Evaluating the Operational Impact of Tactics Enabled by an AI-Based Decision Support

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***Abstract*—Machine learning-based go-around predictions have been discussed in the research community for some years. Much work has been done developing algorithms and testing their accuracy, motivated by the assumption that time-in-advance information on the go-around likelihood of arrival aircraft will benefit air traffic controllers. The question of how to incorporate predictive and probabilistic information into the operation and how to evaluate their operational impact has yet to be investigated. This paper presents a first step toward assessing the operational impact of a machine learning-based decision support tool. Therefore, a low-fidelity, human-in-the-loop simulation exercise with air traffic controllers discovers potential new tactics enabled by a go-around prediction tool and evaluates them regarding safety, resilience, and capacity.**

***Keywords*—Go-around, Decision Support, Air Traffic Control, Safety, Resilience, Machine Learning, Operational Evaluation**

I. Introduction

The COVID-19 pandemic's impact on modern society led to a general debate on a "Resilience versus Efficiency" trade-off in many domains [1]. The author of [2] e.g., transfers [3]'s debate, whether a system trimmed for efficiency, with few unused resources, becomes susceptible to disruptions, for example, to the computing domain.

This debate is also relevant to Air Traffic Management (ATM), as next-generation ATM systems are pushed towards digitization and automation to increase capacity and cost-efficiency and, in parallel, further increase the already high safety and resilience levels. The performance ambitions presented in the European ATM Master Plan envision a 5% - 10% increase of flights performed under Instrument Flight Rules (IFR) by 2035, compared to 2012, at congested airports. Simultaneously, the ambitions expect an increase in safety levels by 100%. [4]

One situation in ATM where increased capacity at congested airports can conflict with safety ambitions is go-arounds. Under certain circumstances, go-arounds can have safety-relevant knock-on effects. At some airports, missed approach procedures conflict with departure routes. In such a case, ensuring separation minima between a missed approach and preceding departure may be challenging at high traffic

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TABLE I. This table provides the ML results of the go-aorund prediction, presented in [10].

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

volume. Especially in Instrument Meteorological Conditions (IMC), the time between the initiation of a go-around and its recognition through the Air Traffic Control Officer (ATCO) can be delayed. In the pilots' tasks, prioritized according to the *aviate, navigate, communicate* paradigm, the coordination with the ATCO comes last, making the go-around handling in the described situation a time-critical and complex task for ATCOs.

To assist ATCOs in these scenarios, several ATM-related research groups investigated machine learning (ML) based predictions of go-arounds. In [5], a missed approach alerting system is discussed for Denver airport, which provides binary go-around predictions for a (rolling) time window. A go-around prediction is presented in [6], providing go-around probabilities continuously along an aircraft's approach. In [7], a prediction of go-arounds was presented, similar to the predictions of unstable approaches discussed in [8], where points for predictions are defined by a distance relative to the runway threshold. Also SafeOPS developed a binary classification algorithm, which provides go-around probabilities for arriving aircraft at defined distances, in the following referred to as prediction points, 6 nautical miles (NM), $4NM$, and $2NM$ from the runway threshold [9]. Based on a refined data pipeline, [10] presents updated results for the binary classification algorithm. Therein, a data set containing 227044 approaches to Munich airport and 646 go-arounds was generated. The go-around rate in this data set is 2.85 per 1000 approaches. Table I summarizes the precision and recall metrics.

While the presented literature discusses technical solutions for go-around predictions, it generally assumes that the investigated solutions will help ATCOs make decisions when handling go-arounds. How to integrate these prediction tools into Tower Control operations has yet to be investigated and discussed.

Defining a concept of operations (ConOps) for potential ML-based tools and performing a safety assessment are requirements in the development process, foreseen in EASA's guidance for machine learning applications. The document aims to develop guidance on the implementation of ML in the domain of civil aviation, as defined in the EASA Basic Regulation (Regulation (EU) 2018/1139) [11].

As part of a ConOps and as an initial step in a safety assessment, it is essential to understand how the operation changes by introducing a potential new tool. We propose a two-step strategy to explore and evaluate possible operational changes arising from introducing the go-around predictor from SafeOPS [10] already at an exploratory research stage. The first step, described in detail in this paper, is a low-fidelity, real-time, human-in-the-loop (HIL) simulation exercise with ATCOs. The exercise aims to define and evaluate possible tactics ATCOs can apply with a go-around prediction. Since ATCOs are expensive and their availability is limited, especially for research at this exploratory stage, the described ML tool's impact over the complete operational domain of departures and arrivals cannot be evaluated with HIL simulations alone. In this step, we identify and document potential new tactics to handle go-arounds enabled by the ML tool in a narrowly defined scenario in which we expect the tool to be helpful.

