Data mining and Machine Learning techniques supporting Time-Based Separation concept deployment

Ivan De Visscher
Wake Prediction Technologies(WaPT)
Louvain-la-Neuve, Belgium
ivan.devisscher@wapt.be

Guillaume Stempfel
Eura Nova
Marseille, France
guillaume.stempfel@euranova.eu

Frédéric Rooseleer
Airport division
EUROCONTROL
Brussels, Belgium
frederic.rooseleer@eurocontrol.int

Vincent Treve
Airport division
EUROCONTROL
Brussels, Belgium
vincent.treve@eurocontrol.int

***Abstract*— The Time-Based Separation (TBS) concept consists in the definition of separation minima for aircraft on the Final approach to a runway based on time intervals instead of distances, as applied in Distance-Based Separation (DBS) operations. TBS allows for dynamic distance separation reductions in strong headwind conditions so as to preserve time spacing across all wind conditions. However, TBS application entails the use of a support tool providing separation distance indicators depending on the applicable time separation minimum, the aircraft speed profile which also depends on the headwind conditions. This paper details two methodologies allowing a system to compute those TBS indicators so as to allow Air Traffic Controllers to accurately and safely deliver the TBS minima using a separation delivery support tool. The first approach is based on "analytical" data mining and modelling whereas the second one is based on a Machine Learning (M/L) procedure. In the framework of the deployment of the TBS concept in Vienna airport (LOWW), those approaches are developed and tested using a database covering one year of traffic and corresponding local meteorological data. The operation of TBS with indicators computed using either approaches leads to substantial diminution of time separations compared to a DBS strategy. However, given the large uncertainties related both to leader and follower aircraft speed profiles, the buffers could be designed only for the most frequent pairs. With the M/L approach (resp. the "analytical" approach), the capacity benefits related to the application of TBS with a separation support tool are of the order of 8% (resp. 2%) in moderate wind conditions, and up to 14% (resp. 10%) in strong wind conditions.**

Keywords—Time-Based Separation, Machine Learning, Data Mining, Air Traffic Management

I. 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 final approach, the wake turbulence and surveillance separation requirements are expressed by distance minima to be applied at a separation delivery point which is usually defined as the runway threshold.

In strong headwind conditions, when applying distance-based separation minima, the impact of the headwind on an aircraft's groundspeed during approach results in decreasing the observed landing rates. This fact generates delays and flight cancellations at airports with significant costs to operators and the travelling public. Moreover, the increase in air traffic further worsens this issue. EUROCONTROL Industry Monitor bulletin in December 2016 [1] indeed estimated a 2.4% overall year growth for European flights (ECAC – European Civil Aviation Conference area) respect 2015.

However, existing arrival wake turbulence separation minima are considered to be over-conservative. The applied separation values indeed 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).

In early 2000, EUROCONTROL started researching Time-Based Separation (TBS), a new operating procedure for separating aircraft by time, instead of distance. TBS addresses headwind disruptions by dynamically reducing the spacing between pairs of aircraft in strong headwind conditions consequently preserving runway throughput. The TBS concept was then further developed and assessed in the framework of the Single European Sky ATM Research Programme, in Project 06.08.01 (SESAR P06.08.01). TBS makes use of the wake more rapid dispersion in strong headwind conditions permitting a safe reduction in the spacing between aircraft. However, the application of such dynamic separation minima needs the development and use of a separation delivery support tool for ATM [2].

The Air Traffic Control (ATC) support tool shall provide the separation indicators depending on the applicable separation minima and the aircraft speed profiles that also depends on the headwind conditions. Because uncertainties exist both in the aircraft airspeed profiles and in the wind profile, buffers have to be added in the separation indicator computation.

This paper describes two methodologies allowing to safely compute the separation indicators in an ATC support tool when operating TBS. The first approach is based on "analytical" data mining and modelling whereas the second one is based on a Machine Learning (M/L) procedure. In the framework of the deployment of the TBS concept in Vienna airport (LOWW), those approaches are developed and tested using two databases covering a total of three years of traffic and corresponding local meteorological data.

This paper is organized as follows. Sections II and III describe the TBS concept and the separation indicators needed for its operation. Section IV details the available Vienna databases used in this study. Section V describes how the TBS minima are obtained. Sections VI and VII focus on the analytical and M/L methodologies developed to compute the TBS indicators. Section VIII compares the results obtained by both methods. Finally Section IX describes how TBS indicator can be computed for non-nominal cases.

II. Time-Based Separation concept and related ATC support tool for operational use

The Time-Based Separation (TBS) concept consists in the definition of separation minima for aircraft on the Final approach to a runway based on time intervals instead of distances, as applied in Distance-Based Separation (DBS) operations. For a specific aircraft pair, when applying DBS, the time separation between the aircraft indeed increases for increasing headwind conditions. TBS allows for dynamic distance separation reductions in strong headwind conditions so as to preserve time spacing across all wind conditions.

However, TBS application entails the use of a support tool providing the separation distance indicator depending on the applicable time separation minimum, the follower speed profile which also depends on the headwind conditions. In order to allow efficient separation delivery, the tool also advises the controller on the expected compression, which depends on both the leader and follower speed profiles.

Two indicators, illustrated in Fig. 1, are thus used. The Final Target Distance (FTD) indicator corresponds to the minimum distance to be applied at the separation delivery point (DP) (e.g., the runway threshold).

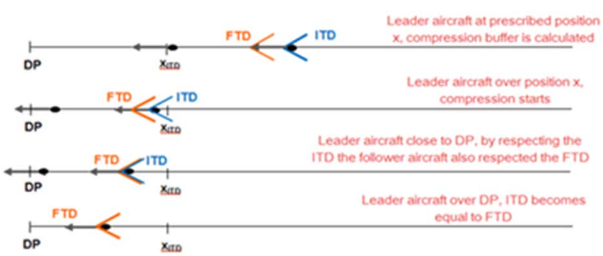

Fig. 1. Schematic view of ITD and FTD indicators

The FTD shall account for all applicable separation and spacing constraints in the prevailing wind conditions. This includes: the applicable wake time separation minimum (TBS), the leader runway occupancy time (ROT), and the minimum surveillance spacing (Minimum Radar Separation, MRS). It is computed based on those TBS, ROT and MRS minima and the time-to-fly profile of the follower aircraft in the prevailing wind conditions.

