Demonstration of Improved Trajectory Prediction Using Future Air Navigation Systems

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This paper aims to demonstrate how current technology can assist to improve ground-based trajectory prediction. The lack of accurate ground-based trajectory prediction is often associated with the inefficiencies resulting from current Air Traffic Control (ATC) practices. To this purpose, results from different ground-based Trajectory Predictors (TPs) — both standard and enhanced with Future Air Navigation Systems (FANS) data-link — are compared using operations into Los Angeles (LAX). At first sight, direct use of trajectory information down-linked through FANS from the aircraft's Flight Management System (FMS) seems logical, but numerous arguments exist against that approach. Instead, this research inferred parameters as speed schedule and aircraft mass from the FMS down-linked trajectory. Contrary to the trajectory data itself, these parameters can be used as input to many legacy TPs and are often unknown such that nominal values must be assumed. This paper indicates that with use of this inferred information significant improvements in ground-based trajectory prediction can be achieved. The 95% spread in the estimate time of arrival and top of descent error were reduced by a maximum 79% and 86%, respectively. The predicted

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trajectories from some enhanced TPs were found to be even more accurate than the original downlink predictions on which the inferred information was based, providing arguments for a combined air-ground solution to trajectory prediction rather than reliance on solely airborne trajectory data.

FANS is standard equipment on most wide-body aircraft, and fitting options exist on the major single-aisle aircraft fleet. With the infrastructure to obtain the required data already in place, the approach proposed in this paper is feasible *today* with minimum investment and aircraft system changes for airlines transitioning towards more advanced concepts and developing technologies.

INTRODUCTION

Internationally, significant work has been performed to analyse projections to air traffic and to propose methodology designed to manage the expected growth [Joint Planning and Development Office, 2007; SESAR Consortium, 2007; Australian Strategic Air Traffic Management Group, 2007]. Connected with a multitude of proposed solutions is a corresponding legion of new technology to be adopted and most importantly funded. Consequently, most of these ideas, although brilliant remain just that – ideas in waiting.

External to the air traffic management (ATM) arena, the global economic downturn has somewhat taken the immediacy from a solution and enabled a certain breathing space to examine priorities and solutions. Assumptions have been challenged and future concepts considered with the perspective of technology already available and deployed today [Bronsvoort, J., 2011; Bronsvoort, J. et al., 2012; McDonald, G.N. and Bronsvoort, J., 2012]. The benefit of this approach is that small and economically feasible steps can be made in the direction of trajectory based operations (TBO), using existing capabilities with minimal risk. Additionally, lessons can be learned for future developments.

Over time airlines have continuously fitted equipment on the promise of air traffic control (ATC) that it will be used to benefit operations. In many cases the use has not eventuated. In addition new equipment standards are being developed that are considered required for air-ground trajectory synchronization essential to TBO. This study, however, has extracted trajectory data from standard airline aircraft that are fitted with Future Air Navigation Systems (FANS) equipment aiming to demonstrate the generally unknown extended potential of this communication surveillance and navigation (CNS) system originally developed for oceanic operations. This extended potential could see results promised under TBO realised through a transition concept while more advanced technology is being developed.

BACKGROUND

To realize improved use of non-radar airspace required by increasing air traffic, the FANS concept was introduced in the early 1990s. The FANS concept involved improving the fields of communication, navigation, and surveillance. Boeing launched its FANS-1 product based on Controller Pilot Data Link Communication (CPDLC) and Automatic Dependent Surveillance Contract (ADS-C) for the 747-400 targeted at operations in the South Pacific. Airbus later developed its similar FANS-A product. The two products are collectively known as FANS-1/A.

A largely unknown aspect of FANS-1/A is the ability to down-link to ATC part of the aircraft's future trajectory as calculated by the flight management system (FMS). Previous work by these authors has compared the accuracy of this FMS calculated trajectory against the accuracy of trajectories predicted by current ground-based systems. The work concluded that ground-based systems can benefit significantly from the trajectory information derived via FANS, both laterally [Paglione, M/ et al, 2010] and longitudinally [Bronsvoort, J. et al., 2011]. Longitudinally, the improved accuracy mainly applies to climb and descent phases as ATC generally systems lack accurate knowledge of speed schedules and aircraft weight [Bronsvoort, J. et al.; Vivona, R.A. et al., 2011; Lopez Leones, J. et al; 2013].

Several attempts have been made to overcome this limitation with the use of aircraft-derived data. The Aircraft Data Aiming at Predicting the Trajectory (ADAPT) studies used aircraft-derived data to off-line tune the aircraft performance model of an existing ground-based trajectory predictor (TP) [Courdacher, T. and Mouillet, V., 2008]. While this methodology provides a solution, the tuning was performed off-line, was flight-specific, and depended on the atmospheric conditions of the day because of the kinematic nature of the TP used.