The second step of our strategy, which will be presented in another publication, is to extend the existing simulation environment with automation that executes the newly found tactics from the HIL simulations. Using subset simulation [12] to efficiently estimate failure probabilities, the extended simulation environment shall examine the tactics identified in the first step across the entire operational spectrum.

In the following, we describe the simulation scenarios, the implementation of the simulation environment, and the metrics used to evaluate the simulation exercise.

II. Simulation Scenario Design

The main benefit of a go-around prediction tool is to help ATCOs maintain separation between a missed approach and a preceding departure. Only a subset of go-arounds happen under the stated IMC conditions, high traffic volume, and conflicting procedures. A go-around prediction tool will thus also only have an impact on a subset of all go-arounds.

In the following, we describe one potential scenario that meets the above-listed criteria and is used as a basis for the simulation. The simulation scenario reflects a mixed-mode runway operation, illustrated in Figure 1. Mixed mode operation describes an operation type where departures and arrivals are handled on the same runway. In case of high traffic volumes, the gap between two arriving aircraft in the final approach is between $4-5NM$, such that the aircraft waiting for departure on the holding point can perform a take-off between the two arriving aircraft. We assume IMC conditions for the simulation. Thus, we take the gap as being $5NM$. We initialize the scenario, with the arrival aircraft second in line (*Arrival 2*) being $7NM$ from the runway threshold. The aircraft awaiting departure has a conditional line-up clearance, which allows the aircraft to line up on the runway once the arriving aircraft (*Arrival 1*) touches down and passes the holding position. Once the touched-down *Arrival 1* vacates the runway, *Departure* receives the take-off clearance. *Departure* plans to follow a departure route with the initial instructions: *'climb on runway course to 1.5 DME DMS or 1900, whichever is later; left turn on heading 178 to intercept R323 OTT'* taken from Munich Airports' Standard Instrument Departures [13, p. AD 2 EDDM 5-7-31]. For *Arrival 2*, the aircraft potentially performing the go-around in the scenario, the approach chart [13, p. AD 2 EDDM 4-2-3] defines the standard missed approach procedure with the instructions to: *'climb straight ahead to 1 DME DMS or 1900, whichever is later; left turn direct to OTT'*. A conflict between the departure route and the missed approach procedure exists for these procedures.

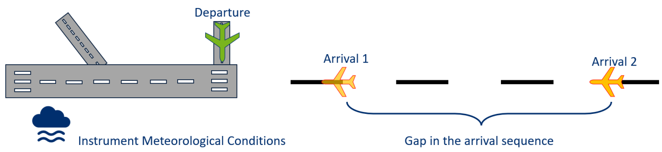

Figure 1. Illustration of the mixed mode runway scenario. The opaque aircraft are the ones, simulated. The transparent aircraft are not simulated and only illustrated to demonstrate the investigated scenario.

To compare state-of-the-art go-around handling with go-around handling supported with a predictive tool, we distinguish between reference scenarios without predictive information and solution scenarios with predictive information. The go-around prediction tool under investigation is a binary classifier. For a complete operational evaluation, true and false predictions of both go-around and no go-around predictions must be investigated. This contribution focuses on the true positive and false positive prediction cases. At this experimental research stage, we assume that the true negative case, where the prediction does not indicate a go-around correctly, is similar to the reference case without a predictive solution in place and the arriving aircraft performing a landing. Similarly, we disregard the false negative prediction case, which we assume to be similar to the reference case of a go-around happening without predictive information available.

Consequently, we further distinguish between true positive and false positive solution scenarios. The reference scenario, to which a solution scenario compares, depends on whether the prediction is true or false. We compare the true positive solution scenario to a go-around reference scenario and the false positive solution scenario to a landing reference scenario since, in the false positive prediction case, the arriving aircraft would perform a landing if the prediction tool was not in place. Lastly, the go-around prediction has three prediction points, and we define a solution scenario for each prediction point. At the time of a prediction, an ATCO will not know if the prediction turns out to be true or false. The chosen tactic thus initially depends only on the prediction being go-around or no go-around. However, the scenarios evolve differently, depending on whether the aircraft will perform a go-around as predicted or continue to land despite a go-around prediction. The following subsections describe all simulation scenarios.

A. Reference Scenarios

We define two reference scenarios for this exercise, a landing scenario and a go-around scenario:

- landing scenario: the departing aircraft gets a take-off clearance after the preceding arriving aircraft vacated the runway. The second arriving aircraft gets a landing clearance and performs a landing.
- go-around scenario: the departing aircraft gets a take-off clearance. The arriving aircraft is assumed to perform an unstable approach and to initiate a go-around at $0.9NM$ from the runway threshold.