The Initial Target Distance (ITD) provides an indication of the spacing to be applied before compression. It is the distance separation applicable when the leader aircraft is at a prescribed glide speed (e.g. 160 kts) before deceleration to final approach speed such that the FTD will be obtained at the separation Delivery Point (DP). It is thus computed using as input the FTD and the leader and follower time-to-fly profiles in the prevailing wind conditions.

However, operationally, uncertainties are found on the time-to-fly profiles of both the leader and follower due to uncertainty on the aircraft airspeed profiles and on the wind conditions. This uncertainty is related to natural variations of aircraft behavior but also to the wind evolution between the time at which the indicator shall be provided to the controller and the time of aircraft actual landing (typically 10 minutes). Therefore, buffers are needed both in the FTD and the ITD computation in order to cope with those uncertainties.

III. TBS indicator design criteria

For the design of those separation buffers, three safety criteria are considered expressed in terms of wake turbulence risk, risk of provision of separation below ROT and risk of catch-up of the FTD when using ITD. Some design "acceptable" error rates are also defined for each safety criterion based on the observed separation conformance of existing operations.

For the wake turbulence risk, the FTD shall be computed such that the obtained time separation distribution obtained when applying TBS in strong wind condition is not statistically lower compared to the time separation distribution observed for that pair in low wind conditions reduced by the "TBS margin" that is function of the total wind. Indeed, in case of strong wind conditions, the positive impact of the (total) wind on the wake decay allows for even further reduction of the time separations even below the TBS minima (by certain "TBS margins" as defined in [3]).

The following criteria are thus defined for the FTD buffer computation. If delivering an aircraft at threshold with a distance separation corresponding to that of the FTD chevron, the delivered time separation shall be:

- Larger or equal to ROT
- Larger than the median TBS reduced by the TBS margin (function of the ground total wind at landing time) for at least 50 % of the pairs
- Larger than the TBS 10th percentile reduced by the TBS margin for at least 90 % of the pairs
- Larger than the TBS 1st percentile reduced by the TBS margin.

This last criteria is conservative and is used to "cut the tail" of the reference time separation distribution to its 1st percentile.

Because designing buffers with a 0% failure rate level would lead to over-conservative design and because Air Traffic Controllers (ATCO) put natural margin compared to the reference minima in their separation delivery, a certain failure rate tolerance is added for the ROT (here corresponding to maximum 1.5% of pair below ROT if all pairs would have been delivered at minima).

The design criteria for the ITD is related to the catch-up risk. The ITD buffers shall be designed such that if ITD was applied at minima when the leader was at the deceleration fix (DF= 5 NM here) and with both leader and follower at the reference glide slope speed (here 160 kts):

- the distance separation obtained at runway threshold is larger or equal to the FTD;

A certain failure rate tolerance is also added here corresponding to 2.5% of the pairs if all would have been spaced at ITD minima.

Note that in order to obtain reference in absolute values for those numbers, those failure rates have to be multiplied by the probability to observe a pair at minima.

The surveillance risk is also accounted for by capping all indicators to MRS. In low wind condition (and therefore for TBS minima computation), MRS is set to 2.5 NM, whereas in strong wind conditions it is set here at 2.0 NM. Note that the application of reduced MRS below 2.5NM (as allowed by ICAO) down to 2.0 NM is under investigation in SESAR project. This value is however here used so as to allow distance separation reduction for Medium-Medium pairs in strong headwind conditions.

IV. DATABASE DESCRIPTION AND PROCESSING

A. Description

To support the TBS separation matrix and system buffer definition, two databases are used.

The first database (referred to as database 1 in what follows) covers almost 2 years of aircraft operations in LOWW airport. It contains RADAR tracks (providing aircraft altitude, coordinates, ground speed), anemometer surface wind at runway threshold and SODAR wind profiler data for about 170,000 flights. However because of the low availability of data for high altitudes, SODAR data cannot be systematically used to characterize aircraft behavior as a function of wind all along the glide.

The second database (referred to as database 2 in what follows) covers one year of aircraft operations in LOWW airport. It contains Mode-S data, providing aircraft altitude, coordinates, ground- and air-speed but also wind as measured by the aircraft and anemometer surface wind data at runway threshold for about 120,000 flights.

Because wind vertical profile is needed for accurate FTD and ITD computation, only the second database is used to build and assess the two approaches for indicator computation whereas the first database is used to determine the local matrix of TBS minima, allowing ones to obtain those TBS minima from an independent dataset.

The Vienna airport has two runways, which can be operated in two directions leading to the definition of four runway thresholds: RWY34 (main arrival runway), RWY29, RWY16 and RWY11. When TBS will enter into operation, a RECAT wake turbulence separation scheme should be used in Vienna airport. In that RECAT scheme, the ICAO HEAVY category is split in two parts:

- the B757 fleet and B767 fleet referred to as LOWER HEAVY (LH),
- all other ICAO HEAVY aircraft types referred to as HEAVY (H).

The ICAO MEDIUM category is also split in two parts:

- the A320 fleet and B737 NG fleet are referred to as UPPER-MEDIUM (UM),
- All other ICAO MEDIUM aircraft types referred to as MEDIUM (M).

The ICAO LIGHT category is not changed and is referred to as LIGHT (L). A category is added for A388 denoted SUPER (S).

B. Filtering

Before being able to use the data for buffer design, the databases are processed and filtered so as to only keep, in the dataset, cases that are realistic and representative of arrival constrained operations for which TBS would be used in the future.