Airservices Australia performed similar research work using FMS trajectory information derived via the ADS-C component of FANS-1/A. The benefit of using ADS-C is that all existing infrastructure, both in the air and on the ground, is already in place. The ADAPT studies on the other hand made use of a data-link originally designed for communications between aircraft and the airline operations center (AOC); as such, forwarding systems from AOC to ATC had to be put in place. In previous research work, Airservices produced a method to improve ground-based trajectory prediction by appropriately combining data extracted from the FMS via ADS-C and data available on the ground. First, the critical pieces of missing trajectory information for descent – speed schedule and aircraft mass - are inferred from FANS-1/A trajectory data. Secondly, using the inferred information, a new prediction is performed by a ground-based TP using an extensive weather forecast assisted by

practical knowledge of how the FMS executes the descent. The accuracy of the new predicted trajectories has proven to be significantly more accurate than the original FMS predictions [Bronsvoort, 2011; Bronsvoort et al., 2012].

STUDY CONTRIBUTION AND OVERVIEW OF METHODOLOGY

The results obtained by Airservices as discussed above were obtained using Boeing 737-800 aircraft operating into Melbourne, Australia. In this paper the technique is extended to Airbus A380-800 aircraft, which are standardly equipped with FANS-1/A, operating into Los Angeles International Airport (LAX). In addition, while in references cited in [Bronsvoort, 2011; Bronsvoort et al., 2012], the information inferred from the FANS-1/A trajectory data was applied by a single TP in one particular method, this paper investigates different methods applied by different TP systems.

At first a baseline was established of current TP performance available to existing ground-based automation supporting LAX operations for a selected pool of flights. For this same pool of flights trajectory information was down-linked via FANS-1/A and recorded for comparison. Different methods of applying the FANS-1/A downlink trajectory information will be discussed on the basis of techniques developed by Airservices Australia. Finally, the performance of several TPs enhanced with data-link will be assessed illustrating the generic applicability of the FANS-1/A data and developed techniques.

Air traffic arriving to LAX, like most busy destinations, is assigned a published Standard Terminal Arrival Route (STAR) procedure prior to top of descent (TOD) as a means to position it in a stream of similarly arriving flights. A STAR prescribes a lateral path containing vertical and/or speed requirements to position the aircraft for vectoring by the TRACON to final approach. The amount of vectoring instructed by the TRACON depends on the number of arriving aircraft to be sequenced to final approach. As the sequencing into LAX is distance-based rather than time-based, specifying how much delay and, hence, vectoring will be applied to any particular aircraft is difficult.

Qantas Airbus A380-800 (A388) flights from Australia to LAX chosen for this study are equipped with ADS-C data-link as standard. The aircraft operate daily to Los Angeles from Sydney and Melbourne, Australia, as long-haul operations and have a flight time from 13 to 14 hours, depending on prevailing winds. The aircraft depart mid-morning from Australia, cross the dateline, and arrive in the United States (US) at a similar, but slightly earlier, time on the same calendar day as they departed.

The A380 is a heavy, wide-body aircraft for which Qantas defines strict operating procedures. The crews manage the aircraft to a company-defined flight plan and cost index calculated for each flight consistent with the current ATC clearance loaded to the FMS. Qantas expects its crews to operate the aircraft in path-managed mode as much as possible and have the aircraft established on a stabilized final from five nautical miles and 1,500 feet from the threshold.

Normal pilot procedures prescribe the crew will load the expected STAR into the FMS prior to TOD so that descent can be planned efficiently assuming an idle descent to the first impacting altitude constraint. Because of ATC interventions required to sequence the aircraft with other arriving traffic, the expected route and, therefore, efficient profile do not always eventuate.

BUFIE is a commonly used STAR into LAX for oceanic arrivals and is depicted in Figure 1. Aircraft are generally allowed to conduct a continuous idle descent at the speed schedule resulting from the cost index down to the fix GOATZ where a speed constraint of 280 knots indicated air speed (KIAS) applies. Santa Catalina (SXC) is a fix of interest for arrival metering with a 12,000 ft. altitude constraint.

In addition to the constraints published as part of the BUFIE procedure, ATC issues an additional constraint to reach 12,000 ft at GOATZ. This constraint is generally issued to the flight crew at the same time as the STAR and is included in the Los Angeles Air Route Traffic Control Center (ZLA-ARTCC) adaption data though not published. For this study, the 12,000 ft at GOATZ was always taken into account.