B. Solution Scenarios

The machine learning algorithm predicts a go-around in case of true positive and false positive predictions. The scenarios evolve differently depending on whether a prediction is true or false. Thus, the following solution scenarios are defined:

- True Positive Solution Scenarios:
  - $2NM$ prediction: The departing aircraft gets a take-off clearance. A go-around prediction is presented to the ATCO, when the arriving aircraft is $2NM$ from the runway threshold and the arriving aircraft initiates a go-around at $0.9NM$ from the runway threshold.
  - $4NM$ prediction: A go-around prediction is presented to the ATCO, when the arriving aircraft is $4NM$ from the runway threshold. The arriving aircraft initiates a go-around at $0.9NM$ from the runway threshold.
  - $6NM$ prediction: A go-around prediction is presented to the ATCO, when the arriving aircraft is $6NM$ from the runway threshold. The arriving aircraft initiates a go-around at $0.9NM$ from the runway threshold.
- False Positive Solution Scenario:
  - $2NM$ prediction: The departing aircraft gets a take-off clearance. A go-around prediction is presented to the ATCO, when the arriving aircraft is $2NM$ from the runway threshold. The arriving aircraft will continue to land, if not commanded otherwise by the ATCO.
  - $4NM$ prediction: A go-around prediction is presented to the ATCO, when the arriving aircraft is $4NM$ from the runway threshold. The arriving aircraft will continue to land, if not commanded otherwise by the ATCO.
  - $6NM$ prediction: A go-around prediction is presented to the ATCO, when the arriving aircraft is $6NM$ from the runway threshold. The arriving aircraft will continue to land, if not commanded otherwise by the ATCO.

III. Simulation Environment

We developed a low-fidelity simulation environment consisting of two aircraft simulation models and a radar screen imitation to simulate the scenarios defined in section II. We use Matlab/Simulink to implement and simulate the aircraft models and Python to visualize the radar screen. The aircraft models and the radar screen simulation are connected using a User Datagram Protocol (UDP) interface.

Aircraft models from commercial off-the-shelf flight simulators would also work for the envisioned HIL simulation. We decided to implement models in Simulink, so our simulation environment is compatible with the Subset Simulation Toolbox [14], necessary for the second part of the strategy, outlined in section I.

We briefly summarize the simulation environment and the assumptions and simplifications made in the following. A more detailed description of the simulation environment, including information on the flight dynamics model and aircraft controls, is beyond the scope of this paper. We kindly refer to [15, pp. 126-144] for detailed information.

A. Simplifications

The simulation environment features two aircraft, one arriving aircraft, labeled *Arrival 2*, and one departing aircraft, labeled *Departure*, illustrated in figure 1. We decided not to simulate the aircraft labeled Arrival 1, as it does not directly affect the quantities of interest resulting from the simulation. The take-off clearance timing, which depends on *Arrival 1* vacating the runway, was determined by *Arrival 2*'s distance from the runway threshold by the ATCOs' experience.

Also, the simulation does not include an implementation of the go-around prediction from [10]. We hardcoded the predictive information displayed on the radar screen and the relevant scenarios for several reasons. Since, for this study, we are interested in identifying new tactics for ATCOs enabled by a go-around prediction for subsequent safety assessments, we presume that ATCOs are willing to work with the predictive information. Furthermore, given the statistics of the occurrences of go-arounds and the limited availability of ATCOs for this work, a study that represents an actual distribution of go-arounds and landings is not feasible.

The simulation model for both aircraft is the same and differs only in the set model parameters. The simulation model is designed to reference a common medium wake turbulence category, two-engine aircraft. Furthermore, we perform the simulations only with one set of parameters per aircraft, as varying overall potential parameters would result in too many simulation trials, given the limited availability of ATCOs. The following summarizes the relevant parameters and control strategies for each aircraft.

B. Arrival Aircraft

The arrival aircraft is programmed to automatically follow the Instrument Landing System's (ILS) guidance, with an approach speed of $135kts$. The mass of the aircraft is fixed to a constant $60.14t$. For a reference go-around and true-positive solution scenario, the aircraft automatically initiates a go-around $0.9NM$ from the runway threshold and follows the standard missed approach procedure, defined in section II. The ATCOs defined the $0.9NM$ go-around initialization point as roughly the point where the departing aircraft's speed matches the arriving aircraft's speed, thus resulting in minimum separation distances in the scenario. For a reference landing or false-positive solution scenario, the aircraft automatically follows the ILS until touchdown. The automatic control can be overwritten in all scenarios if the ATCO requests a new target heading, target altitude, target speed, or go-around.