In order to keep relevant and reliable data, some filtering steps are applied on both databases using physics-based arguments and in order to keep data representative of peak operations. The following exclusion criteria are used:

- flights not established on the glide at 6 NM from runway threshold
- go arounds
- helicopter flights
- cases without reliable wind data
- cases with abnormal ground speed values
- cases with final approach true air speed above 160 kts
- cases with final approach true air speed outside the 95% variation envelope observed for that aircraft
- cases with deceleration to final approach speed before 6 NM from runway threshold
- cases without preceding aircraft in the 10NM in front of them.

The remaining filtered databases finally contain about 111,000 flight tracks for database 1 and more than 90,000 flight tracks for database 2.

C. Data split

In order to assess and compare the TBS buffer computation approaches, three samples are built using database 2: two samples used for model computation and calibration and one sample for model testing and assessment. The samples are generated by randomly picking some days of measurements in the database with about 65 % (40% in computation sample 1 + 25% in computation sample 2) of the database for model computation and calibration and 35 % for model testing and assessment (denoted as assessment sample). Note that for "analytical" approach the two computation samples are not distinguished.

D. *Database 2 processing*

When using the TBS ATC separation delivery support tool, the controller shall ask the pilot to maintain a reference air speed (here set at 160 kts) or lower when positioned on the ITD before deceleration to final approach speed. This reference speed is indeed used in the ITD computation to predict the expected pair compression. However, in the recorded flight tracks, the observed TAS before deceleration are most of the time above 160 kts. The observed TAS profiles are therefore corrected assuming a capping of the TAS to 160 kts. In other words, from the closest distance to threshold at which the aircraft is observed to be at 160 kts to 15 NM from the runway threshold, the aircraft is assumed to be at 160 kts. The ground speed and corresponding time-to-fly profiles are then recomputed from this new TAS profile combined with the measured Mode-S wind profile.

In order to perform an analysis covering a maximum of possible cases that could be observed in Vienna airport, a database of aircraft pairs is built from database 2 considering that all aircraft arriving in a 10 minutes time period could have been an observed pair. This leads to a total of about 370,000 aircraft pairs allowing us to better cover the tails of the statistical distributions of possible observed pairs in Vienna. It is considered as a conservative approach since some of those pairs might not represent cases that are realistic if an ATCO would have been in the loop.

For the buffer results assessment, the wind conditions are divided in three categories based on ground headwind value:

- low wind corresponding to headwind ranging from 0 to 5 kts;
- moderate wind corresponding to headwind ranging from 5 to 10 kts; and
- strong wind corresponding to headwind ranging from 10 to 30 kts.

V. TBS MATRIX COMPUTATION

As explained in Section II, the principle behind TBS concept is to maintain constant time separation between aircraft pairs across all wind conditions. As explained in [4]: "The time based separation minima are derived from the distance-based wake turbulence separation minima in wind conditions when the achieved arrival capacity with the DBS rules are currently acceptable to busy capacity constrained arrival runway operations. From operational experience this is in low headwind conditions."

The time separation minima, noted TBS, are thus calculated for each aircraft pair as the observed time required for the follower aircraft to fly the DBS minima to threshold in low wind condition (defined as ground wind below 5 kts).

However, because of differences in speed profiles, in calm wind conditions (here, ground total wind below 5 kts and with maximum ground tailwind of 2 kts), significant variation of time-to-fly is observed for each aircraft type. Those distributions are characterized for each aircraft type using the RADAR tracks from database 1. Because of these variations of time-to-fly, a reference time-to-fly has to be defined for TBS minima computation. As suggested in [4], the TBS minima are computed based on the median (=p50) of observed time-to-fly measured in low-wind conditions.

However, even if the database covers almost 2 years of operations, for some aircraft types, no sufficient amount of tracks in such calm wind conditions are found. For those aircraft types, an alternative has to be defined. Because, aircraft are slower (in ground referential) under stronger headwind conditions, for those aircraft with too low number of low wind tracks, all tracks measured in all wind conditions are used to conservatively estimate the median time-to-fly profile and the corresponding TBS minima. For this study, the minimum number of data required to estimate the median time-to-fly profile has been set to 10. In order to have an estimate of the TBS minima independent from the database used for indicator buffer estimates, database 1, which cannot be used for chevron buffer evaluation because of lack of Mode-S data, is primarily used. However, because of traffic evolution, some aircraft types from database 2 are not found in database 1 (or not in sufficient amount). For those aircraft types, database 2 is used for TBS minima computation using primarily low wind conditions or all wind conditions as for database 1. If TBS minima cannot be determined from either datasets due to lack of data, the FTD will be computed as equal to the applicable DBS minimum. Note that this approach is conservative as it provides larger TBS minima for less well characterized aircraft types. It also provides less benefits (i.e. less allowed separation reduction) for less frequent aircraft types (as not frequent in the local database) and hence has only limited impact on capacity benefits. Those TBS minima are used for FTD computation. However, in the design of the indicator buffers, TBS application shall ensure that similar time separation distribution (potentially reduced by the TBS margin described in Section III) is observed across all wind conditions. In other words, because time separation below those minima are observed when applying DBS in low wind conditions, separations below those TBS minima are also acceptably safe when applying TBS if occurring with the same probability. Therefore, for TBS buffer computation, the matrices of TBS 10th and 1st percentiles are also computed.

VI. ANALYTICAL INDICATOR COMPUTATION

The analytical methodology makes use of a time-to-fly profile model built per aircraft type and depending on the headwind vertical profile.

For the aircraft True Air Speed (TAS) profile, a 4-parameter model, illustrated in Fig. 2, is used. The model is divided in three zones:

- Constant glide slope speed (V_{glide}) down to deceleration fix (DF);

- Linear deceleration from DF to the stabilization fix (SF) to reach the final stabilized approach speed;
- Constant stabilized final approach speed (V_{app}) down to runway threshold.

The values of the parameters have been determined based primarily on analyses of database 1 measurements and then on analyses of database 2 both in low wind conditions. V_{glide} is fixed to 160 kts as it is the instructed flight speed on the glide if the aircraft is close to the ITD.