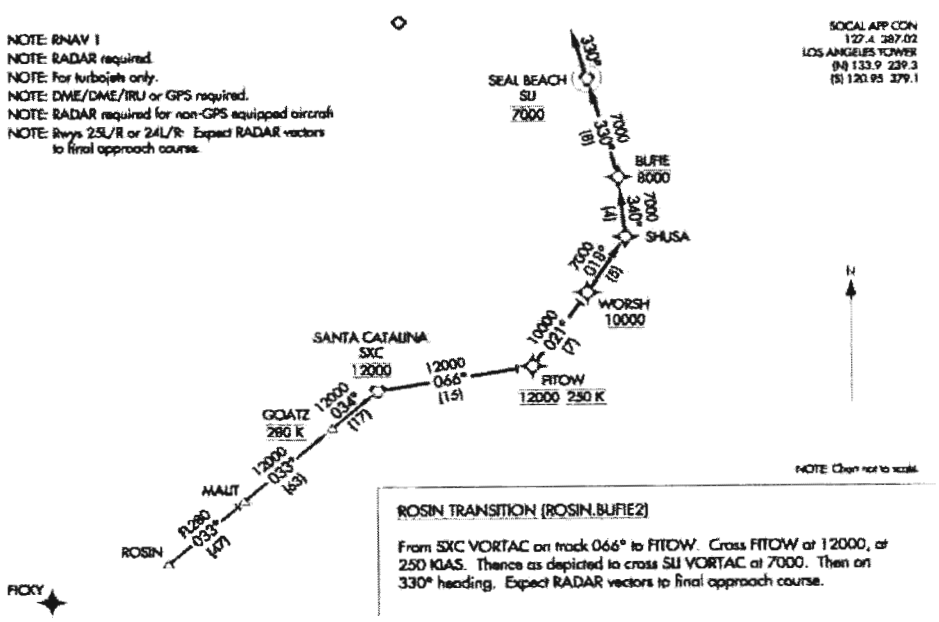

Figure 1. BUFIE TWO STAR Procedure.

With the STAR and additional constraints loaded into the FMS when still on cruise, the FMS can compute the optimal descent profile for the selected cost index. A representation of this optimal profile can subsequently be down-linked to ATC with use of ADS-C.

DATA SOURCE DESCRIPTION

For research purposes Airservices Australia established a duplicate ATC system to collect data from any FANS-1/A equipped aircraft through ADS-C. ADS-C should not be confused with ADS-Broadcast (ADS-B), as ADS-C is not a general broadcast function but a unique specific data-link contract between aircraft and ATC [Roberts, 2009]. The data collection system is located in Melbourne and carries the SITA address "THAL." Any FANS-1/A equipped aircraft can log on to THAL identically to the way it would log on to any operational system like Oakland Oceanic (KZAK) in the US. Through the agreement with Qantas, all A380 flights arriving to LAX during April, May, and June, 2012 participated in the data collection trial. A temporary pilot instruction was released by Qantas for their crews to log on to THAL manually 2 hours prior to their arrival at LAX. The ADS-C contract rate was set to 2 minutes to allow maximum data collection. En route radar data for the same flights were collected from the US host computer system (HCS). No special treatment from ATC was provided to the participating flights.

To compare TP performances fairly, the study data were limited to flights that performed an uninterrupted descent according to the BUFIE STAR and successfully transmitted ADS-C data. Flights with significant cross-track deviations from the cleared route were disregarded, which provided consistent and known lateral intent to all TPs. Only flights arriving through the BUFIE STAR were selected, as this procedure requires the FMS to plan the descent to a fixed point in space (7,000 ft at Seal Beach [SLI], see Figure 1) essential for optimization.

In total 119 flights participated in the trial, of which 62 arrived through the BUFIE STAR. Of those 62 flights, 25 flights were disregarded because of significant lateral deviations. The resulting data pool therefore contained 37 flights of radar track and clearance data and extracted from the ZLA en route center's HCS in common message set (CMS) format. Data from the operational ATC system, the En Route Automation Modernization (ERAM) system, were unavailable to this study, and, therefore, the research platform Java En Route Development Initiative (JEDI) developed by The MITRE Corporation was utilized. JEDI is often used by the FAA to emulate ERAM, to simulate the US ground automation system including trajectory prediction [Young et al., 2012]. A benefit of using JEDI

is the ability to simulate ERAM in different scenarios without interfering with the operational system. The ZLA-ARTCC adaptation and weather forecast data were collected for the trial period to allow simulation of the US ground automation system. Track positions were derived from radar and available about every 12 seconds.

To compare the performance of different TP systems correctly, common initial conditions for the predictions had to be selected. In this study the initial conditions were taken as the point at which the correct arrival procedure (BUFIE STAR plus 12,000 ft at GOATZ) was loaded into the aircraft's FMS. From this point on the aircraft's intent should remain consistent (stable TOD and descent profile) and, hence, allows for the actual trajectory flown to be compared against the prediction. The point at which the arrival procedure is loaded can easily be obtained by observing the contents of subsequent ADS-C down-links. These initial conditions were anywhere between 150 nmi and 300 nmi from GOATZ, with the majority around 200 nmi.

METRICS

A set of common metrics is defined to evaluate the accuracy of a given TP and allow comparison of different TPs later in this paper. Metrics of interest are the errors in predicting the following: (1) time of arrival at Santa Catalina (SXC), (2) TOD position, and (3) average descent rate over the unconstrained part of the descent.

As a first metric, the estimated time of arrival (ETA) at SXC is compared to the actual time of arrival (ATA) from flight data. These times are indicated in Figure 2 as ETA (for SXC) and ATA (for SXC).

