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DYNAMIC PAIRWISE WAKE VORTEX SEPARATIONS FOR ARRIVALS USING PREDICTIVE MACHINE LEARNING MODELS

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Abstract

The potential encounter of wake vortices from a preceding flight is at the origin of the wake separation minima between aircraft on the final approach. Wake separations ensure safety under all conditions, but have been shown to be over-conservative in some meteorological conditions which directly penalises runway performance. This paper describes the Dynamic Pairwise Wake Separation for Arrivals (D-PWS-A) concept which has been developed in order to safely reduce, when possible, wake separation minima between consecutive arrivals on the final approach based on wake risk monitoring. Aircraft wake behaviour and meteorological information is monitored and processed using Machine Learning (ML) algorithms which determine the wake separation minimum reductions that can be safely applied between subsequent arriving aircraft. The use of wake behaviour monitoring combined with ML techniques allows us to maximise the conditions under which wake separations can be reduced. The model is developed and tested based on field data collected in Paris-CDG airport.

Keywords: airport capacity, ATM, machine learning, quantile regression, runway throughput.

1. Introduction

In today's efficient operations, landing aircraft are separated either by wake turbulence separation rules or by runway and surveillance separation rules that apply when wake turbulence separation minima are not required. For arrivals on the final approach, the wake turbulence and surveillance separation requirements are normally expressed by distance minima to be applied at a separation delivery point which is usually defined as the runway threshold. In strong wind conditions, the impact of the wind on an aircraft's groundspeed during approach results in decreasing the observed landing rates. Reduced landing rates generates delays and flight cancellations at airports with significant costs to operators and the travelling public. However, existing arrival wake turbulence separation minima are considered to be over-conservative in some meteorological conditions. The applied separation values do not take into account the prevailing meteorological condition impact on the transport and decay of the wake turbulence. A dynamic and flexible application of separation could lead to a more efficient way of mitigating wake encounter risks, without affecting the safety level of the Air Traffic Management (ATM).

Within the Single European Sky ATM Research (SESAR) 2020 Wave 2 programme, work is being conducted on a solution that allows for the dynamic definition of wake separation reduction between arrival traffic based on wake risk monitoring using predictive Machine Learning (ML) techniques. This solution is called Dynamic Pairwise Wake Separations for Arrivals (D-PWS-A). D-PWS-A relies on the monitoring of the wake behavior of previous aircraft wake tracks measured through LiDAR (Light Detection And Ranging) technology, meteorological conditions (here using METAR data) and flight information, combined with ML models.

During recent years, knowledge about wake vortex behavior in the operational environment has increased thanks to a number of wake data collection campaigns to obtain measured data and an improved understanding of the physical processes (e.g. [1][2][3][4][5][6][7][8]). This improved knowledge has made the design of new wake separation concepts possible, with some of them already deployed in Europe and US, enabling the optimization of airport/runway throughput and efficiency whilst maintaining acceptable levels of safety. The work on D-PWS-A builds on previous work conducted by EUROCONTROL and NATS within the SESAR framework, which aim to optimize wake separation schemes in order to increase runway throughput. This work includes the static separation schemes developed in the RECAT-EU[1] and RECAT-PWS[2] projects [9][10][11] as well as the dynamic separation reduction solutions, Time Based Separations (TBS) [12] and Weather Dependent Separations (WDS) [13]. TBS is an operating procedure for separating aircraft by time, instead of distance. TBS was developed to address headwind disruptions by dynamically reducing the spacing between pairs of aircraft in strong headwind conditions consequently preserving runway throughput. WDS consists in the conditional reduction or suspension of wake separation minima on final approach, applicable under pre-defined wind conditions; so as to enable an increase in runway throughput. Such reductions of wake separation are achievable under WDS on the basis that the wake turbulence generated by the lead aircraft is either wind transported out of the path of the follower aircraft on final approach, or has decayed sufficiently to be acceptable by the follower aircraft; if encountered. However, one of the limitations of WDS is that the wind conditions/criteria under which the wake separations can be significantly reduced or even fully suspended and the associated wind prediction capabilities are rarely met in many operational environments. Hence, the application of WDS for arrivals in operations can be limited, as can the benefits that can be gained.

One of the main aims of the Dynamic Pairwise Wake Separation for arrivals (D-PWS-A) concept is to increase the opportunities under which time-based wake separations can be either reduced compared to WDS and TBS.

The present work was developed based on field data measurements collected at Paris-CDG airport and covering about 24,000 flights measured in 2016 and 2017.

This paper is organized as follows. Section 2 introduces the dataset used to develop and test the D-PWS-A solution. Section 3 describes the methodology used for wake separation reduction design. Section 4 details the solution architecture. Section 5 presents the obtained results and related benefits based on the Paris-CDG airport test case.

2. Dataset

This paper uses field operational data collected in 2016 and 2017 from Paris Charles De Gaulle (CDG) airport. The database consists of LiDAR [14], METAR and RADAR measurements. LiDAR data contain temporal evolution of position and intensity of wakes generated by several aircraft flights. For each wake track, RADAR data contains the corresponding information of the aircraft flight, such as the aircraft type and its ground speed. METAR data include wind, atmospheric and weather measures collected every 30 minutes.

3. Methodology

As a consequence of its lift, an aircraft generates a complex vortex wake, emanating from the wing and horizontal tail plane that rolls-up to form, in the far-field, a pair of counter-rotating vortices that can last for several minutes after the aircraft has flown by. These vortices, whose initial circulation and lateral spacing depend on the aircraft characteristics, are transported and decay depending on the

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[1] RECAT-EU – a revised European 6 category wake turbulence scheme

[2] RECAT-PWS - a pairwise wake separation scheme based on aircraft type as opposed to aircraft wake category

environmental conditions. The encounter of such a vortex pair by a follower aircraft can be hazardous due to the induced rolling moment and down-wash velocity.