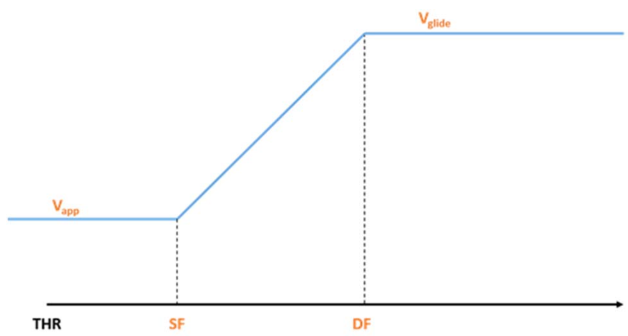

Fig. 2. Airspeed profile model used for analytical approach

The wind profile is estimated from Mode-S data. A wind database is computed through averaging all wind measurement available on a 10 minutes period on 0.25 NM segments at various distances from the runway threshold and with a sampling rate of 30 s. This allows us to obtain a database of the best wind profile estimate as available at a given time period. The average is also only considered to be valid if at least 3 measurements are found in the considered time and space interval. Finally, a wind vertical profile is considered to be usable if it contains valid data for a least one altitude below 200 m (~2NM from runway threshold) and at least one data for altitudes above 385 m (=4NM from runway threshold). This guarantees that the profile provides an indication on the shape of wind evolution with altitude and hence allows us to compute the related separation compression. That wind profile is complemented by the anemometer wind measured at 10 m height.

Because the FTD and ITD indicator have to be computed and displayed to the ATCO before the follower has intercepted the glide and because artificial pairs will be created for analysis purpose, see above, the wind used in the analysis correspond to the wind as available 10 minutes before the considered follower aircraft has landed and five minutes before the leader aircraft has landed.

From the time-to-fly model described above, the FTD is computed following three steps.

- Compute the distance corresponding to the time required to fly the applicable leader ROT increased by the ROT buffer
- Compute the distance corresponding to the time required to fly the applicable TBS increased by the TBS buffer. That distance is capped to the applicable DBS (since DBS is allowed in all weather conditions)
- Compute FTD as the maximum of those two distances and of the applicable MRS

For each pairs of the database, the FTD is first computed starting with TBS and ROT buffers equal to 0. The corresponding delivered time separations at threshold are then computed. The wake and ROT risk failure rates are then evaluated. The TBS and ROT buffers are then iteratively increased by steps of 1 s and the corresponding time separations are re-computed until the wake and ROT constraint criteria are met (i.e. until the failure rates fall below the design criteria).

Using the time-to-fly model described above, the ITD is computed following two steps.

- Compute the distance separation minimum required at deceleration fix to obtain, at delivery point, a time separation corresponding to the FTD separation increased by the ITD buffer
- Compute ITD as the maximum of the obtained distance and FTD (even if decompression is expected) such that FTD or more will be observed everywhere.

As for FTD, the ITD is first computed for each created pair starting with 0 buffer. The corresponding delivered distance separations at threshold are then computed and compared to the FTD values. The catch-up failure rate is then evaluated. The ITD buffers are then iteratively increased by steps of 1 s until the catch-up failure rate falls below the design one.

VII. M/L INDICATOR COMPUTATION

In this section, we propose another strategy to estimate FTD and ITD, by making use of a regularized regression method. The strategy aims at predicting the trajectory of an aircraft 10 minutes before its landing, by taking into account various features such as wind profile, aircraft type, airline, landing time. The learning pipeline is composed of 3 stages. From the computation sample 1, a model is learnt to predict the trajectory. This model, applied to both leader and follower flights, allows to infer a predicted FTD and ITD to meet TBS, DBS and ROT constraints. From the computation sample 2, an estimation of the FTD and ITD buffers is made to ensure that the separation distribution meets the set of conditions described in Section III. Then, the prediction quality is tested on the assessment sample, and compared to the ground truth.

A. Problem setting

In a regression framework, learning aims at predicting continuous targets from a set of description features. Our objective is to estimate the time-to-fly at several distances from the runway threshold from the following descriptive features, without making any hypothesis on the on-glide speed evolution:

- the headwind, the crosswind and the absolute crosswind on the landing runway 10 minutes before landing (3 dimensions)
- the integrated headwind, crosswind and absolute crosswind as a function of distance from the runway. The integration is made by taking the median measurements in the last ten minutes by ranges of distance from the runway. Ten ranges are defined,

from 0 to 20 km from the runway threshold, by step of 2 km (30 dimensions).

- the temperature integrated as it is done for the wind (10 ranges thus 10 dimensions) and centered
- the pressure integrated as it is done for the wind (10 ranges thus 10 dimensions) and centered
- the aircraft wake turbulence RECAT category. Since most learning algorithms are not designed to work directly with categorical variables, we proceed to one-hot-encoding of the aircraft category. One hot encoding consists in transforming a categorical variable of cardinality X to a vector of X Boolean values, each vector dimension corresponding directly to a given value of the categorical feature. By consequent, for each sample, only one dimension is set to true (6 dimensions)
- the aircraft type. As for aircraft category, we use one-hot-encoding for this feature (181 dimensions)
- the landing runway, one-hot-encoded (5 dimensions, including unknown runway)
- the origin airport of the flight, using its ICAO code for the area, the country and the airport, one-hot-encoded (803 dimensions)
- the airlines, deduced from the 3 first digits of the call sign, one-hot-encoded (826 dimensions)
- the sines and cosines of the landing hour, landing day of week and landing week of year (periods of these features are respectively of one day, one week and one year). We also include one-hot-encoding for these 3 variables (89 dimensions)

Each flight is thus described through a vector of 1963 features. The time-to-fly target is represented through 80 time-to-fly values (expressed in seconds) when the aircraft is on the glide, computed at several distances from the runway threshold, contained between 0 to 20 km by steps of 250 meters.

B. *Learning a predictor*

The classifier selection was made through a cross-validation procedure performed on a subset of the dataset. Several algorithms have been tested, with a large set of parametrization. Among them:

- LASSO linear regression (L1-regularized) [5]
- Ridge linear regression (L2-regularized) [6]
- Elastic-Net linear regression (L1 and L2 regularized) [7]
- Support Vector Regression with linear, polynomial and RBF kernels [8]

Finally, we end up with an Elastic-Net linear regression using a features rescaling to harmonize orders of magnitude.