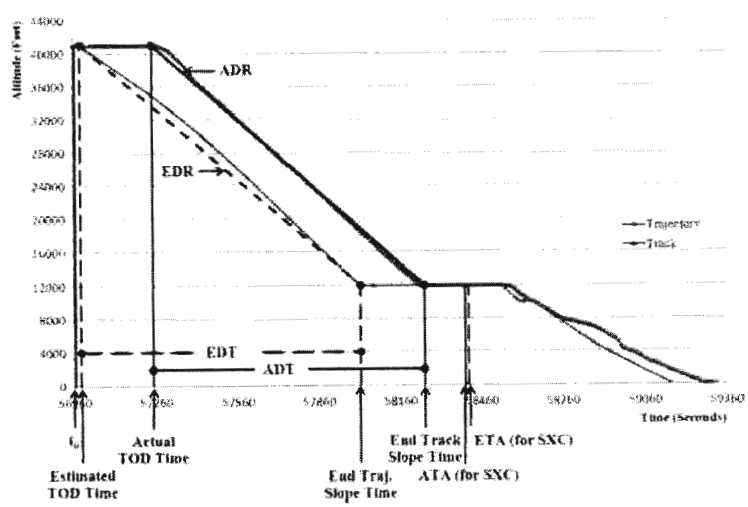

Figure 2. Metric definitions.

The error in the ETA tends to increase as the time from trajectory build (t_0) to metering fix, or the prediction horizon ATA-t_0, increases. This increase poses a problem when comparing the ETA error for different flights as the time to run from the prediction start point to SXC is different for each flight. For example consider a situation in which the ETA error for two flights is 30 seconds; Flight A with 10 minutes to run and flight B with 15 minutes to run. In absolute terms the errors are equal; however, flight B has a longer prediction horizon. The ETA for flight B is, therefore, better in relative terms (30/15 vs. 30/10). To account for different prediction horizons, a relative error metric is used by dividing the absolute ETA error (ETA – ATA) by the prediction horizon (ATA-t_0),

$$\varepsilon_{ETA-MF} = \frac{ETA - ATA}{ATA - t_0} \quad [\%]. \tag{1}$$

The distance between the estimated horizontal position at the TOD, denoted as ETOD, and the actual horizontal position at the TOD, denoted as ATOD, is an important metric for aircraft arrivals as it defines the uncertainty in the start of the descent phase. The position data are provided in stereographic coordinates, and for ease of calculation the Euclidean distance between the points is used,

$$\varepsilon_{TOD} = s * dist(ETOD, ATOD) \quad [\text{NM}]. \tag{2}$$

The sign s is defined such that a negative value indicates the actual descent began *after* the predicted position of descent. Note that flights with significant *cross-track* deviation from the cleared route were removed from the sample, and, hence, the metric solely represents the *along-track* TOD error.

An altitude deviation metric at SXC is not of any use as the BUFIE procedure specifies an AT 12,000 ft constraint at that point. Instead the average descent rate error for the unconstrained descent is included in this paper. The difference between the estimated descent rate (EDR) and the actual descent rate (ADR) forms a good general indication of how well the TP predicts the constant or unconstrained descent phase of flight, as seen in Figure 2. The metric is given by

$$\varepsilon_{DR} = EDR - ADR \quad [\text{fpm}]. \tag{3}$$

In this study all trajectories matched the aircraft in altitude at TOD, and all trajectories matched the aircraft in altitude at the bottom of the constant descent phase of flight due to the altitude constraint at GOATZ. Therefore the numerators of the descent rates (altitude descended) will be the same on a per flight basis, while the denominators (time during descent) may vary.

The errors in TOD position and average descent rate are presented as absolute metrics because they are not as dependent on prediction horizon as the ETA error. While an aircraft is cruising, the drift in ETA for SXC is mainly caused by errors in the predicted groundspeed resulting from differences between actual and forecast winds (and temperature). Provided the aircraft is still cruising and a TP does not make any aircraft intent changes, e.g. speed schedule, and does not update its meteorological model, the descent trajectory should not change except for a constant shift in ETAs along that descent trajectory.

BASELINE TP PERFORMANCE AND OPERATIONS

This section examines the accuracy of the US ground automation system as represented by JEDI for the selected pool of flights based on the metrics introduced above.

JEDI was configured to perform trajectory predictions for the trial pool of 37 flights. JEDI requires a radar position update to provide the initial conditions for the prediction. Therefore, the first radar position update was selected after the aircraft transmitted the ADS-C position report that was defined as the common initial condition in the section on Data Source Description. The resulting difference is small and in theory limited to the radar update period of 12 seconds; this difference is accounted for by using relative metrics for the affected performance indicators (ETA at metering fix).

The predicted trajectories were compared to the actual track data and error statistics were determined for given set of metrics. The summary statistics for the US ground system are given in TABLE I. The bracketed values show the 95% confidence interval of the mean and standard deviation. These results are elaborated upon in the remainder of this section.

