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Machine Learning Supporting Enhanced Optimized Spacing Delivery between Consecutive Departing Aircraft

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Abstract. The Optimised Spacing Delivery (further referred to as OSD) tool has the objective of calculating the necessary time spacing between two consecutive departing aircraft in order to fulfil all required spacing and separation constraints. OSD, developed in SESAR 2020 Wave 1 [1] is based on analytical models [2] to predict aircraft trajectory and speed profiles. The use of this tool by Air Traffic Controller supports the safe, consistent and efficient delivery of the required separation or spacing between consecutive departure pairs by providing the time required between departure aircraft pairs via an automated count-down timer to the tower runway controller. In order to improve OSD, this paper introduces the enhanced Optimised Spacing Delivery (further referred to as eOSD) tool which builds on the OSD tool using Machine Learning techniques to make more accurate predictions of aircraft behaviour (e.g. trajectory/climb profile, speed profile) and wind on the initial departure path, so further optimising spacing delivery between consecutive departures. Zurich airport data were used to develop and asses the performance of the eOSD tool compared to the OSD tool.

1 Introduction

Prior to the covid pandemic, airport capacity was considered one of the major bottlenecks in the European ATM system, with several major European airports being capacity constrained during the peak traffic periods. This in turn impacted the capacity of the overall European network. Traffic predictions show that traffic level will rise back and exceed 2019 traffic levels in the future putting significant pressure once again on the European Airport and network capacity.

Runway throughput directly depends upon the applied spacing between successive aircraft on the final approach or on departure. The applied spacing is constrained by separation and spacing minima between aircraft either related to Wake Turbulence (WT) rules, runway spacing, radar separations or specific spacing minima when aircraft are using same departing routes. These separation requirements are expressed either in time (e.g., for WT between departures) or in distance (e.g., radar surveillance minima).

Within the Single European Sky ATM Research (SESAR) programme, EUROCONTROL has been developing solutions to increase runway throughput at those airports that are capacity constrained without the need for additional infrastructure. These solutions have involved the development, for both arrivals on the final approach and departures, of optimised separation / spacing minima, on one hand and, on the other hand, of controller support tools to optimize separation delivery and to enable the application of these more complex but more efficient minima.

Amongst those solutions, in SESAR 2020 Wave 1, solution PJ.02-01-02, EUROCONTROL developed a Controller support tool allowing Optimised Spacing Delivery (OSD) for departures [1]. The OSD tool consists of an automatic digital countdown timer which provides an optimized clearance time ensuring that all separation and spacing constraints will be satisfied between the consecutive departure pair. The advantage of such a tool is that it also supports (and hence enables) the application of complex separation schemes, such as pairwise separation scheme or weather dependent separation, whether time or distance-based.

For each aircraft pair, the OSD tool takes into consideration all applicable separation and spacing minima and displays the most constraining on the countdown timer. The calculation of the optimised clearance requires prediction models for the trajectory and the ground speed profile of both leader and follower aircraft both in the air and on the runway. In the OSD tool, these prediction models were calibrated using traditional analytical techniques. However, due to the variability of aircraft behaviour and wind on the initial departure path, the uncertainties related to the use of these analytical models can be significant. As a result, buffers must be added to the OSD clearance time calculations to ensure they are safe. Yet, these buffers are often over-conservative for some pairs which reduces the related achievable capacity benefits.

The enhanced Optimised Spacing Delivery (eOSD) tool, presented in this paper, and developed in SESAR 2020 Wave 2, further improves the OSD tool by using Machine Learning (ML) techniques instead of traditional analytical techniques to more accurately predict aircraft departure behaviour, i.e. rolling time, rolling distance, airspeed profile and climb profile, and the associated model uncertainty. These more accurate predictions of aircraft behaviour allow the eOSD time calculations to be reduced compared to OSD through reductions of the required buffers. This leads to more efficient spacing delivery between departing aircraft and hence an increase in departure throughput during peak operations. This has a direct impact on network delays and on the environment. Furthermore, as the spacings are more accurately tailored per aircraft pair there is no negative impact on safety.

The paper describes the eOSD solution and the ML techniques and models used to predict aircraft departure behaviour and the model uncertainty. Based on one year of Zurich airport operational surveillance and meteorological data, it also provides the initial results of the benefits that can be achieved with the use of ML techniques in the eOSD solution compared to the traditional analytical techniques used in the OSD tool.