C. *Features influence*

In this section, we study the influence of different features on the trajectory prediction quality by comparing the accuracy of classifiers computed on various subsets of features. For the sake of concision, we limit the comparison at one particular statistic: the quantile 1 of the absolute prediction error (the 1% largest errors) at 9.25 km (roughly 5 NM) of the threshold.

Because the air speed is imposed to 160 kts on the glide before deceleration fix (which is roughly located at to 9.25 km), this distance approximately corresponds to the largest distance at which significant speed variance is observed. Also, we are more interested in the extreme quantile than in the median (or average) behavior since the targeted failure rates are very low.

In a first step, we focus on 4 features sets to evaluate the influence of the aircraft category and type:

- Ground anemometer only
- Ground anemometer + a/c category
- Ground anemometer + a/c type
- Ground anemometer + a/c category and type

The results are displayed in Fig. 3

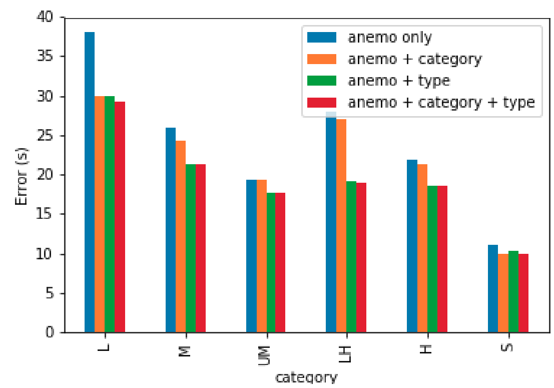

Fig. 3. Quantile 1 of absolute prediction error by aircraft category for 4 datasets, under moderate wind conditions

For most of categories, including the type in the model seems to allow the error to decrease more than the aircraft category. This is particularly true for LH, where the decreasing reaches 10 seconds. On the other hand, the category has a large influence on the accuracy for L aircraft. It may signify that the behavior of LIGHT aircraft is in essence very different from the others. The fact that the type doesn't help so much for LIGHT may be the consequence of a larger variety of types in this category, most of them being very rare, and so hard to characterize accurately.

In a second step, we study the role of landing runway, landing time, origin airport and airline. We take the anemo + category + type as the basis, and we compare it to 4 other datasets (see Fig. 4):

- Basis + landing runway
- Basis + landing time (hour, weekday and week)
- Basis + origin airport
- Basis + airline

In general, none of these 4 additional features allows the error to consistently decrease. Nevertheless, it seems that origin airport and time are slightly more interesting than the others from this point of view.

Finally, we have a look to the influence of vertical profiles extracted from Mode-S data. We take the anemo + category + type as a basis, and we compare it to 5 other datasets (Fig. 5)

- Basis + Mode-S vertical wind profile
- Basis + Mode-S temperature
- Basis + Mode-S pressure
- Basis + Mode-S wind, temperature and pressure
- Basis + Mode-S wind, temperature and pressure + landing runway + landing time + airline + origin airport

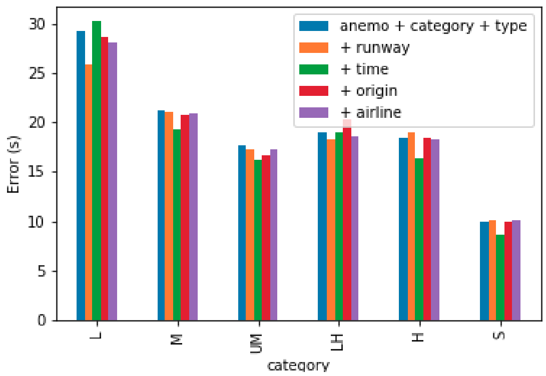

Fig. 4. Quantile 1 of absolute prediction error by aircraft category for 5 datasets, under moderate wind conditions

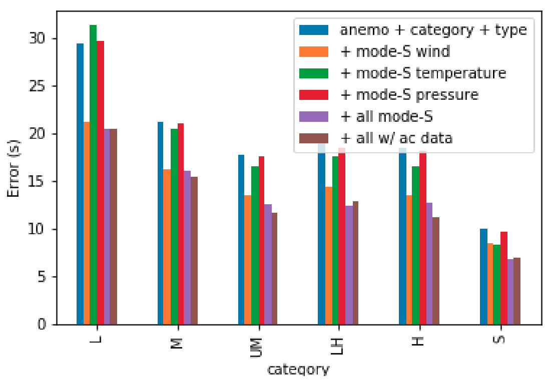

Fig. 5. Quantile 1 of absolute prediction error by aircraft category for 5 datasets, under moderate wind conditions

The use of Mode-S wind helps in reducing the prediction error up to 25%. The wind vertical profile is then essential to increase the precision level; this is by far the most influential feature. We note also that the temperature has a positive effect too whereas the pressure influence is nearly negligible. In the case where both temperature and pressure are added to Mode-S wind, we improve consistently the model accuracy, except for LIGHT aircraft, for which predictions seem to be more unstable.

Finally, adding airline, origin airport, runway and time to the model helps in reducing slightly the error especially for UM and H categories even if we state above that the individual contribution of these features are marginal.

In the following, all the studies are made using this last trajectory predictor which seems to have the best behavior.

D. Trajectory prediction quality

In this subsection, we give some insights on the evolution of the trajectory prediction quality, depending on the distance to runway threshold and on the headwind speed. In Fig. 6 and Fig. 7, we supply the quantile 1 on the absolute error estimation by category under two settings:

- under moderate wind conditions, at 1.5, 3.0, 5.0, 8.0 and 10.0 NM from the threshold
- at 9.25 km from the threshold, under low, medium and strong wind conditions

For all categories, the error is globally increasing with the distance. Nevertheless, note that this increment is clearly weaker after 5 NM (for LH, we even observe a slight decreasing). This is not surprising, since we know that the air speed variance is lower before the deceleration fix.