D-PWS-A allows for wake separation minimum reductions based on two concepts: wake vortex transport and wake vortex decay. These two concepts and related wake separation design criteria are defined as follows:

3.1 The wake transport-based concept

The transport-based concept aims at reducing the time separation between two arrival flights based on the position of the wake. To do so, models are built to predict the evolution of the wake vortices position with time. The objective is to have no vortices expected within a corridor defined per leader-follower pair.

The initial two vortex system generated by an aircraft is centered on the generator aircraft position and with a lateral vortex spacing b_0 equal to a fraction of the wing span b: b_0=s b, with s ranging from about 0.65 to 0.8 for aircraft in approach configuration. In case of crosswind the vortices will be blown by the crosswind component. In ground proximity, due to the interaction with the ground, the vortices also tend to separate from each other. The vortex moving in the wind direction due to ground effect is then denoted downwind vortex whereas the one moving in the opposite direction to the wind in case of ground proximity is denoted upwind vortex (see further description in, e.g. [5]). In case of crosswind, the worst case (and hence the design case) consists in the encounter by the following aircraft of the upwind vortex that, due to the combined ground and wind effect, would remain in the follower vicinity ([3]).

For D-PWS-A transport-based separation design, we here consider that both vortices must have been transported such that they are located at least one-half vortex spacing from the follower' closest wing tip, as illustrated in Figure 1. The vortex is indeed conservatively assumed to have a characteristic diameter (i.e., the region around the vortex core where the effect of the encounter can be felt) of one vortex span.

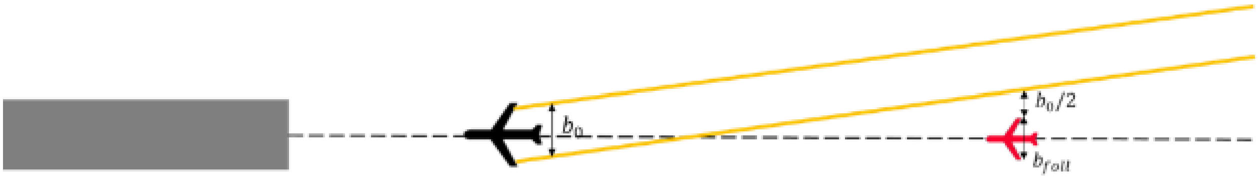


Figure 1 - Schematic view of required minimum vortex lateral displacement considered for WDS-XW design.

This distance should be increased by the navigation uncertainty of the follower aircraft. According to EUROCONTROL Navigation experts, the lateral Total System Error (TSE) on final approach (typically at 1 NM from runway threshold) is about 35 m for standard navigation procedures in busy airports (e.g. ILS).

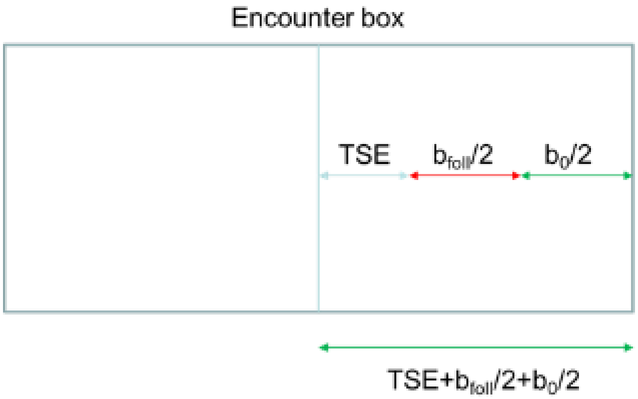


Figure 2 - Scheme of the encounter box defined for transport-based D-PWS-A concept.

This leads to the definition of an encounter box in which no vortex must be found at reduced separation time, see Figure 2, defined accounting for:

- Follower navigation uncertainty (TSE),
- Vortex span $b_0/2$ (function of generator aircraft), and
- Follower wingspan.

Using the above definition and typical wing span and vortex span values defined per wake turbulence category (e.g., RECAT-EU for the case of Paris-CDG airport), the encounter box half-widths considered for D-PWS-A transport-based separation design for each pair wake turbulence category have been defined.

Furthermore, the separation reductions are designed based on an “acceptable error rate”. The latter shall be defined as a lower bound of what is observed today locally in terms of probability to have a vortex in the encounter box. For the case of Paris-CDG, analysis of the database showed that for 3% of all pairs, a vortex was observed in the encounter box when applying distance-based minima. The 3% represents an average across all wind conditions. In low wind conditions, the probability is larger. Targeting 3% is thus conservative. Note also that this error rate is defined as if Air Traffic Control (ATC) applies exactly the separation at minima. Since ATC usually takes some margins with respect to the targeted separation distance either on purpose or for operational reasons (e.g., vectoring, speed control…), those error rates shall not be taken as absolute numbers of wake encounter.

The wake separation design criteria for transport-based D-PWS-A concept is thus that the wake separation minima can be reduced down to the minimum time at which the probability to observe a vortex in the encounter box in below the acceptable error rate (here 3%). In case the obtained time separation is larger than that obtained when applying current wake separation minima (e.g., distance-based RECAT-EU minima for the case of Paris-CDG airport), the separation minima are not reduced and current minima are still applied.