2 eOSD definition and design criteria

2.1 General description

The eOSD automated countdown timer is a tool that determines the clearance time between consecutive departing pairs of aircraft, ensuring that all separation and spacing constraints will be satisfied. As such, it has the same definition as the OSD automated countdown timer [1]; the difference lying in the way the clearance time is calculated.

In order to predict the clearance time to be applied between a pair of departures, a model of the trajectory and the speed profile of the aircraft along the runway and in the air during the first phase of their flight is required.

For that purpose, four Machine Learning (ML) models were defined: 1) a Rolling Time ML model, 2) a Rolling Distance ML model, 3) an Altitude to Time ML and, 4) a Time to True Air Speed (TAS) ML model. The rolling time and rolling distance models are needed to describe the aircraft when it is moving along the runway before the rotation point. The altitude to time model describes the time needed by the aircraft to reach a specific altitude while flying along the Standard Instrument Departure (SID) path. The time to TAS model provides the TAS of the aircraft as a function of time while the aircraft is flying along the SID route. The trajectory and speed profile were modelled this way as it is assumed that the altitude to time and time to TAS models, do not depend on the wind; meaning that wind data was not required for the training of these ML models.

In addition to the four ML models required for predicting the trajectory and the speed profile of the aircraft, an additional ML model, called the buffer model, was also defined. The buffer ML model is required to cover any uncertainties caused from the previous four models as well as from the wind variability on the initial departure path.
Finally, a set of coverage functions was introduced. The objective of the coverage functions is to ensure that for a given aircraft pair, the ML models are sufficiently reliable and can be used to support operations. If the aircraft pair is not considered covered by the coverage functions, the eOSD tool will output the required clearance time from the OSD solution (i.e. the clearance time based on traditional analytical techniques as opposed to Machine Learning) which will generally be more conservative. This coverage function is required to ensure the clearance times provided by the tool are always safe.

2.2 Separation and spacing constraints
Each airport has specific separation and spacing constraints that need to be adhered to during the departure phase of the aircraft. All of these constraints are taken into account by the eOSD tool, when defining the clearance time to be applied per departing aircraft pair. Specifically, for Zurich airport the following types of separation or spacing constraints have been taken into account (see also [1]):

- Minimum Surveillance Radar Separation (MRS)
- Vertical Separation (VS) at take-off (VS_TO) and in altitude (VS_Alt)
- Runway occupancy time (ROT)
- Standard Instrument Departure spacing (SID)
- Time based wake turbulence separation (TBS)

To derive the final clearance time to be applied per aircraft pair, the following three steps must be followed to ensure that all the necessary separation and spacing constraints are taken into account by the eOSD tool:

- Step 1 - ensures that the Minimum Surveillance Radar Separation and the Vertical Separations are respected by taking the minimum time between the two.
- Step 2 - takes into account this last defined value with the Standard Instrument Departure spacing and the Time-based wake turbulence separation taking the maximum time required between the three.
- Step 3 - the maximum between this last value and the Runway Occupancy Time is taken as the final clearance time for the given flight pair.

2.3 Assumptions
In order for the eOSD tool to define safe, yet efficient, clearance times between departing aircraft pairs, some assumptions are made on the flight operations:

- The aircraft are assumed to closely follow their preassigned SID path. This assumption should not be restrictive since aircraft are intended to follow their predefined SID path, not only to comply with traffic regulations, but also for example, to ensure possible noise abatement regulations in benefit of the population nearby the airport.
- The aircraft are assumed not to perform rolling take-offs (i.e., start of the take-off acceleration just after entering the runway). This assumption should neither be restrictive as rolling take-off are not frequent during peak operations for which the use of the eOSD tool is intended.
- It is assumed that aircraft will perform a strict climb during their flight just after take-off.

2.4 Error rates
Generally, it is always interesting and important to control the errors produced by any ML model developed. As it is envisaged that the eOSD tool will be used in an operational environment, the need for monitoring and managing errors in the ML model / eOSD tool is critical from a safety perspective. In this particular context, it is considered to have an error if the predicted clearance time to be applied is smaller than the ground truth clearance time to be applied (i.e., the minimum clearance time that would have been required to satisfy all applicable spacing constraints). However, designing a system with a zero-error rate would require adding over-conservative buffers in the clearance time calculations

and would make then the system inefficient, even if safe. For the design of the eOSD tool, it is thus suggested to determine an "acceptable" error rate that would correspond to a fraction of the under-spacing rate observed locally in current operations without the use of the tool. Very low error rates, of around a few percentages, are thus here considered as acceptable for the different separation / spacing constraints since in current operations very low error rates are observed.