C. Departure Aircraft

The departure aircraft automatically performs the take-off and departure sequence, defined in section II. Similar to the arrival aircraft, the mass of the departure aircraft is a constant $77.14t$ throughout the simulation, and the automatic control can be overwritten similarly to the arrival aircraft.

D. Radar Screen Simulation

The visualization provides simulated aircraft's position, altitude, indicated airspeed, and vertical rate information. Additionally, the radar screen visualization includes color coding. Yellow indicates an arriving aircraft, light blue indicates a departing aircraft, and red indicates a predicted go-around—the radar screen visualization centers on the two runways, illustrated as thick white lines. The thin white lines represent the extended runway center line. The dashed white line at the right and bottom right mark the airport's control zone. Figure 2 provides a screenshot of the radar screen visualization. Deutsche Flugsicherung GmBH's Aeronautical Information Publication provides the geographic information of runway coordinates [13, pp. AD 2 EDDM 1-4 - 1-6] and control zone boundaries, underlying the radar screen visualization [13, p. VFR Terminal Chart].

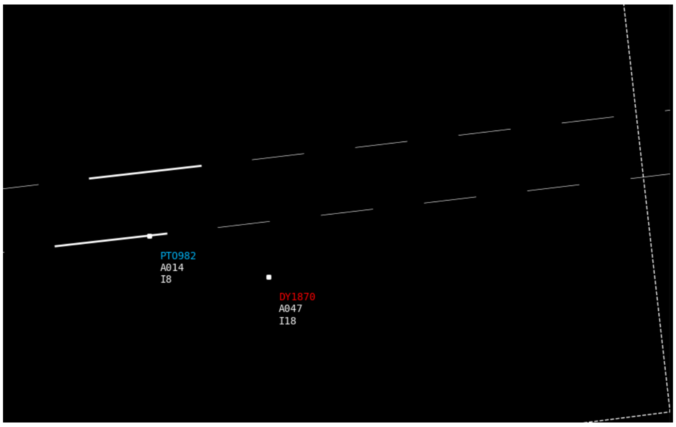

Figure 2. A cropped screenshot of the live radar screen visualization. The blue dot illustrates an aircraft performing the take-off. The red dot illustrates an aircraft performing a go-around. For both aircraft, airspeed and altitude are displayed as additional information to the call signs.

IV. Simulation Exercise and Evaluation

In the scope of the project SafeOPS, we performed the HIL exercises with five ATCOs in workshops held from June 2022 to August 2022. The radar-screen imitation, described in section III, was shown to an ATCO, illustrating the simulated aircraft's states in real time. Based on the information from the radar screen, the ATCO gave commands to a simulation controller, who controlled the simulated aircraft, following the ATCO's instructed vectors. These workshops aimed to identify possible tactics for the scenario defined in section II, enabled by the go-around prediction, and evaluate their operational impact.

To evaluate the simulations, we identified the Key Performance Areas *safety and capacity/resilience*, as defined in the SESAR JU's Performance Framework [16], as most relevant at this early stage of research. In terms of safety, Mid Air Collisions (MAC), Wake Vortex Encounters, Loss of Control in Flight (LOC-I), and Controlled Flight Into Terrain (CFIT) are the most relevant accident types given the go-around situation. We exclude CFIT and LOC-I, since, at this stage, we focus on the ATC-related accidents, and the chosen airport for the simulation has no geographic obstacles. Additionally, both simulated aircraft are of medium wake turbulence category. Therefore, wake vortex separation is not applicable. To evaluate the risk of MACs, resulting from a go-around, we investigate the radar separation distances as a Safety Performance Indicator. This is motivated through Eurocontrol's Accident Incident Models (AIM) [17] for MACs in the Final Approach Phase and Initial Departure, which identify an imminent minimum radar separation infringement as a precursor for MACs. Related to go-arounds, the following separation minima, defined in ICAO DOC 4444 [18], are relevant:

- 300m vertical separation, ([18, section 5.3.2a])
- 3NM horizontal separation ([18, section 8.7.3.2a])
- Runway separation, ([18, section 7.9.1]). In case of a successful landing, both separation minima stated above are not applicable, and the aircraft are separated according to the runway separation criteria.

Regarding capacity, we evaluate whether the landing of *Arrival 2* is successful (not a go-around). Additionally, we evaluate if the departure aircraft was able to use the planned gap in the arrival sequence.