As expected, the error increases with the headwind speed. From an aircraft category point of view, we observe that the heavier is the aircraft, the smaller is the prediction error. It is particularly true for LIGHT aircraft, for which the error is up to 1.5 times larger than for M, and 4 times larger than for S. This category is intrinsically difficult since it contains numerous types of aircraft, some of them being very rare. This category contains also more non-regular, non-recurrent flights, which increases the variance.

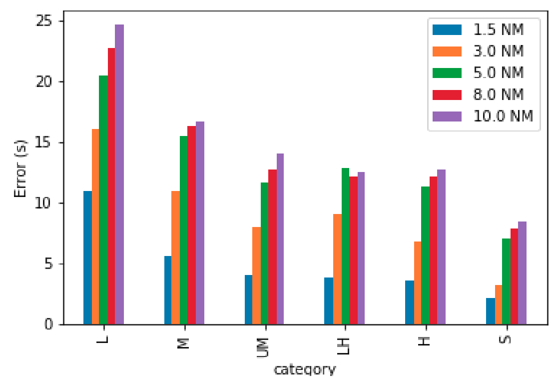

Fig. 6. Quantile 1 of absolute estimation error by category for 5 distances (1.5, 3.0, 5.0, 8.0, 10.0 NM) under moderate headwind (between 5 and 10 kts)

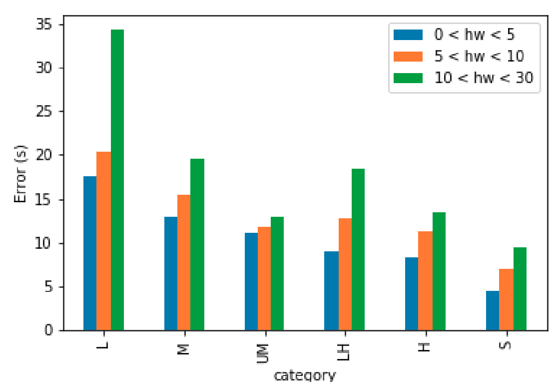

Fig. 7. Quantile 1 of absolute estimation error by category at 9.25 km (5.0 NM) under low, medium and strong headwind conditions

E. Buffers computation

Once trajectories of leader and follower aircraft have been predicted, we are able to compute theoretical FTD and ITD. In order to ensure that these FTD and ITD computed from the trajectory predictions meet the constraints described in Section III, we may have to define a set of additional buffers to tackle the uncertainty. They are defined as a ratio of the input, which is either the ROT or the TBS, and are expressed in m/s. These buffers are then added to the predicted FTD and ITD. Note they can be negative to take advantage of TBS margins.

To compute these buffers, we use the computation sample 2, independent from the computation sample 1, and we build leader/follower couples as explained in Section IV.D. We have at our disposal around 80,000 couples.

As FTD and ITD are non-immediate consequences of trajectory predictions, as the data is highly heteroscedastic, the distributions of errors made on FTD/ITD are hard to characterize mathematically. Then, we rely to an empirical strategy: we estimate the buffers values allowing to fulfill the constraints with high confidence from the error distribution computed on the computation sample 2.

VIII. COMPARISON AND GAIN RELATED TO THE USE OF M/L

The assessment of the two methodologies is performed using the assessment sample of database 2, independent from those used to compute the predictors and the associated buffers. It is composed of more than 90,000 leader/follower couples, mainly involving MEDIUM and UPPER MEDIUM aircraft categories. We then limit our study to these categories, for which the number of data ensures sufficient statistical confidence to reach the design failure rates. For those pairs, all the failure rates are below the thresholds defined in Section III (e.g. catch-up failure rates usually range between 2.0 and 2.5% and the ROT failure rates are marginal).

The evaluation is first performed by comparing the gain in time separation obtained when applying TBS at FTD minima with those obtained when applying DBS at minima. Results are also grouped by headwind range: low (0-5 kts), moderate (5-10 kts) and strong (10-30 kts). In order to highlight the effect of headwind, the gain is estimated compared to DBS operations in low wind conditions. The results are provided in TABLE I. We notice that, for a given pair, the separation times when applying TBS are almost constant in all wind conditions, whereas the separation times increase with the wind under DBS strategy.

When operating DBS, a 3 to 4% increase of the mean time separation (and hence a decrease of runway throughput) is observed in moderate wind conditions and of 7 to 9% in strong wind conditions. When applying TBS with analytical FTD (and related buffers) computation, this increase of mean time separation is reduced to 1.5-2% in moderate wind conditions (hence still with a decrease of throughput compared to low wind conditions). For strong wind condition, thanks to the TBS margin allowing time separation delivery below TBS minima, the mean time separation is even seen to decrease compared to low wind conditions with throughput increase ranging from 1.5 up to 4%.

When applying TBS with M/L FTD (and related buffers) computation, increase of runway throughput is observed in all wind conditions (even in low wind condition) with value reaching up to 6% compared to DBS in low wind which represent a gain of up to 13% compared to DBS in strong wind conditions. The benefits related to TBS with M/L FTD is seen to be superior to those obtained for TBS with analytical FTD for all investigated pairs and in all wind conditions.

The assessment is then performed by comparing the gain in time separation reduction obtained when operating TBS at ITD minima delivered at the deceleration fix (i.e. here at 5 NM from runway threshold). In order to perform fair comparison, the time separation obtained at runway threshold when delivering ITD at minima at 5 NM from runway threshold are compared to the time separations obtained when delivering at runway threshold at separation corresponding to DBS increased by a buffer of 0.5 NM (which typically corresponds to what is applied by the controllers in peak condition [9]).