2.5 Baseline: OSD solution for clearance time calculation

A baseline solution to calculate the clearance time to be applied per aircraft pair is defined and further referred to as OSD. For each of the ML trajectory and speed profile models (Rolling Time, Rolling Distance, Time to TAS and Altitude to Time) a corresponding baseline is defined as the mean by aircraft type and surface runway headwind band.
Baseline buffer models are then also defined to account for any uncertainties caused from the previous models and from the wind variability on the initial departure path. The baseline buffer models are designed to target the specific acceptable error rates based on statistics by leader/follower aircraft type and follower surface runway headwind band. One baseline buffer model is defined per separation/spacing constraint. Specifically, for the SID baseline buffer model also the preassigned SID path of the flights is taken into account.

3 Database description and processing

The learning and testing of the various ML models described above require data. Those data shall describe the aircraft 3D trajectory, speed and climb profile, the wind and the flight information.

3.1 Data sources

One year (2019) of operational surveillance and meteorological data from Zurich airport has been used to calibrate and test the various models. Three data sources are used.
The first one is Mode-S data that provide, with a refresh rate of 4 seconds, the aircraft trajectory (timestamp, aircraft 3-D position, ground and true air speed, heading and bank angle), the wind (speed and heading) and the flight information (aircraft type, callsign and destination airport).
The second source is Advanced Surface Movement Guidance and Control System (A-SMGCS) data. For Zurich airport, this is the only source available with ground operation data since for most flights the Mode-S recordings start from when the aircraft is already in the air. The A-SMGCS features used in the ML pipeline are flight information (aircraft type, callsign, destination airport), aircraft trajectory (timestamp, 3-D position and ground speed). The A-SMGCS refresh rate is around 1 to 2 seconds.
Finally, runway surface anemometer data are used containing recordings of the wind speed and direction recorded by anemometers positioned near the runways. The recording refresh rate is 3 seconds.

3.2 Data processing

From the data sources just described, some features are used directly, whilst other features need to be computed. For each flight, the take-off runway and the runway entry are detected from the A-SMGCS data. Also, the acceleration and the end of rotation points are computed from the A-SMGCS data. These two specific points allow the definition of the Rolling Time and the Rolling Distance. The Mode-S data is used to detect the followed SID route. Finally, the anemometer data is used to define for the runway of interest its surface head and cross wind.
A total of around 40,000 tracks, from one year of recordings, are used after data processing and filtering, they then form a total of around 70,000 couples (any two flights departing with a maximum 10 minutes interval) of which around 13,000 will be used as test set to assess the quality of the models.

4 Machine learning pipeline for the eOSD tool

4.1 Aircraft behaviour ML models

The four machine learning models defined to describe the trajectory (rolling time, rolling distance, altitude to time and time to TAS) are very similar in their structure. Their general model architecture applicable to all of them is here described.

In general, the model used to predict the target of interest takes as input: the aircraft type, airline, wake turbulence category (WTC), distance between origin and destination airport, surface head and cross wind along the runway, runway entry distance (X0), hour, month and day of the week of the flight.
The model used is composed of one Gradient Boosting Regressors (GBR) [3] for the rolling time and distance models and by GBR for the altitude to time and time to TAS models. This model allows ones to describe non-linear relationships between the features and the targets. The model can handle only numerical data so the categorical data, for example airline or aircraft type, are previously targeted encoded. Target encoding is a technique to encode strings to numerical values taking into consideration the targets of the model [4].

4.2 Ground-Truth and eOSD-predicted optimised clearance time computation

Before being able to train the buffer models, the error/uncertainty of the eOSD tool calculations obtained based on the aircraft behaviour ML models explained above has to be quantified. For that purpose, the ground truth clearance time is computed for each pair of flights using the recorded rolling time, rolling distance, X0 and flight trajectory from the A-SMGCS and Mode-S source data. Note that the distance spacings to fulfil MRS and SID constraints are computed as a difference of travelled distance between the leader and the follower. This is valid under the hypothesis that the two aircraft follow the exact same trajectory. The formulas used to compute the clearance times are described in [1].
These values are then compared, for each pair of flights, to the predicted eOSD clearance time calculated using the ML models without buffers.