According to [19], resilient systems are those that can anticipate or adapt to disruptions from regular operation, e.g., from operational contingencies. The coordinative actions of ATCOs, necessary to handle a situation, can thus be used to assess resilience. One can determine how the tower controller returns to regular operation after a rare event and how his actions change if he is prepared for a go-around beforehand. Reducing peak workload by providing a larger time frame to take action and shifting tasks into less demanding periods or decreasing the overall tasks increases the cognitive flexibility of the ATCOs.

Table II summarizes the resulting metrics used to evaluate the simulation exercises. Note that for metrics $S1 - S3$, we evaluate the simulation only when both aircraft are airborne after initiating a go-around.

TABLE II. METRICS USED TO EVALUATE THE SIMULATION EXERCISE

ID	Metric
S1	Minimum three dimensional distance between A/Cs in meters.
S2	Minimum vertical distance between A/Cs in meters, when the horizontal distance is below $3NM$.
S3	Minimum horizontal distance between A/Cs in nautical miles, when vertical separation is below $300m$.
C1	Arrival aircraft successfully landed.
C2	Departing aircraft could use foreseen gap for departure.
R1	Number of overall coordinative actions of the ATCO
R2	Number of coordinative actions of the ATCOs after the initiation of a go- around, if departure and missed approach are airborne.

V. Results

This section summarizes the simulation results. For each simulated scenario, we describe the applied tactic by a table that lists the necessary coordinative actions of the ATCO, and for the go-around scenarios, a visualization of the simulated trajectories that emerged from applying these tactics. Similarly to section II, we separate between reference scenarios without predictive information and solution scenarios with predictive information.

A. *Reference Scenarios*

In this subsection, we document the ATCOs' tactics from the reference scenarios and their evaluations. Table III lists the metrics introduced in section IV, for both reference scenarios. Note that the two safety metrics are not applicable (n.a.) for the landing scenario, as separation is always maintained through runway separation, and the risk of a MAC between a departing aircraft and an aircraft performing a missed approach procedure is not existent in case of a successful landing.

TABLE III. THE METRICS FOR THE REFERENCE SCENARIOS

Scenario	S1	S2	S3	C1	C2	R1	R2
Reference Landing	n.a.	n.a.	n.a.	$true$	$true$	3	0
Reference Go-Around	$3579m$	$48m$	$1.93NM$	$false$	$true$	6	3

1) Landing: Table IV lists the ATCO's coordinative actions in the reference landing scenario. The ATCO provides a conditional line-up clearance to the departing aircraft. When the departing aircraft is in position for take-off, and the runway is free, the departing aircraft receives a take-off clearance. At this instance, the simulated arriving aircraft is $2.7NM$ from the runway threshold in our simulation scenario. When the ATCO can reasonably assure that runway separation will be maintained, the arriving aircraft receives the landing clearance. Since the arriving aircraft performs the landing as planned in this scenario, no further coordinative actions from the ATCO are necessary.

TABLE IV. THE ATCO'S COORDINATIVE ACTIONS IN THE REFERENCE LANDING.

# Action	Actor	Action	Receiver
1	Tower Controller	Conditional Line-Up Clearance	Departure Aircraft
2	Tower Controller	Take Off Clearance	Departure Aircraft
3	Tower Controller	Landing Clearance	Arrival Aircraft

2) Go-around: Table V provides the necessary coordinative actions if the arriving aircraft performs a go-around at $0.9NM$ from the runway threshold. The initial three actions are similar to the reference landing scenario. However, after the arriving aircraft initiates a go-around, the ATCO vectors the arriving aircraft with a heading of 180 to resolve a potential conflict with the departing aircraft. Also, the ATCO vectors the departing aircraft to continue on the runway heading, restoring radar separation as fast as possible. Additionally, the ATCO coordinates both deviations from the planned routes with the Sector Controller.

TABLE V. THE ATCO'S COORDINATIVE ACTIONS IN THE REFERENCE GO-AROUND.

# Action	Actor	Action	Receiver
1	Tower Controller	Conditional Line-Up Clearance	Departure Aircraft
2	Tower Controller	Take Off Clearance	Departure Aircraft
3	Tower Controller	Landing Clearance	Arrival Aircraft
	Arrival Aircraft	Informs about ongoing go-around	Tower Controller / Departure Aircraft
4	Tower Controller	Vectors heading 180	Arrival Aircraft
5	Tower Controller	Vectors to continue runway heading	Departure Aircraft
6	Tower Controller	Coordinate missed approach and adapted departure	Sector Controller

Figure 3 illustrates the resulting trajectories of the arrival aircraft as yellow and the departing aircraft as blue. It further indicates the points of closest proximity between the aircraft in the simulation as a black line. The vertical cyan lines indicate the position of the arriving aircraft when the departure aircraft receives the line-up clearance, take-off clearance, and lifts off. The initiation of the go-around happens shortly after lift-off.