JEDI employs a kinematic trajectory predictor. For each aircraft type, airspeed and descent rate are provided in a static table against

Table 1. Summary Statistics For US Ground System

		Metric Distribution Characteristics			
Metric	TP	Mean	Standard Deviation	50% range	95% range
$\varepsilon_{ETA\text{-}MF}$ [%]	US System	0.9 [−0.2, 2.0]	3.4 [2.8, 4.5]	3.3	14.5
ε_{TOD} [nmi]	US System	−43.0 [−51.1, −34.9]	25.2 [20.5, 32.7]	21.2	97.4
ε_{DR} [ft/min]	US System	28 [−8, 63]	110 [90, 143]	147	388

altitude (performance tables) tuned to current operations of that aircraft type (not necessarily comprising only uninterrupted flights) [Vivona et al., 2011]. When modelling the trajectory, JEDI first calculates the descent phase of the flight and ensures that all altitude constraints of the BUFIE STAR and the 12,000 ft at GOATZ are met when placing the TOD position. Even though the altitude restriction is modelled correctly, the average error in TOD position is 43 nmi before the true TOD position with a standard deviation of 25 nmi. The average error in SXC crossing time is 16 seconds late, with a standard deviation of 51 seconds. This crossing time error is also expressed as a percent error in look-ahead time when crossing the fix, producing 0.9% average late with a standard deviation of 3.4%. The descent rate resulted in an average error being 28 feet per minute (fpm), about 1.4 % of a standard average descent rate of 2000 fpm, with a standard deviation of 110 fpm.

The results shown in Table 1 indicate a larger error in TOD, yet the descent rate error and ETA error are relatively low. As the descent rate is fairly accurate, the generic descent rate in the performance tables used by the US system represents the general Qantas A380 operation well in this parameter. Note, however, that as JEDI assumes no physical link between descent rate and descent speed, this effectively implies that the true physics impacting the descent rate, e.g. speed and mass, were fairly consistent throughout the actual operations and little variance in this parameter. If, however, an aircraft flew a different speed on descent, the descent rate assumed by JEDI would no longer be representative of the operation and the variance (and bias) in the descent rate error will grow, i.e. the performed tuning of the performance tables is operation specific and does not allow for dynamic changes.

The large negative bias in TOD, meaning that the aircraft descended before the predicted point, indicates that the assumed speed in the performance tables (~300KIAS) is possibly too high for the Qantas A380 operations. Note that in this kinematic TP, altitude and distance covered are effectively integrated independently; speed determines the distance covered over the descent, and descent rate determines the time. Thus, the higher the speed, the longer the distance travelled and, hence, the negative bias in TOD. A high speed would intuitively lead to a negative bias in the ETA which is not the case. Because of the independence of descent rate and speed, however, the physics of the system is disturbed, and it is no longer trivial to comprehend what constitutes the ETA error.

The above results give insight into the typical difficulty of predicting trajectories accurately by the ground automation even when these trajectories are specifically chosen for consistent intent information, i.e. no intervention from ATC or crew. Previous research by these authors and many others identified the lack of accurate

knowledge on speed intent and aircraft mass, and TP operating logic to be main contributors to the poor performance of current ground-based prediction systems [Bronsvoort et al., 2011; Lopez Leones et al., 2013; Mondoloni, 2006]. The subsequent sections of this paper will demonstrate that the trajectory information down-linked via FANS (ADS-C) available in aircraft today can assist and provide significant benefit to current and future operations.

FANS INTERMEDIATE PROJECTED INTENT

In addition to the surveillance and communications for non-radar airspace, FANS data-link provides a way for the ground to access airborne trajectory data through ADS-C. These trajectory data are termed intermediate projected intent (IPI) and consists of a sequence of up to ten trajectory change points. A trajectory change point can be a profile change (e.g. top of climb [TOC] and top of descent [TOD]), a bearing change, and/or a speed change. Note that an air traffic system (ATS) waypoint will appear in the IPI only if a trajectory change occurs at that point. IPI is limited to ten TCPs within a maximum look-ahead time of 4 hours. Therefore, the entire trajectory might not be visible to ATC with each report. Laterally, trajectory change points are given as a sequence of bearing and distance from the position at which the FMS generated the ADS-C report. Each trajectory change point also holds an estimate for the crossing altitude and time.

As described before, for each of the trial flights the first ADS-C report was taken after the arrival procedure was loaded into the FMS. At that time the destination was well within the look-ahead time, and the limit of ten TCPs was always sufficient to have a representation of the FMS trajectory to SXC and most often all the way to the runway threshold. The trajectory constituted by the IPI was subsequently compared against the actual track data, and statistics were calculated for the same set of metrics as used for the US ground system and summarised in Table 2.

The information provided in the IPI from the A380 FMS is clearly more accurate than the predictions from the US ground system for this aircraft type. The TP in the Honeywell FMS models the appropriate relations between related variables as descent speed, mass, and descent rate rather than the use of a static performance table as used by JEDI. The most significant improvement from the down-linked data are in TOD prediction. This should come as no surprise as the trajectory computed by the FMS is used as reference for the guidance system. With the automation in control and the appropriate settings, the guidance function will command the descent at the FMS computed descent point resulting in very little variation. Some of the variation observed could also be due to the logic assumed as to identify the