4.3 ML Buffer models

The ML buffer models are designed to respect the design error rates for each separation/spacing constraint, as defined in Section 2.4. Each constraint has one associated ML buffer model to learn the buffer needed to ensure the targeted error rates. The target variable to learn the required buffer is defined by the difference between the predictive eOSD clearance time value (without buffer) and its ground truth value.
The model takes as inputs the following features, for both the leader and the follower aircraft: aircraft type, airline, WTC, distance to destination, runway head and cross wind, X0, hour, month, day of the week of the flight and SID. It uses a Gradient Boosting Regressor [GBR] [3] with a quantile loss set to enforce the targeted error rate.

4.4 Coverage function

The coverage functions are required to determine on which cases the predictive models can be used with sufficient confidence, or not. In order to assess the accuracy of the predictive models, an independent dataset from the one used to train the models is used. For all aircraft pairs in this dataset, all clearance times corresponding to all spacing constraints are computed using only predictive models (trajectory models and buffer models).
The error rates regarding the target constraints are then computed on several subsets of this dataset. A subset is defined by the value of one or several features. If the target error rates are respected with enough confidence for all constraints on a subset, then this subset is considered as covered with regards to the feature/set of features of interest. A coverage function is then computed for each feature of interest.
A set of six coverage functions are defined for each spacing constraint, except SID constraint:

- Runway,
- Triple: leader category / follower WTC/ runway,
- Head wind range,
- Leader aircraft type,
- Follower aircraft type,
- Leader airline,
- Follower airline.

For the SID constraint, the triple coverage function is replaced by: leader category / follower WTC / SID.
A couple is considered to be covered if and only if all coverage functions are true. For couples for which one or multiple coverage functions are false, the final clearance time is given by the OSD solution.

4.5 Final optimised clearance time values

To obtain the final eOSD clearance time value, the process described in Section 2.2 shall be followed. Each node corresponding to a separation/spacing constraint is substituted with the combination of the predicted clearance time for that constraint and the corresponding buffer. The different rules are then applied and a final clearance time is obtained.

5 ML model evaluation

The performance of each of the four machine learning models is assessed by comparing the results obtained by the four ML models to a respective baseline model. The baseline models are here defined as the average target per aircraft type and surface runway headwind band.
Table 1 illustrates the explained variance scores obtained with the baseline and ML rolling time and rolling distance models. It can be seen that the explained variance increased with the ML model compared to the baseline model by around 8% for the Rolling Time and by around 11% for the Rolling Distance.

	Rolling Time	**Rolling Distance**
Baseline	0.50	0.61
Machine Learning	0.54	0.68

Table 1: Rolling time and distance explained variance scores obtained with the baseline and the ML models on the testing set. The values can range from 0 to 1 with 1 being the best.

Figure 1 and Figure 2 illustrate the explained variance scores obtained with the baseline and ML altitude to time and time to TAS models. In can be observed that it was possible, with the use of the ML model, to increase the explained variance compared to the baseline model by up to around 70% for the altitude to time and by up to around 135% for the time to TAS.

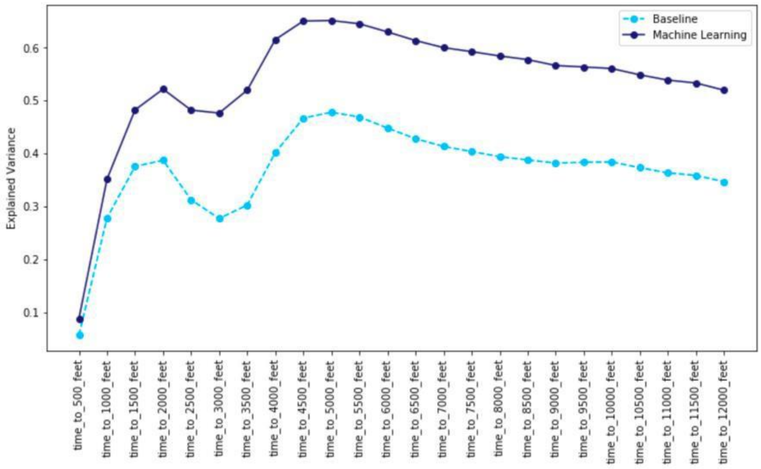

Figure 1: Explained variance scores for the altitude to time obtained with the baseline and the ML models on the testing set. The values can range from 0 to 1 with 1 being the best.