3.2 The wake decay-based concept

The decay-based D-PWS-A concept aims at reducing, when possible, the time separation between two arrival aircraft based on the wake’s circulation reduction. The idea is to reduce separation minima down to a time separation at which the distribution of possibly encountered wake circulation is bounded by the distribution of wake circulation that could be encountered at current Distance-Based Separation (DBS) minima in Reasonable Worst Case (RWC) conditions. The RWC situation for an arrival aircraft to encounter a wake vortex was defined at ICAO level for wake separation design, in terms of weather (low wind, low turbulence and low stratification conditions) and flight conditions and in terms of encounter geometry [8]. This is illustrated in Figure 3. For this purpose, models to predict the probabilistic reduction of wake vortex circulation intensity with time were built.

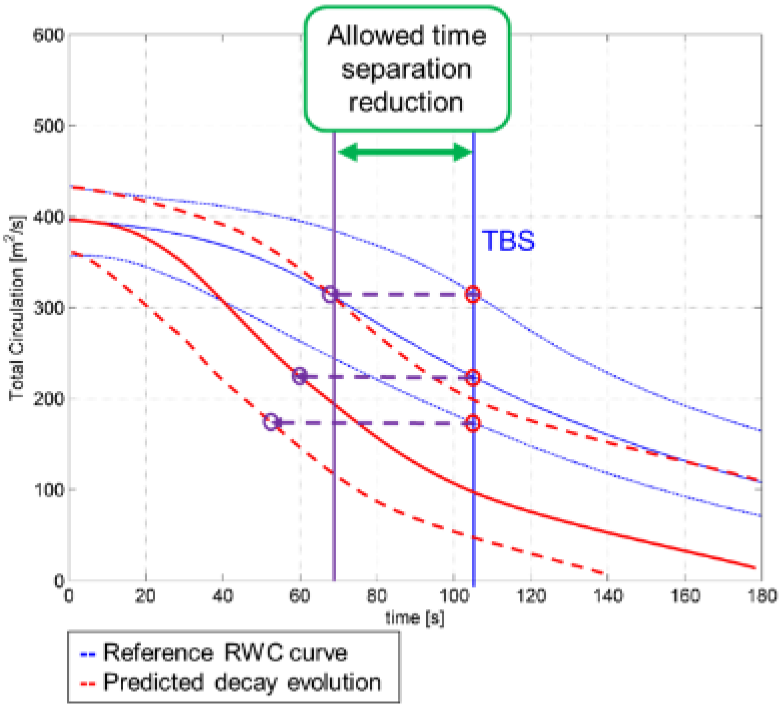
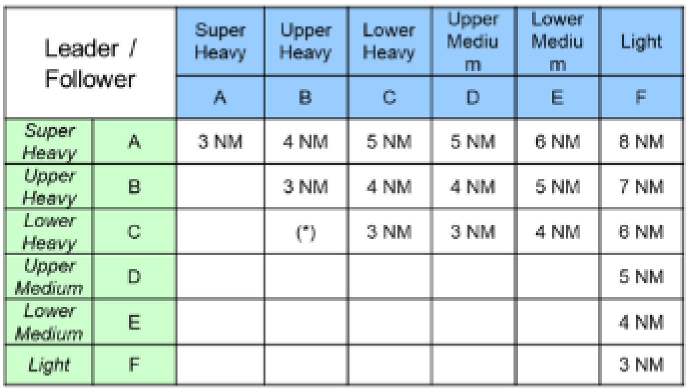


Figure 3 - Illustrative example of distribution (median in solid, p10/p90 in dash) of circulation for a given generator aircraft type in RWC (blue) and for a particular test case condition (red).

The definition of the reference circulation distribution for separation minima determination then relies on several building blocks described below.

1) Baseline Distance-Based Separation scheme

In order to define the acceptable wake severity level in RWC conditions, the applicable Distance-Based Separation (DBS) minima must first be defined. For the present study, since the used data have been measured in Paris-CDG environment, the corresponding applicable DBS scheme will be used, namely RECAT-EU separation scheme [15], recalled in Table 1.



Leader / Follower		Super Heavy	Upper Heavy	Lower Heavy	Upper Medium	Lower Medium	Light
		A	B	C	D	E	F
Super Heavy	A	3 NM	4 NM	5 NM	5 NM	6 NM	8 NM
Upper Heavy	B		3 NM	4 NM	4 NM	5 NM	7 NM
Lower Heavy	C		(*)	3 NM	3 NM	4 NM	6 NM
Upper Medium	D						5 NM
Lower Medium	E						4 NM
Light	F						3 NM

Table 1 - RECAT-EU separation scheme.

2) Baseline Time Separation matrix

In order to characterize the baseline wake circulation distribution and because circulation decay with time, it is important to characterize the time separations corresponding to DBS minima in RWC conditions. These time separations are defined per follower aircraft type from equivalent median time-to-fly the RECAT-EU DBS minima in calm wind conditions defined as total wind lower than or equal to 5 kts and without surface tailwind condition. Those time-to-fly profiles were determined using surveillance data and surface wind data collected in the framework of the Paris-CDG TBS project and covering more than one year of local operations at Paris-CDG. Note that the median TBS are only computed if at least 10 samples are found for that follower aircraft type in calm wind conditions. In case, no sufficient calm wind data are available for an aircraft type, the follower is discarded and D-PWS-A cannot be applied for that follower aircraft type (which should have limited operational impact given the aircraft is rare). Note also that in reality, some variability is observed in the time separations corresponding to a given DBS minimum even in calm wind due to aircraft airspeed variability. This distribution of the time separation around the median is ignored in this relative assessment providing the allowed time separation reduction compared to the median value.