Table 2. Summary Statistics For A388 FANS IPI

		Metric Distribution Characteristics			
Metric	TP	Mean	Standard Deviation	50% range	95% range
$\varepsilon_{ETA\text{-}MF}$	US System	0.9 [−0.2, 2.0]	3.4 [2.8, 4.5]	3.3	14.5
[%]	A388 IPI	0.9 [0.4, 1.3]	1.4 [1.1, 1.8]	1.6	4.9
ε_{TOD}	US System	−43.0 [−51.1, −34.9]	25.2 [20.5, 32.7]	21.2	97.4
[nmi]	A388 IPI	4.1 [2.8, 5.5]	4.1 [3.3, 5.3]	3.5	13.8
ε_{DR}	US System	28 [−8, 63]	110 −[90, 143]	147	388
[ft/min]	A388 IPI	−13 [−37, 11]	74 [61, 97]	48	286

true TOD in the radar track data. As mentioned previously, radar updates are available every 12 seconds on average, at an average groundspeed of 8 nmi per minute; these 12 seconds contribute to about 1.5 nmi of noise. Interesting to note as well is that the bias in the ETA metric is about identical between JEDI and the IPI data (though different confidence levels). No plausible explanation can be given at this stage, and therefore, the similarity is attributed to coincidence considering the relatively small sample.

The results demonstrate that the information in the FANS datalink has great potential, as was also concluded in previous work [Bronsvoort, et al., 2011]. Taking it a step further, this information can be applied to enhance the ground-based automation system.

A GROUND PREDICTOR WITH DOWNLINKED INTENT

The first part of this section will explain how the down-linked trajectory information can be used by ground-based TPs. Subsequently different TPs making use of this information will be discussed and finally the results will be presented.

Parameters Inferred from Down-Link Trajectory

The previous sections and referenced literature have demonstrated that significant improvements can be obtained when using the FANS IPI information in ground-based trajectory prediction. One method is to make direct use of the information and "overwrite" the trajectory held by the ground system with the airborne one. While this will

synchronize the trajectories between air and ground, it would not support the ground in cases it would like to perform "what-if" scenarios [Bronsvoort, 2011; Vivona et al., 2011]. Klooster et al. provide more arguments against direct use of airborne trajectory information [Klooster et al., 2010].

If instead, an approach is chosen where the down-linked data are used as input to the trajectory prediction process, different problems arise. As mentioned FANS IPI consists of a series of four dimensional TCPs, and is an output to the trajectory prediction process rather than an input. For example, the trajectory data might indicate where the aircraft has planned its TOD, but this information can in general not be accepted by conventional trajectory predictors as an input. Instead, the approach chosen in this research is to infer trajectory prediction input variables from the FANS IPI data. While many variables can be chosen, only a limited number can be successfully inferred from the limited information provided in the IPI. A logical choice is to infer the target speed schedule on descent and the mass of the aircraft at TOD. As identified before the target speed schedule on descent is considered a critical piece of missing aircraft intent. The mass of the aircraft is in general also unknown to ATC and knowledge of this variable would provide synchronisation to the initial conditions of the trajectory prediction process. Especially for climb (and also descent) operations, the mass of the aircraft can have a significant impact on the accuracy of the predicted trajectory.

Therefore, instead of direct application of the FANS IPI, this information was used to infer the target speed schedule and mass of the aircraft with use of experimental tools developed by Airservices Australia [Bronsvoort, 2011]. This inferred speed schedule and/or aircraft mass can subsequently be used to replace the default or nominal information present in ground-based automation systems.

Several previous attempts have been made to infer parameters relevant to the trajectory prediction process from operational data. Thippavong et al. followed a different approach and used preceding radar track data to estimate the aircraft mass from the observed energy rate [Thipphavong et al., 2013]. This estimated mass was subsequently used in a kinetic three-degree-of-freedom model to predict the remainder of the climb trajectory. A similar study was performed by Alligier et al. [Alligier et al., 2013]. The approach of Thippavong et al. and Alligier et al. are both related to real-time adaptive trajectory prediction and can be applied only if the aircraft is performing an unimpeded steady climb as sufficient preceding track data must be available. The method could be adapted for descent operations, but will provide a benefit only as the aircraft has commenced descent. Seen FANS IPI data provides information on the aircraft's future trajectory rather than solely state

information, an attempt can be made to infer the mass from this trajectory information ahead of commencing descent.

The algorithm developed by Airservices Australia is based on an optimization scheme that uses a TP to find a target descent speed schedule and mass that result in a computed trajectory with minimum deviation from the IPI in a least squares sense. In essence the algorithm uses the longitudinal equations of motion to match the vertical profile of trial-trajectory (trajectory for a certain descent CAS and mass) with the IPI. Because of differences between any of the terms in the longitudinal equations of motion between the FMS and the inferring algorithm, among others thrust and drag, the inferred mass acts as a pseudo-mass. This pseudo-mass is a combination of the mass assumed by the FMS and several terms that correct for differences between the two predictors. If, subsequently, the same predictor is used to compute the trajectory with the inferred pseudo mass, the pseudo mass theoretically acts as a calibrator.

JEDI/ERAM

As explained previously the TP in JEDI (and ERAM) uses static performance tables to model aircraft behavior. The inferred information could be used to update the performance tables to better reflect the operation of the aircraft, similar as to what was done in the ADAPT studies [Courdacher and Mouillet, 2008]. As the performance tables are static, they must be updated off-line to better model the average aircraft behaviour. This approach is successful only if all operations of the aircraft type modelled by that table are consistent. For this study only data from Qantas A380 operations were available; very likely, another airline operates the same aircraft differently.