TABLE I. COMPARISON OF TIME SEPARATION REDUCTION [%] COMPARED TO DBS LOW WIND WHEN APPLYING DBS, TBS WITH ANALYTICAL FTD, TBS WITH M/L FTD

Pair type	Ground HW range [kts]	DBS	FTD Analytical	FTD M/L
UM-UM	0-5	0.0%	0.3%	0.5%
UM-UM	5-10	-3.1%	-2.2%	2.5%
UM-UM	10-30	-7.2%	3.0%	5.6%
UM-M	0-5	0.0%	0.0%	0.3%
UM-M	5-10	-3.9%	-1.7%	0.8%
UM-M	10-30	-8.7%	1.4%	3.1%
M-UM	0-5	0.0%	0.3%	0.5%
M-UM	5-10	-3.1%	-1.4%	2.5%
M-UM	10-30	-6.9%	3.9%	5.8%
M-M	0-5	0.0%	0.4%	0.0%
M-M	5-10	-4.0%	-1.7%	1.0%
M-M	10-30	-8.7%	1.8%	3.2%

As for FTD, the gain is estimated by comparison with DBS + 0.5NM operation in low wind conditions. The results are provided in TABLE II. When operating DBS with or without buffer, the same order of magnitude of increase of the mean time separation (and hence of decrease of runway throughput) are observed (i.e. 3 to 4% in moderate wind conditions and 7 to 9% in strong wind conditions). When applying TBS with analytical ITD (and related buffers) computation, this increase of mean time separation is reduced to 0.5-2.5% in moderate wind conditions (hence still with a decrease of throughput compared to low wind conditions). For strong wind condition, the mean time separation is seen to decrease compared to low wind conditions for UM followers with throughput increase reaching up to 3% whereas for M followers, the time separation increases are limited to maximum 0.8% compared to

9% when applying DBS. Note that significant benefits are also observed for low wind conditions.

When applying TBS with M/L ITD (and related buffers) computation, increase of runway throughput is observed in all wind conditions with value ranging from 3% up to 7% compared to DBS+0.5NM applied in low wind which represent a gain of up to 14% compared to DBS+0.5Nm applied in the same strong wind conditions. The benefits related to TBS with M/L ITD is seen to be superior to those obtained for TBS with analytical ITD for all investigated pairs and in all wind conditions.

TABLE II. COMPARISON OF THE TIME SEPARATION REDUCTION [%] COMPARED TO DBS+0.5NM BUFFER IN LOW WIND WHEN APPLYING DBS +0.5 NM BUFFER, TBS WITH ANALYTICAL ITD AND TBS WITH M/L ITD

Pair type	Ground HW range [kts]	DBS+0.5 NM	ITD Analytical	ITD M/L
UM-UM	0-5	0.0%	2.9%	6.0%
UM-UM	5-10	-3.2%	-1.1%	6.3%
UM-UM	10-30	-7.4%	2.8%	6.9%
UM-M	0-5	0.0%	3.1%	5.5%
UM-M	5-10	-4.0%	-0.4%	4.7%
UM-M	10-30	-9.0%	-0.4%	3.0%
M-UM	0-5	0.0%	1.2%	2.8%
M-UM	5-10	-3.2%	-2.2%	3.6%
M-UM	10-30	-7.1%	1.2%	3.3%
M-M	0-5	0.0%	1.5%	3.3%
M-M	5-10	-4.2%	-2.5%	3.1%
M-M	10-30	-9.0%	-0.8%	2.5%

IX. NON NOMINAL CASES

The results detailed in the above sections can only be used when the aircraft is sufficiently frequent so that its speed behavior has been characterized and when wind vertical profile data are available. Yet, operationally, rare aircraft can be observed and wind profile data can sometimes not be available. When using Mode-S, this is for instance the case for the first few flights of a peak hour for which no wind information are available since no or few preceding aircraft flights were observed. However an indicator should be provided to the ATC separation support tool. A methodology to compute the FTD and ITD is here proposed for those scenarios.

A. *No Mode-S wind vertical profile*

In operations, Mode-S data (or another wind profile) are not systematically available, for example for the few first aircraft of the day. But, even with these missing data, it can still be valuable to use TBS instead of DBS. To evaluate how the strategy is affected by incomplete data, we compare in this section the ITD obtained for the 4 main couple categories through 2 M/L predictors:

- The predictor with full information studied in the Section VII
- The same predictor without Mode-S data (so with anemometer, type, category, landing time and runway, airline and origin airport)

The buffer computation is performed following the methodology described in Section VII.E for both predictors. The results are summarized in TABLE III. using the same comparison as that described in Section VIII.

Adding Mode-S data to the model always allows the predictor to decrease the separation time between aircraft. For categories with acceptable failure rates, compared to DBS+0.5NM in the same wind conditions, the gains are typically of 7-9 % when the wind is low, and up to 14 % in strong wind conditions.

Nevertheless, it is still highly valuable to use the downgraded predictor, since it reduces the time separations, compared to those obtained with DBS + 0.5 NM in the same wind conditions, by several percent (2-6 % in moderate wind conditions, 4 to 9 % in strong wind conditions).

TABLE III. COMPARISON OF TIME SEPARATION REDUCTION[%] COMPARED TO DBS+0.5NM BUFFER IN LOW WIND WHEN APPLYING DBS +0.5 NM BUFFER, TBS WITH M/L ITD WITH MODE-S DATA AVAILABLE AND TBS WITH M/L ITD WITHOUT MODE-S DATA AVAILABLE.

Pair type	Ground HW range [kts]	DBS+0.5 NM	ITD with Mode-S	ITD without Mode-S
UM-UM	0-5	-	6.0%	3.5%
UM-UM	5-10	-3.1%	6.3%	2.6%
UM-UM	10-30	-7.4%	6.9%	2.0%
UM-M	0-5	-	5.5%	3.5%
UM-M	5-10	-4.0%	4.6%	-0.1%
UM-M	10-30	-8.9%	2.9%	-4.5%
M-UM	0-5	-	2.8%	0.8%
M-UM	5-10	-3.1%	3.6%	0.2%
M-UM	10-30	-7.1%	3.3%	-0.1%
M-M	0-5	-	3.3%	0.6%
M-M	5-10	-4.2%	3.1%	-2.5%
M-M	10-30	-9.0%	2.5%	-5.0%

B. *Rare/new aircraft type*

For rare or new aircraft types, TBS cannot be applied because the uncertainty related to the aircraft speed behavior is too high. Because those aircraft are by definition rare, it is proposed to follow a very conservative approach which will provide too large separation minima for those pairs but with limited operational impact given the low frequency of occurrence.