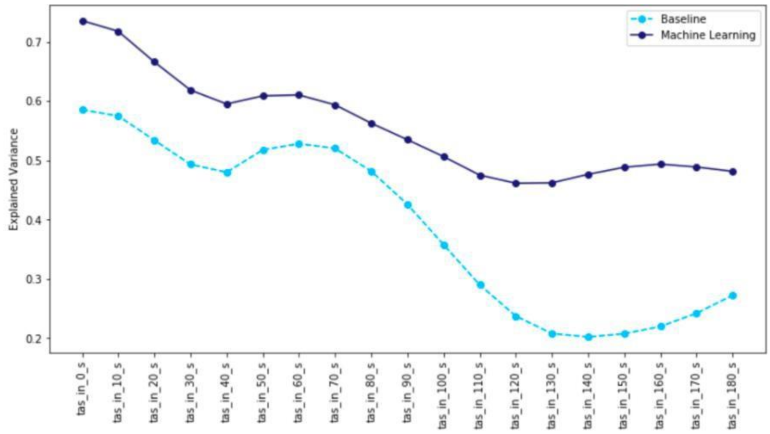

Figure 2: Explained variance scores for the time to TAS obtained with the baseline and the ML models on the testing set. The values can range from 0 to 1 with 1 being the best.

6 eOSD solution benefits compared to OSD solution

The benefits related to the use of ML models to calculate the clearance time to be applied between departing aircraft pairs compared to traditional statistical approach was assessed. For that purpose, the final clearance time values, obtained using the eOSD ML pipeline described in Section 4 are compared to those obtained from the baseline approach (OSD), defined in Section 2.5. It should be noted that both eOSD and OSD clearance time calculations are calibrated to lead to same acceptable error rate allowing for a fair comparison.

Around 42 % of the aircraft pairs in the test set are considered to be covered by the coverage functions, described in Section 4.4. For those covered aircraft pairs, an average time separation reduction of around 13 % is obtained with eOSD compared to OSD with still very low error rates (below the error rates used for the design criteria).

For non-covered aircraft pairs, the OSD clearance time outputs are used. When considering all pairs, 5% overall average benefit compared to OSD is achieved with very low error rates.

By increasing the size of the training dataset, an improvement in the model accuracy and an increase of the coverage can be expected allowing an overall benefit compared to OSD tending towards 13 %.

	Gain of eOSD respect to OSD
On covered couples (42 %)	13 %
On covered and non-covered couples	5 %

Table 2: Gains of the eOSD solution respect to OSD only on covered aircraft pairs and overall considering also the non-covered aircraft pairs.

7 Conclusion

The present paper described the enhanced Optimized Spacing Delivery (eOSD) solution, an ATC support tool which consists of an automated digital countdown timer. The eOSD allows for the application of complex separation scheme such as Pairwise Wake Separations for departures as well as ICAO and RECAT-EU wake separation schemes and also ensures the safe, consistent and efficient delivery of the required spacing between consecutive departure pairs on initial phase of climb.

With eOSD, the clearance times required between consecutive aircraft pairs are calculated making use of Machine Learning (ML) techniques for the prediction of rolling time, rolling distance, airspeed profile and climb profile. ML models are also used to calculate the required buffers to be added to the clearance time calculations when combining the ML models in order to obtain safe, yet efficient, separation delivery. Finally, coverage functions are developed and trained in order to establish in which conditions the ML models can be considered as reliable and hence used operationally. For each departure pair considered as non-covered by these coverage functions, a conservative approach is followed. eOSD solution builds on the OSD solution previously developed by EUROCONTROL and for which the

clearance times required between departing aircraft pairs were calculated using traditional statistical methods (used here as baseline for assessment of eOSD).
The ML models and their use for the eOSD tool have been trained and tested based on one year of surveillance and meteorological data from Zurich airport. The individual ML models for rolling time, rolling distance, airspeed profile and climb profile have all been shown to be significantly superior to the baseline ones (i.e., those used in OSD solution), allowing for hence more efficient / reduced spacings between departing aircraft. When combined and used for the eOSD clearance time calculations, the ML models have been shown to provide an average of 13% of time spacing reduction for the covered pairs compared to OSD. With the current dataset, the coverage that was achieved was 42% leading to a global average benefit of 5% for eOSD compared to OSD. By increasing the size of the dataset, an improvement in the model accuracy and an increase of the coverage can be expected allowing an overall eOSD benefit compared to OSD tending towards 13 %.
The use of such eOSD tool therefore allows an increase in departure throughput during peak operations in those airports that are capacity constrained, hence reducing runway congestion, which also has direct impact on network delays and on the environment.
Future work will aim to explore the performance of the eOSD tool in other airport environments. It would also be of interest to explore how the models and coverage could be improved through a multi- airport solution where airports, under specific agreements, could share data between each other.

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