As will be discussed in the upcoming section on NextGen Applicability, the FAA has a program underway to explore major enhancements for a future release of ERAM's TP. To support this initiative, the EUROCONTROL R&D TP CINTIA and experimental Airservices Trajectory Predictor (ATP) were configured for the LAX scenario to demonstrate how FANS technology can assist in improving the performance of ground-based TPs.

EUROCONTROL CINTIA TP

The EUROCONTROL CINTIA TP has been developed to predict time constrained trajectories supporting the generation of speed and descent advisories for a close-loop advanced arrival manager. The definition of the trajectory to be computed is based on three threads of aircraft intent: lateral for maneuvers, vertical for altitude

changes, and speed. Any aircraft intent target in the vertical and speed threads can be linked to a target in the other threads.

CINTIA uses the EUROCONTROL Base of Aircraft Data version 4 (BADA4) (EUROCONTROL Experimental Centre, 2012) as aircraft performance model. BADA4 is an extension of BADA3 for better accuracy across the flight envelope and an extension to cover the non-clean configuration phases. The aircraft operating procedures are a combination of the default airline procedure part of BADA4 and speed and altitude constraints resulting from the airspace.

While CINTIA is a highly adaptable TP, modelling the 12,000 ft altitude constraint at GOATZ and subsequent level segment to SXC proved to be very difficult without performing potentially significant and time-expensive changes to the code. The descent segment from cruise level to 12,000 ft was simulated by introducing a level deceleration at 12,000 ft from the en route descent speed to the intermediate descent speed (250 KIAS) but affected at SXC instead of FITOW (Figure 1). This modification allowed the performance of the CINTIA TP during the descent segment to be assessed, but it could not constrain the position at which 12,000 ft was reached (somewhere between GOATZ and SXC).

Airservices Trajectory Predictor

Airservices Australia has developed an experimental trajectory predictor simply referred to as ATP. The speed and mass information inferred from the IPI and fed to CINTIA are intermediate products of ATP (Figure 3). ATP currently uses BADA3 for aircraft performance.

As shown in Figure 3, ATP can be run in two modes, traditional, referred to as ATP-trad, and path, referred to as ATP-path. In traditional mode ATP is very similar to CINTIA and uses the provided inferred speed intent to construct a descent trajectory assuming the speed will be held at idle thrust. During this process, speed and altitude constraints specified in the arrival procedure are respected. For example in case of the BUFIE STAR such constraints are the 12,000ft and 280KIAS at GOATZ.

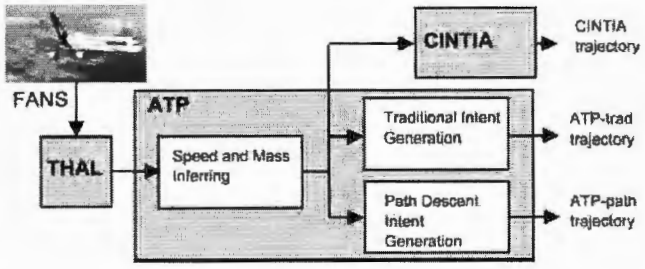

Figure 3. Trajectory Predictors overview and information flow.

In path mode ATP goes a step farther and simulates the path managed descent (path-on-elevator) at idle thrust, where the FMS reference path is built from geometric segments provided by the FANS IPI. In essence, the methodology uses those dimensions of the down-linked FMS computed trajectory that are controlled in closed-loop by the aircraft. The remaining open dimensions are predicted by ATP. In case of the path-managed descent (preferred by Qantas), the lateral and vertical path are controlled in closed-loop, leaving speed free within set limits, and, thus, time is open. Effectively, the methodology takes the FMS computed trajectory, strips off the times to reduce the trajectory to a 3D path, and subsequently re-computes the times along that path. In this process the methodology makes use of the inferred mass and an extensive environmental model. The inferred target speed is used to set limits to the speed that is allowed to vary in the prediction as result of holding the FMS path at idle thrust. By integrating this variable speed, new times along the trajectory are predicted [Bronsvoort, 2011]. The ATP-path has been designed specifically to make optimal use of FANS IPI and can work only if IPI information is available, while default information can be fed to ATP-trad.

Results

The CINTIA TP and ATP-trad were run twice for the set of 37 sample flights. For the first run the BADA default information (DEF) was used, i.e., M0.85/300 KIAS speed schedule and 350,000 kg mass. This situation represents how legacy TPs would operate today by assuming nominal conditions for unknown aircraft intent and initial conditions.

For the second run the FANS-inferred speed schedule and mass were used (INF). ATP-trad does not use the default Mach number of 0.85, but uses the last cruise Mach number in the flight plan and assumes this Mach number to be propagated into the constant Mach part of the descent. ATP-path was run only with the provided FANS IPI; without IPI this method defaults to ATP-trad. The results in terms of the selected metrics are provided in Table 3.