For the FTD computation, the chevron shall be computed based on the applicable DBS minima since no TBS minima is defined for a rare aircraft.

For the ITD computation, for each category and based on the observation of the other aircraft of that category, it is proposed to build a "worst case" speed profile leading to maximum catch-up scenario, illustrated in Fig. 8. When used as a leader, the aircraft has then an early deceleration from glide speed to a minimum stabilized final approach speed observed for aircraft types of that category. When used as a follower, the aircraft has a late deceleration from the glide speed to a maximum stabilized final approach speed observed for the aircraft of that category. Given the operational constraints, we consider that the earliest deceleration point for constrained pairs is located at 6 NM from threshold (with a stabilization at 5 NM) and the latest deceleration point is located at 3 NM from threshold (with a stabilization at 2 NM). The minimum and maximum final approach speed values are taken from the final approach speed analysis (i.e. minimum and maximum value of the 95% envelope limits obtained for all aircraft of the considered category). Those speed profiles are then used together with the wind and the buffers computed for the considered category to estimate the ITD using the analytical approach.

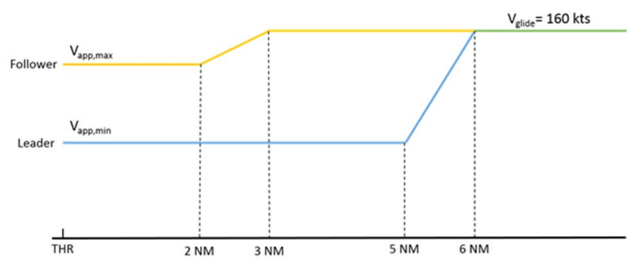

Fig. 8. Air speed profile used for follower and leader rare aircraft types

X. CONCLUSIONS

This paper detailed two methodologies allowing a system to compute the Time-Based Separation (TBS) indicators so as to allow Air Traffic Controllers to accurately and safely deliver the TBS minima for arrival aircraft flights using a separation delivery support tool. The first approach is based on "analytical" data mining and modelling whereas the second one is based on a Machine Learning (M/L) procedure. In the framework of the deployment of the TBS concept in Vienna airport (LOWW), those approaches were developed and tested using one database covering one year of traffic and corresponding local meteorological data.

The "analytical" approach makes use of an analytical model for the aircraft airspeed profile combined with the wind profile as available 10 minutes before landing. Time separation buffers are calibrated, based on a subset of the database, until the error rates fall below the design ones. In the M/L approach, the arrival time-to-fly profile is predicted through a regularized linear regression strategy. The produced model makes use essentially of headwind (both at runway threshold, and on glide), aircraft category and type, airline, temperature, landing time and origin airport. These features are all either known or available in operational environment. The gain on the trajectory prediction accuracy obtained by taking into account additional features was quantified.

The operation of TBS with indicators computed using either approaches leads to substantial diminution of time separations compared to a DBS strategy. However, given the large uncertainties related both to leader and follower aircraft speed profiles, the buffers could be designed only for the most frequent pairs. With the M/L approach (resp. the "analytical" approach), the capacity benefits related to the application of TBS with a separation support tool are of the order of 8% (resp. 2%) in moderate wind conditions, and up to 14% (resp. 10%) in strong wind conditions.

Due to the still limited size of the database covering the Vienna traffic mix, the present study did not yet allow us to obtain the applicable safety buffers for all aircraft pairs and in all wind conditions. A methodology was then defined to cover those rarer events based on conservative assumptions, allowing application of TBS to the whole fleet with a limited cost in terms of additional buffer.

ACKNOWLEDGMENT

The authors wish to express gratitude for the collaboration with various organizations and their representatives, and in particular to Günther Borek, Christian Kern, Lukas Strauss and Martin Steinheimer from Austro Control. Part of this work has been conducted in the framework of the TBS4LOWW deployment project funded by INEA/CEF under SESAR Deployment Manager (SDM) coordination.

REFERENCES

[1] EUROCONTROL. Industry Monitor - Issue N°189, 2016

[2] V. Cappellazzo, V. Treve, I. De Visscher, and C. Chalon. "Design Principles for a Separation Support Tool Allowing Optimized Runway Delivery", 2018 Aviation Technology, Integration, and Operations Conference, AIAA AVIATION Forum, AIAA 2018-4237

[3] I. De Visscher, F. Rooseleer, V. Treve and G. Borek, "Procedural Wind-Based Reduction of Separation on Final Approach: Design, Safety Assessment and Application to Vienna Airport", in Proc. *7th EASN International Conference on Innovation in European Aeronautics Research,* Warsaw, Poland, Sept 26-29, **2017***, ISSN 2523-5052*

[4] EUROCONTROL, "Time-Based Separation Minima as alternative to distance-based separation for Final Approach (TBS Minima)" Safety case ed 1.0, 2016, under EASA review.

[5] R. Tibshrani, "Regression Shrinkage and Selection via the Lasso", Journal of the Royal Statistical Society (Series B) 58 (1996)

[6] A. E. Hoerl and R. W. Kennard, "Ridge regression: Biased estimation for nonorthogonal problems", Technometrics 12, no.1 (1970): 55--67

[7] H. Zou and T. Hastie, "Regularization and Variable Selection via the Elastic Net", Journal of the Royal Statistical Society: Series B (Statistical Methodology) 67, no. 2 (2003): 301--320

[8] H. Drucker, L. Kaufman, A. Smola and V. Vapnik, "Support vector regression machines", Advances in Neural Information Processing Systems 9 (1997): 155-161

[9] G. Van Baren, C. Chalon-Morgan and V. Treve, "The current practice of separation delivery at major European airports", 11th USA/Europe Air Traffic Management Research and Development Seminar (ATM2015), 2015