3) EUROCONTROL generic dimensionless RWC wake decay curves

The reference distribution of dimensional circulation evolution in RWC is obtained from the generic dimensionless RWC wake decay curve that was obtained in the framework of RECAT-EU and RECAT-EU-PWS projects and documented in [8]. Those generic dimensionless curves provide the median but also 10th and 90th quantiles of circulation evolution in RWC, see Figure 4.

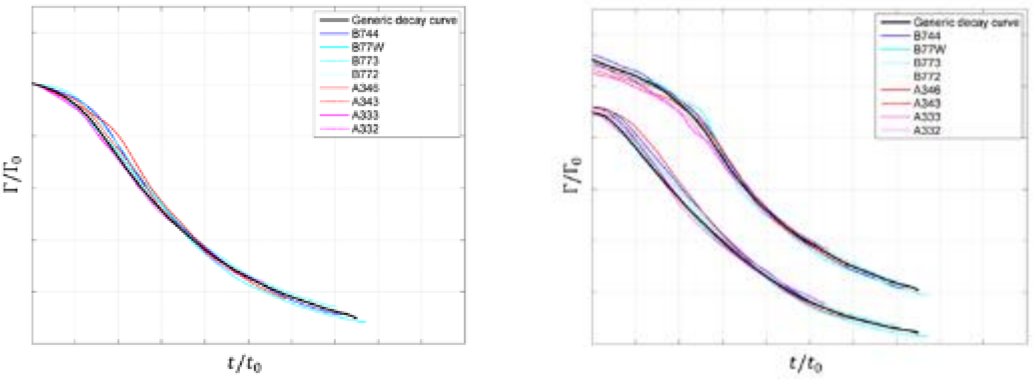


Figure 4 - Generic dimensionless RWC decay curves: median (left), p10/p90 (right) from [8].

4) Vortex spacing and initial circulation database

The dimensionless circulation evolutions are made dimensional using the initial circulation value and the vortex spacing defined per generator aircraft type. For that purpose, a database is used that was determined based on LiDAR measurements from various airports in the framework of RECAT-EU and RECAT-EU-PWS.

Using the 4 building blocks defined above, four matrices are eventually built providing for a set of leader and follower aircraft pairs:

1. The reference time separation at DBS minimum in calm wind condition
2. The median circulation for that pair at DBS minimum in RWC conditions

3. The 10th quantile of the circulation for that pair at DBS minimum in RWC conditions
4. The 90th quantile of the circulation for that pair at DBS minimum in RWC conditions

The machine learning algorithm used for the decay-based D-PWS-A concept development shall them aim at determining the time (=vortex age) such that the circulation is:

- Lower than the p90 design circulation in at least 90% of the cases,
- Lower than p50 design circulation in at least 50% of the cases, and
- Lower than p10 design circulation in at least 10% of the cases.

This time corresponds to the decay-based D-PWS-A separation minimum, thus defining the design criteria for the decay based concept. Note that, in case the obtained time separation is larger than reference time separation, the separation minima are not reduced and current DBS minima are still applied.

4. Machine Learning Models

For each concept, transport-based and decay-based, a Machine Learning (ML) model targeting the associated design criteria is built with the aim that at least one of the two design criteria, transport or decay, is achieved. By combining the wake transport and wake decay ML models the frequency with which separation minima can be reduced under D-PWS-A should be increased.

For each flight, a prediction is done using both the transport and the decay models and the smallest between the two predictions is taken as the final predicted wake separation minima. To replicate a real use case, all the wake separation minima predictions will be based on data available at least 15 minutes before the aircraft landing, simulating what would be required in an operational environment (i.e. Air Traffic Controller shall be made aware of possible separation reduction prior to aircraft landing to be able to apply it). The benefits related to the use of the ML models are assessed compared to a baseline corresponding to the application of current distance-based separation minima (here RECAT-EU), demonstrating the ability of this solution to reduce time separation in specific conditions. The distances from the RECAT-EU table are converted into time by taking into account the decreasing aircraft speed over time. In case the obtained predicted time separation from the ML transport and decay models is larger than the reference one, current DBS minima are still applied. For all operational conditions, it is proven that the separation reductions determined by ML models maintain the wake encounter risk to an acceptable safe level defined by the separation design criteria.

In the case of the decay model, the wake intensity quantiles (10, 50, 90) at prediction time are computed to verify that they are below the ones encountered in RWC conditions. To respect these design criteria, a possible approach is to use a particular type of regression called quantile regression [17]. In contrast to the classical regression, the quantile regression estimates the conditional quantile of the response variable.

In both cases, the transport and decay ML models are based on a gradient boosting algorithm called Catboost that proved to perform well in quantile regression scenarios [18][19].

4.1 Wake Transport Machine Learning Model

To develop the ML model for wake transport,T_n, is introduced, that is the time it takes for both the wakes to be at least n meters away from the runway centreline. The time is measured from the first wake measurement. Several models are built for each selected n ∈ N_t = (40, 60, 80,100,120,140) expressed in meters. Each model ($M_{transport\_n}$) will predict a time value for the associated n class, $t_{transport\_n}$. To compute the predicted separation time, the encounter box halfwidths, defined in Section 3.1, are used to determine the right n that needs to be predicted. Once the n is defined, the predicted time is computed as the linear interpolation between the two closest $t_{transport\_n}$ predicted by the model. The values of n were chosen to take into account all the possible values of encounter box halfwidths but at the same time guarantee enough granularity to make the linear interpolation accurate.