Figure 3. Simulation result of the reference go-around.

B. *True Positive Solution Scenarios*

This section describes the true positive prediction scenarios and provides their evaluation. First, table VI summarizes the metrics for the three scenarios. After that, the three tactics are described in more detail. In the $4NM$ and $6NM$ prediction cases, both aircraft, once airborne, are separated vertically throughout the complete simulation. Therefore, $S3$ is not applicable.

TABLE VI. THE METRICS' EVALUTATION FOR THE TRUE POSITIVE SOLUTION SCENARIO AND THE REFERENCE GO-AROUND SCENARIO

Scenario	S1	S2	S3	C1	C2	R1	R2
$2NM$ solution	$3837m$	$44m$	$2.07NM$	$false$	$true$	6	3
$4NM$ solution	$4514m$	$1058m$	n.a.	$false$	$true$	4	1
$6NM$ solution	$5482m$	$1067m$	n.a.	$false$	$false$	5	1
Reference Go-Around	$3579m$	$48m$	$1.93NM$	$false$	$true$	6	3

1) 2NM True Positive Prediction: This solution scenario is similar to the reference go-around scenario and is illustrated in figure 4. The prediction of the go-around happens at the $2NM$ point, illustrated by the change of the arriving trajectory's color from yellow to red. At this point, the ATCO already cleared the departing aircraft for take-off, as indicated by the second cyan vertical bar. Thus, the ATCOs argue for a similar tactic described in the reference go-around scenario. The black line visualizes the minimum three-dimensional distance between the aircraft in the simulation.

TABLE VII. THE ATCO'S COORDINATIVE ACTIONS IN THE 2NM SOLUTION SCENARIO.

# Action	Actor	Action	Receiver
1	Tower Controller	Conditional Line-Up Clearance	Arrival Aircraft
2	Tower Controller	Take Off Clearance	Departure Aircraft
3	Tower Controller	Landing Clearance	Arrival Aircraft
	Prediction Tool	Predicts go-around	Tower Controller
	Arrival Aircraft	Informs about ongoing go-around	Tower Controller / Departure Aircraft
4	Tower Controller	Vectors heading 180	Arrival Aircraft
5	Tower Controller	Vectors to continue runway heading	Departure Aircraft
6	Tower Controller	Coordinate missed approach and adapted departure	Sector Controller

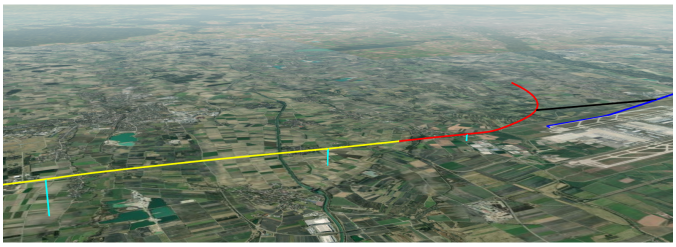

Figure 4. Simulation result of the 2NM prediction scenario.

2) 4NM True Positive Prediction: A positive prediction for the arriving aircraft at the $4NM$ point appears after the departing aircraft receives the line-up clearance, however, before the departing aircraft receives the take-off clearance. In this case, the ATCOs argued not to provide a take-off clearance for the departing aircraft on the runway, awaiting an imminent go-around. Since the runway is blocked by the departing aircraft, the ATCO commands the arriving aircraft to go-around. Once the arrival aircraft, performing the go-around, turns away from the runway heading, the departing aircraft is cleared for take-off. Figure 5 illustrates the trajectories resulting from the proposed tactic.

TABLE VIII. THE ATCO'S COORDINATIVE ACTIONS IN THE 4NM SOLUTION SCENARIO.

# Action	Actor	Action	Receiver
1	Tower Controller	Conditional Line-Up Clearance	Arrival Aircraft
	Prediction Tool	Predicts go-around	Tower Controller
2	Tower Controller	Runway blocked $\Rightarrow$ go-around, heading 180 when passing MVA	Arrival Aircraft
3	Tower Controller	Take-off clearance, for separation restrict departing traffic	Departure Aircraft
4	Tower Controller	Coordinate missed approach and adapted departure	Sector Controller

Figure 5. Simulation result of the 4 NM prediction scenario.

