scenario ID	Departure Configuration	Approach Configuration
FP.1	RS.Landing.1	Dep.Cfg.1	App.Cfg.1	SS.FalsePositive.1	Dep.Cfg1	App.Cfg.6
FP.2				SS.FalsePositive.2		App.Cfg7
FP.3				SS.FalsePositive.3		App.Cfg.8
FP.4	RS.Landing.2	Dep.Cfg.2		SS.FalsePositive.4	Dep.Cfg2	App.Cfg.6
FP5				SS.FalsePositive.5		App.Cfg.7
FP.6				SS.FalsePositive.6		App.Cfg.8
TP.1	RS.GoAround.1	Dep.Cfg.1	App.Cfg2	SS.TruePositive.1	Dep.Cfg1	App.Cfg.3
TP.2				SS.TruePositive.2		App.Cfg4
TP.3				SS.TruePositive.3		App.Cfg.5
TP.4	RS.GoAround.2	Dep.Cfg.2		SS.TruePositive.4	Dep.Cfg2	App.Cfg.3
TP.5				SS.TruePositive.5		App.Cfg4
TP.6				SS.TruePositive.6		App.Cfg.5

# Simulation Results

## Summarizing results

True Positive				False Positive			
Prediction Point	Safety	Resilience	Capacity	Prediction Point	Safety	Resilience	Capacity
2NM	0	0	0	2NM	0	0	0
4NM	+	+	0	4NM	0	-	-
6NM	+	+	-	6NM	0	-	-



# Conclusion

- ! • **Simulation Exercise is limited through**
  - 2 aircraft types
  - 1 fixed go-around initialization point
- ! • **Monte Carlo based simulations needed**
  - To many variable parameters in the simulation
  - Not possible to cover the complete operational context with humans in the loop
- ! • **Use Case Frequency is relatively low:**
  - Go-arounds are 'rare'
  - Most relevant when conflicting SID and missed approach procedure
  - Increase of use cases, in case ATM Master Plan ambitions will be (partially) achieved
- ! • **Safety Capacity Trade-Off:**
  - Cost evaluation needed
  - ☐ Define requirements for the minimum acceptable precision

# Next Steps



## Define the Operational Design Domain:

- Which types of aircraft are covered?
- Which performances are covered (swing overs)?
- Which weather conditions are covered?



## Data Quality Requirements:

Objective DM-01<sup>1</sup>: The applicant should capture DQR for all data pertaining to the data management process...

- ☐ Avoid "Garbage In, Garbage Out"



## Demonstrate real time capabilities:

- Pre-processing
- Feature computation

<sup>1</sup><https://www.easa.europa.eu/en/downloads/134357/en>



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