The target variable $T_n$does not always have a value. This can be the case when the wind was so low that the wake did not reach any target n or when there was a problem with the measurement. To deal with this, a second model called the support ML model ($M_{support}$) is introduced. The support model will tell if the main model has been trained with enough data in similar wind conditions and therefore it is confident that the results are correct. The support model is a classification model that predicts P(T_n) that is the probability of $T_n$to exist. It is based on a random forest classifier [20]. DBS minima is applied to every flight for which the support model predicts T_n not to exist.

As explained in Section 3.1, the average probability to observe a vortex in the encounter box at DBS minima was found to be 3% in the dataset and therefore defined as target error rate. The transport model will target this same quantile during the training phase. A custom loss function has been designed to minimise the Mean Squared Error (MSE) from the desired quantile. The performance of the model was analysed to reduce time separation but at the same time prevent the error rate from exceeding the 3% threshold for different wind conditions and aircraft pairs.

Different features have been extracted from the historical LIDAR, METAR and RADAR data used in the development of the model. From the list of all the features, only some of them proved to be relevant for the transport scenario:

- Cross wind speed, Head wind speed: computed from METAR data;
- Cross gust speed: computed from the gust speed, if present, from the METAR data;
- Left/Right wind direction: computed as the outermost left and right wind directions measured during the half an hour interval included in METAR data;
- Initial gamma: computed as the average initial wake intensity for the given aircraft type;
- Previous initial gamma: measured as the initial wake intensity of the previous wake's aircraft;
- Previous wake speed_n: computed as the average speed of the previous wake during the first n meters of lateral movement using LIDAR data.

The output of the transport ML model is the predicted transport wake separation minima $t_{transport}$, computed as illustrated in Figure 5.

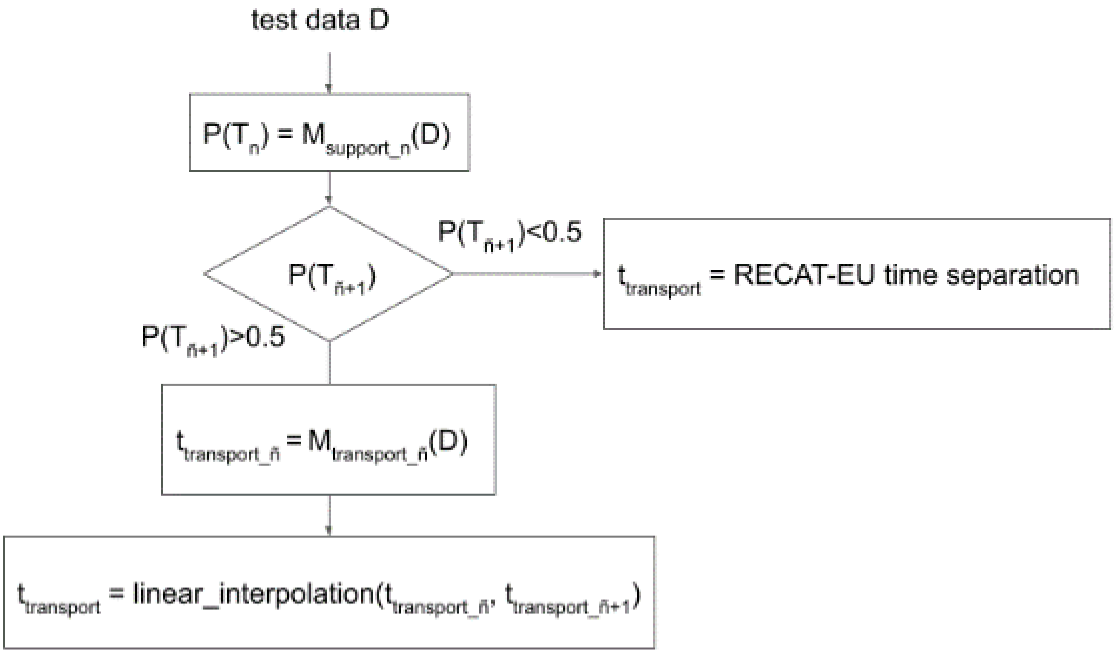


Figure 5 - Transport ML model prediction flow.

In Figure 5, D is the test dataset and $M_{support\_n}$ are the support ML models. ñ and ñ+1 are the consecutive values ∈ N_t for which ñ < e < ñ+1 where e is the reference from the encounter box halfwidths. $M_{transport\_n}$ are the n wake transport ML models.

4.2 Wake Decay Machine Learning Model

Similarly, the decay model targets Γ_n, which is the time that it takes for both the wakes to be below intensity n expressed in m^2/s starting from the first measurement. Several models ($M_{decay\_n\_q}$) are built for each selected n ∈ N_d = (50, 100, 150, 200, 250, 300, 350, 400, 450, 500, 550, 600) and for each of the three targeted quantiles q ∈ Q = (10, 50, 90). The value of q defines the quantile value targeted by the regression algorithm. For the decay ML model, predictions are based on circulation minima at RWC computed for the different aircraft types. The goal is not to pass the intensity values for the three quantiles computed at TBS p50. The three pairwise matrices of p10, p50, p90, defined in Section 3.2, are used to define, at prediction time, the target n for the Γ_n target. The values of n were chosen to take into account all the possible intensities present in the p10, p50, p90 tables. Three different predictions are made for the three quantiles q and the biggest value, the one that complies with the all the quantiles, is taken as the predicted decay wake separation minima.