3) 6NM True Positive Prediction: Figure 6 illustrates the trajectories, simulated in the case of a prediction at the $6NM$ point. The red line shows the arriving aircraft's trajectory. The ATCO does not provide a line-up clearance for the aircraft. Since the runway is empty, the ATCO clears the arriving aircraft for landing. If the arriving aircraft performs a go-around, the ATCO vectors the missed approach to heading 180 when passing Minimum Vectoring Altitude (MVA). Once the aircraft performing the missed approach overflies the runway threshold, the aircraft waiting for departure is cleared for line-up, indicated by the first cyan, vertical line. The The ATCO clears the departing aircraft for take-off, once he observes the missed approach to turn away from the runway heading, indicated by the second cyan, vertical line. The black line indicates the minimum three-dimensional distance between both airborne aircraft.

TABLE IX. THE ATCO'S COORDINATIVE ACTIONS IN THE 6NM SOLUTION SCENARIO.

# Action	Actor	Action	Receiver
	Prediction Tool	Predicts go-around	Tower Controller
1	Tower Controller	Landing Clearance	Arrival Aircraft
	Arrival Aircraft	Informs about ongoing go-around	Tower Controller Departure Aircraft
2	Tower Controller	Vector heading 180 when passing MVA	Arrival Aircraft
3	Tower Controller	Line up clearance	Departure Aircraft
4	Tower Controller	Take-off clearance	Departure Aircraft
5	Tower Controller	Coordinate missed approach	Sector Controller

C. False Positive Solution Scenario

This section describes the false positive prediction scenarios and provides their evaluation. First, table X summarizes the metrics for the three scenarios. Thereafter, the three tactics are described in more detail. In the $2NM$ and $6NM$ prediction cases, both arriving aircraft perform a landing despite the false positive go-around prediction. Thus, separation is maintained by runway separation, similar to the reference landing scenario, and metrics $S1$ - $S3$ are not applicable.

Figure 6. Simulation result of the 6 NM prediction scenario.

TABLE X. THE METRICS, EVALUATED FOR THE FALSE POSITIVE SOLUTION SCENARIOS AND THE REFERENCE LANDING SCENARIO.

Scenario	S1	S2	S3	C1	C2	R1	R2
$2NM$ solution	n.a.	n.a.	n.a.	$true$	$true$	3	0
$4NM$ solution	$4514m$	$1058m$	n.a.	$false$	$true$	4	1
$6NM$ solution	n.a.	n.a.	n.a.	$true$	$false$	3	0
Reference Landing	n.a.	n.a.	n.a.	$true$	$true$	3	0

1) 2NM False Positive Prediction: The ATCO applies a similar tactic as in the $2NM$ true positive prediction case. Since the go-around prediction, provided at $2NM$ from the runway threshold, arises after the ATCO cleared the departure for take-off, the ATCO can clear the arriving aircraft, falsely predicted to go around, for landing. Since the aircraft performs a landing in this scenario, the coordinative actions of the ATCO in this scenario, listed in table XI, are similar to the reference landing scenario from table IV.

TABLE XI. THE ATCO'S COORDINATIVE ACTIONS IN CASE OF A FALSE PREDICTION AT $2NM$ FROM RUNWAY THRESHOLD.

# Action	Actor	Action	Receiver
1	Tower Controller	Conditional Line-Up Clearance	Departure Aircraft
2	Tower Controller	Take Off Clearance	Departure Aircraft
	Prediction Tool	Predicts go-around	Tower Controller
3	Tower Controller	Landing Clearance	Arrival Aircraft

2) 4NM False Positive Prediction: The simulation for the false positive go-around prediction at $4NM$ from the runway threshold produced a similar result as the true positive go-around prediction scenario. Since the ATCO decided not to provide a take-off clearance for the departing aircraft, which is line-up on the runway when the prediction arises, the ATCO commands a go-around to the arriving aircraft since the runway is blocked. Therefore, the coordinative actions and trajectories are the same as in table VIII and figure 5.

3) 6NM False Positive Prediction: The ATCO applies the same tactic as in the scenario for true positive prediction at $6NM$ and does not provide a line-up clearance for the departing aircraft, waiting at the holding point, and therefore skips a possible gap in the arrival sequence. Despite the prediction, the ATCO clears the arriving aircraft for landing. After the successful landing, the departing aircraft is cleared for line-up and take-off. The coordinative actions are listed in table XII.

TABLE XII. THE ATCO'S COORDINATIVE ACTIONS IN THE 6NM SOLUTION SCENARIO.

# Action	Actor	Action	Receiver
	Prediction Tool	Predicts go-around	Tower Controller
1	Tower Controller	Landing Clearance	Arrival Aircraft
2	Tower Controller	Line up clearance	Departure Aircraft
3	Tower Controller	Take-off clearance	Departure Aircraft

VI. DISCUSSION

For both solution scenarios, with assumed true positive and false positive predictions at the $2NM$ prediction point, we find that the prediction has no impact on the operational outcome of the scenarios. The capacity- and resilience-related metrics, provided in tables VI and X, do not change from solution to reference scenarios. The safety-related metrics $S1 - S3$ from the true positive solution scenario deviate from the go-around reference scenario. However, the deviations of the safety metrics are within a range that has to be credited to the experimental imprecisions.