Similar to the transport scenario, different features have been computed:

- AC type, Previous AC type: computed as the target encoding of the aircraft type coming from RADAR data;
- Initial gamma: computed as the average initial wake intensity for the given aircraft type;
- Previous initial gamma: computed as the initial wake intensity of the previous wake's aircraft;
- Previous gamma decay: computed as the time it took to the previous wake to decay to 10%, 50%, 90% of the initial wake intensity. They are computed from LIDAR data;
- Cross wind speed, Head wind speed: computed from METAR data;
- Temperature, dew point, pressure: retrieved from METAR data;

The predicted decay wake separation minima t_{decay} is computed as illustrated in **Figure 6**.

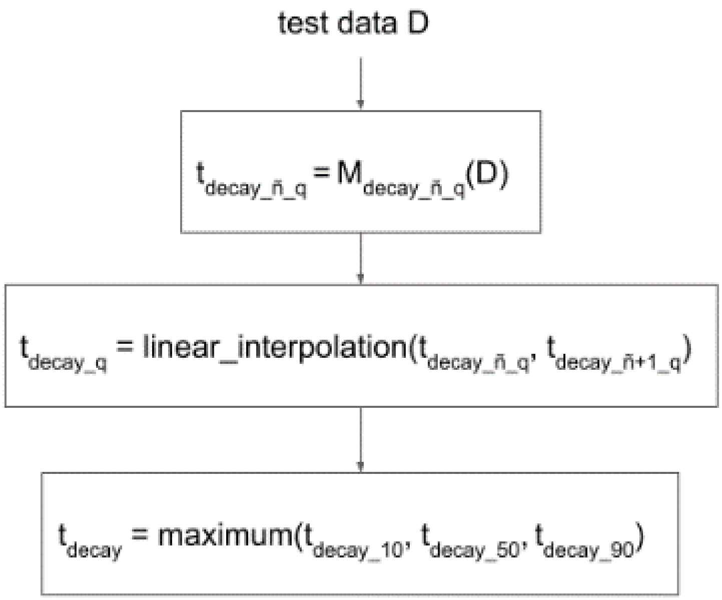


Figure 6 - Decay ML model prediction flow.

In Figure 6, D is the test dataset and ñ and ñ+1 are the consecutive values $\in N_d$ for which $\tilde{n} < p < \tilde{n}+1$ where p is the reference from p10, p50 or p90. $M_{decay\_n\_q}$ are the n*q wake decay ML models.

4.3 Dynamic Pairwise Wake Separation combined model

The final predicted wake separation minima $t_{predicted\_separation}$ is computed combining the transport- and decay-based ML predictions. It reads:

$$t_{predicted\_separation} = minimum(t_{transport}, t_{decay}) \tag{1}$$

5. Results

In this section the D-PWS-A combined model is empirically evaluated. The experiments are designed to assess the quality of the D-PWS-A combined model to reduce time separation in different conditions and meanwhile preserve the desired safety level. The models were trained on the Paris-CDG data and the information of previous wakes (latest wake measured 15 minutes before the current one) is used as a feature to estimate the behaviour of future wakes in both scenarios.

The dataset was split in two, 2016 data was used to train the model and 2017 data was used to test the results and produce the graphs present in this section.

For both the models (wake transport ML and wake decay ML) we compute the feature importance to better interpret the results of the predictions. The importance is computed averaging the feature importance for all the n models and it is based on the GINI importance [21].

In Figure 7, the importance of each feature used in the transport ML model is illustrated to better understand what influences wake transport. As expected, a strong correlation between the model performance and the intensity of cross wind is noticed. Moreover the lateral speed of the previous wake plays an even more important role (more than 50% of importance) in the predicted time, justifying the use of LIDAR data.

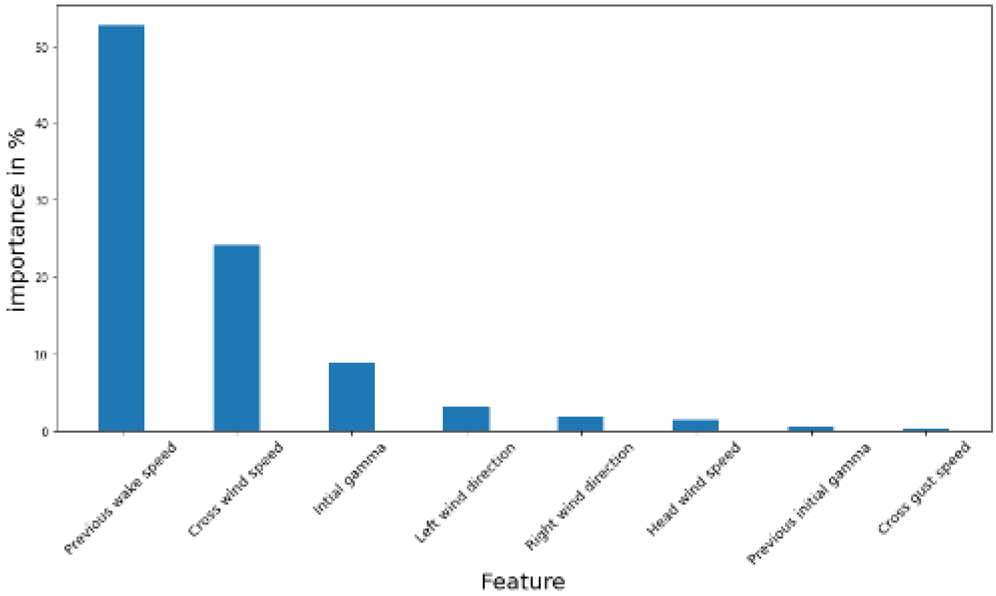


Figure 7 - Transport model feature importance.

In Figure 8, the feature importance in the decay scenario has been analysed and is illustrated. The initial wake intensity together with the aircraft type constitutes the two most important features of our model with an importance of about 21% and 19% respectively. Both wind components play an important role as well.

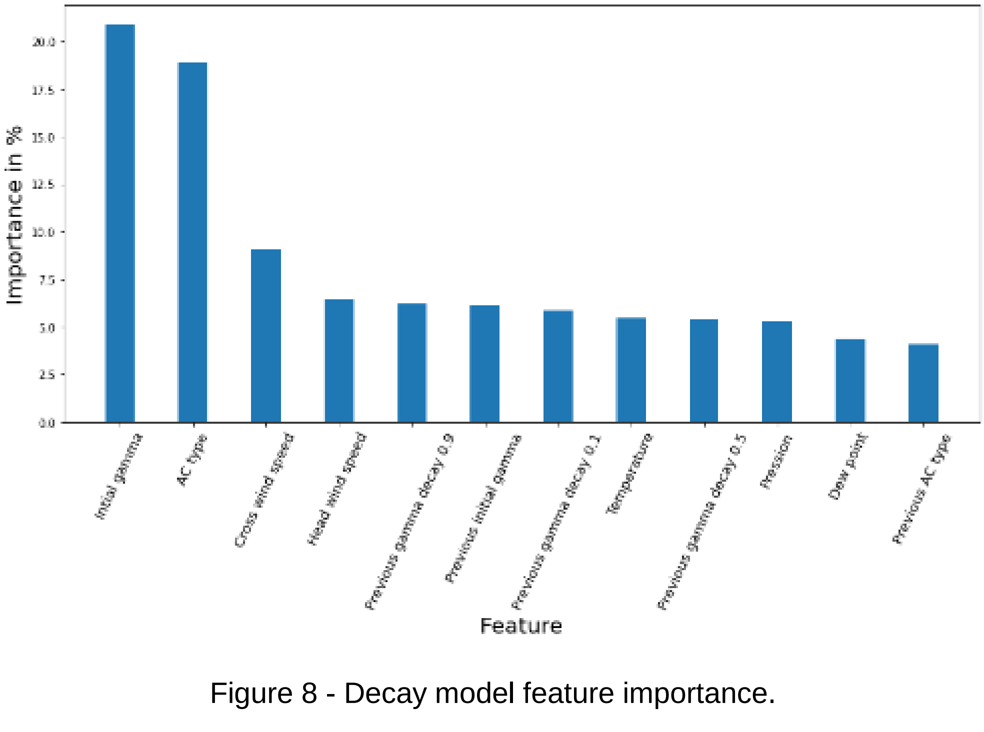


Figure 8 - Decay model feature importance.

Then, the overall performance of the D-PWS-A combined model, was analysed to evaluate the quality of the separation reduction. The preliminary aggregated results show that time separation can be reduced in more than 50% of the considered flights compared to RECAT-EU separation minima with an average separation reduction of 9s. This depends mainly on the wind conditions (Figure 9) and the considered aircraft. In Figure 9 the percentage of improved flights and the average separation reduction using the D-PWS combined model, in different cross wind conditions is illustrated. The average reduction in time separation ranges from 3s in mild cross wind conditions up to 37s in strong cross wind conditions.

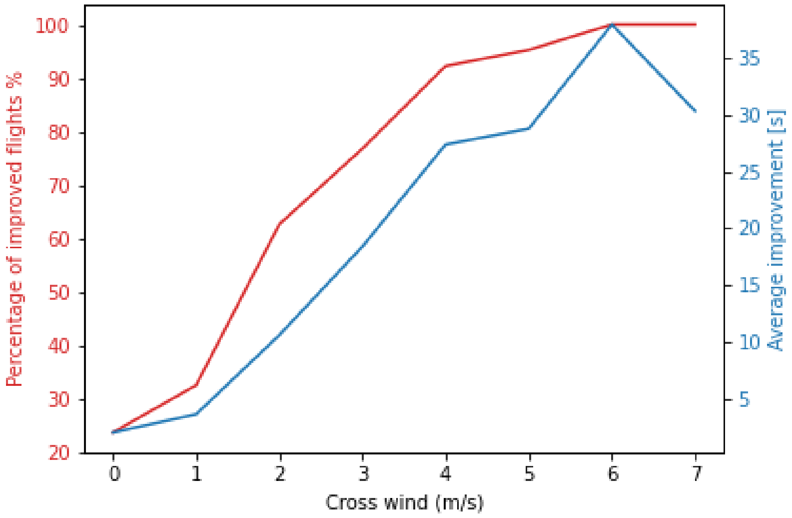


Figure 9 - D-PWS-A overall improvement for different cross wind conditions.

By comparing the distribution of the predicted $t_{separation\_minima}$ and the RECAT-EU separation time (Figure 10), an overall improvement of the time separation is observed with the D-PWS-A combined model. The density illustrates which wake separation times were more probable for each curve. The predicted time extends down to very low values (between 20s and 40s) when the cross wind is strong. Note that, operationally, such very low separation could not be applied due to other separation and spacing constraints (e.g., surveillance minima and runway occupancy time).