For the true positive solution scenario with a prediction at $4NM$, the safety-related metrics $S1 - S3$ improve compared to the reference go-around. Throughout the complete simulation, separation is maintained by vertical separation. Also, the minimum three-dimensional distance between the aircraft increases. Furthermore, the coordinative actions overall and when both aircraft are airborne are reduced. For the false positive solution scenario with a prediction at $4NM$, the ATCO commands a go-around to an aircraft that would perform a landing in the reference scenario. Even though the go-around itself is uncritical regarding the separation metrics $S1 - S3$, as vertical separation is maintained throughout the simulation, it adversely affects the capacity since the arrival aircraft does not land and has to perform a second approach. Additionally, this scenario increases the workload of the ACTO, compared to the reference scenario by one coordinative action.

For the true positive solution scenario with a prediction at $6NM$, the safety-related metrics $S1 - S3$ improve compared to the reference go-around. Throughout the simulation, separation is maintained by vertical separation. The minimum three-dimensional distance between the aircraft increases. Furthermore, the coordinative actions overall and when both aircraft are airborne are reduced. However, since the ATCO does not provide a line-up clearance to the aircraft waiting for departure, one gap in the arrival sequence cannot be used, compared to the reference go-around, resulting in a loss of capacity. For the false positive solution scenario with a prediction at $6NM$, the ATCO does not provide a line-up clearance to the aircraft waiting for departure. The arrival aircraft, predicted to go around, does land. Thus, this scenario reduces the airport's capacity by not using a gap in the arrival sequence for a departure, which was successfully used in the reference scenario.

For both the $4NM$ and $6NM$ prediction points, we observe positive impacts for true predictions and negative impacts for false predictions. One important aspect is that false predictions do not adversely affect the investigated safety-related metrics. However, false predictions negatively affect capacity in case of the $4NM$ prediction also workload and resilience. True predictions, on the contrary, positively affect the safety and resilience metrics but do not positively affect capacity. To put these findings into perspective, it is important to outline that go-arounds are rare. The discussed scenario will thus not be relevant for most approaches but only for missed approaches for which routes conflict with departure traffic and which also happen in high traffic volumes. Finally, from the precision of the go-around prediction tool, documented in table I, one can expect one false positive prediction for six to seven true positive predictions on average.

Whether the described trade-off and at which ratio of true/false predictions is acceptable is the logical next question raised by the presented findings. The result shows that the ratio of this trade-off is directly linked to the precision of the prediction. If this trade-off is included in a cost vs. benefit analysis, a minimum required precision could be determined as a requirement for developers of such prediction tools.

VII. Conclusion and Outlook

The presented study aimed to evaluate the impact of an ML-based prediction tool with three possible prediction points in a narrowly defined operational scenario of a Tower Controller. Therefore, a low-fidelity HIL simulation exercise with ATCOs was performed. The simulation exercise was only performed for a set of fixed parameters, which can vary over a wide range in daily operations. Thus, the safety-related findings cannot be easily generalized beyond the simulated scenario. We propose a second analysis step to tackle this shortcoming, following the one presented in this paper. Therein, the tactics documented in the HIL simulations shall be implemented in the simulation environment in an automated fashion, e.g. by an event-driven state machine. The expanded simulation environment shall test the scenario regarding the safety-related metrics over a broader range of parameters using a Monte Carlo-based simulation approach, such as subset simulation.

The study also focused on the true and false positive predictions, omitting the true and false negative predictions at this investigation stage. Furthermore, human factor-related aspects are not considered at this stage. Higher fidelity simulator exercises with a larger group of ATCOs must be designed to reliably capture these effects. This might become possible once the concept matures beyond the exploratory research stage.

The results obtained from this study indicate that a go-around prediction point at $2NM$ from the runway threshold is too close to the runway to have a measurable impact on the operational outcome, independent of predictions being false or correct. Furthermore, the study points out a potential trade-off between safety and resilience vs. capacity, resulting from go-around predictions. True predictions at both prediction points, $4NM$ and $6NM$ from the runway threshold, provide safety and resilience benefits over the respective reference scenarios. In case of false predictions, the resilience- and capacity-related metrics indicate negative impacts. If and at which rate of occurrence the positive impacts on safety and resilience outweigh the negative impacts on capacity is a question that directly arises from the presented results and should be investigated in future work.

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