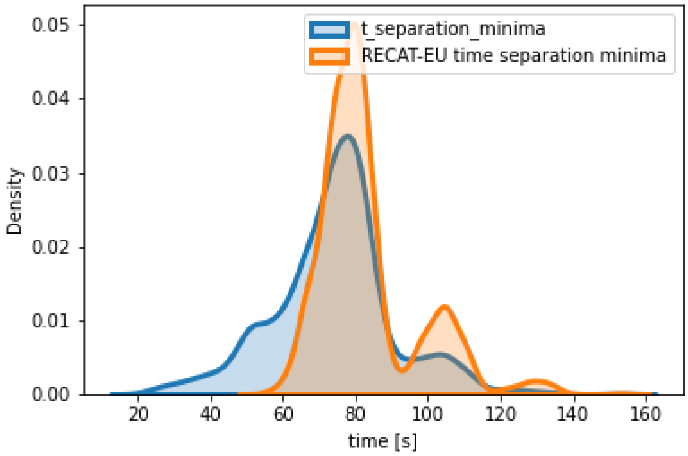


Figure 10 - Comparison predicted time and RECAT separation.

Meanwhile all the separation design criteria are still respected for both the transport and decay ML models. We make sure that the error rate is below 3% for the transport ML model for different cross wind conditions (Figure 11) and aircraft types. As can be seen, the red line (error rate) remains always below the dashed line (target error rate), meaning that the model meets the design criteria and associated safety level in all wind conditions assessed. Similarly, the decay test set quantiles with the design criteria for the 10, 50, 90 percentile models were compared under different cross wind conditions. In Figure 12 the quantile values and their correlation with the wind speed is illustrated. The quantiles look stable for different crosswind speeds and the values are always above the respective thresholds (dashed lines), hence indicating that the design criteria are met in the wind conditions assessed. The same analysis is also performed for each combination of leader/follower aircraft.

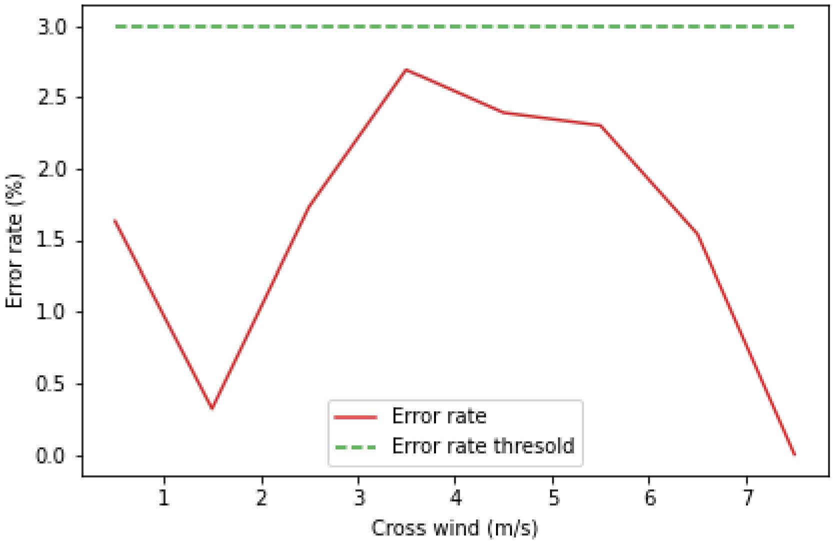


Figure 11 - Error rate transport ML model for different cross wind conditions.

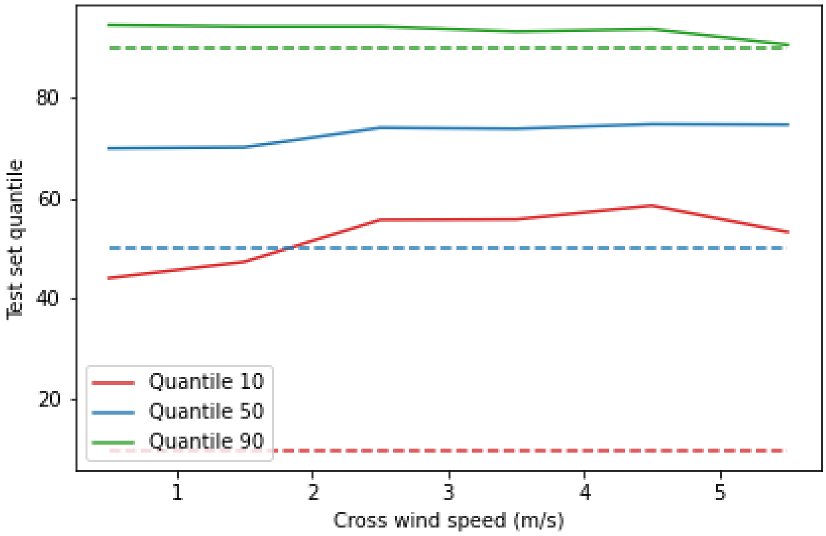


Figure 12 - Test set quantiles decay ML model for different cross wind conditions.

6. Conclusions

This paper showed how the D-PWS-A concept uses ML techniques to safely reduce wake separation between consecutive arrivals on the final approach based on the real time monitoring of wake risks. It was demonstrated that this solution provides benefits in a real use case scenario using only operational information as available 15 minutes before the landing. The combination of both a wake transport and a wake decay ML model developed for D-PWS-A permits the reduction of the time separation in most of the conditions compared to static distance-based separation. Although it was expected that time separation could be reduced in strong wind conditions, the combined use of wake transport and wake decay ML models showed that time separations could also be reduced to some extent in milder wind conditions. For both the decay- and transport-based concepts, larger and more frequent separation reductions can be obtained for larger baseline separations. This is to be expected as the wake has then more time to decay or being transported. In addition, it was verified that the models comply with the separation design criteria across the wind conditions.

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8. Copyright Statement

References

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