To assess the improvement achieved when using the FANS inferred information, Figure 4 illustrates the results graphically. The three graphs represent the relative ETA error, TOD position error, and average descent rate error, respectively. The performance of a TP in terms of a metric is plotted as a scatter of the respective mean and standard deviation. Thus, the better the performance, the closer the TP is to the origin of the graph, meaning zero bias and zero variance. The results for CINTIA and ATP-trad in "default" mode are connected to their respective results in "inferred" mode showing an arrow with the direction of the change to indicate the improvement when using FANS inferred information. For both CINTIA and ATP-trad the standard deviation is slightly improved (not statistically significant for the sample size), but the biggest improvement is in the mean.

Table 3. Summary Statistics For All TPs

		Metric Distribution Characteristics			
Metric	TP	Mean	Standard Deviation	50% range	95% range
$\varepsilon_{ETA\text{-}MF}$	US System	0.9	3.4	3.3	14.5
		[−0.2, 2.0]	[2.8, 4.5]		
[%]	A388 IPI	0.9	1.4	1.6	4.9
		[0.4, 1.3]	[1.1, 1.8]		
	CINTIA (DEF)	−5.9	5.5	8.8	18.4
		[−7.6, −4.1]	[4.4, 7.1]		
	CINTIA (INF)	−3.4	5.3	7.7	18.4
		[−5.1, −1.6]	[4.3, 6.9]		
	ATP-trad (DEF)	−3.1	0.9	1.3	4.0
		[−3.4, −2.8]	[0.8, 1.2]		
	ATP-trad (INF)	0.1	0.9	1.2	3.3
		[−0.2, 0.4]	[0.7, 1.2]		
	ATP-path	−0.1	0.8	1.0	3.1
		[−0.4, 0.2]	[0.7, 1.1]		
ε_{TOD}	US System	−43.0	25.2	21.2	97.4
		[−51.1, −34.9]	[20.5, 32.7]		
[nmi]	A388 IPI	4.1	4.1	3.5	13.8
		[2.8, 5.5]	[3.3, 5.3]		
	CINTIA (DEF)	48.9	8.2	9.3	30.8
		[46.2, 51.5]	[6.7, 10.7]		
	CINTIA (INF)	41.3	8.8	9.9	32.1
		[38.5, 44.1]	[7.2, 11.4]		
	ATP-trad (DEF)	11.3	4.9	4.3	17.2
		[9.8, 12.9]	[4.0, 6.3]		
	ATP-trad (INF)	2.4	5.0	4.7	16.6
		[0.8, 4.1]	[4.1, 6.5]		
	ATP-path	4.2	4.0	3.5	13.8
		[2.9, 5.5]	[3.2, 5.2]		
ε_{DR}	US System	28	110	147	388
		[−8, 63]	[90, 143]		
[ft/min]	A388 IPI	−13	74	48	286
		[−37, 11]	[61, 97]		
	CINTIA (DEF)	495	106	98	431
		[460, 529]	[86, 138]		
	CINTIA (INF)	190	101	107	372
		[157, 222]	[82, 131]		
	ATP-trad (DEF)	294	93	104	285
		[264, 324]	[75, 121]		
	ATP-trad (INF)	−25	75	92	291
		[−49, 0]	[61, 98]		
	ATP-path	2	63	44	255
		[−19, 22]	[51, 81]		

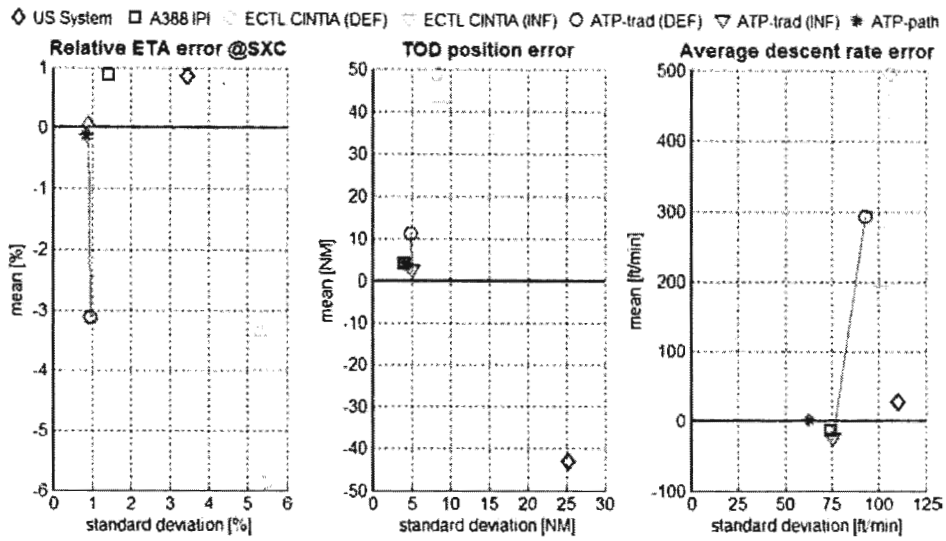

Figure 4. Trajectory predictors performance overview.

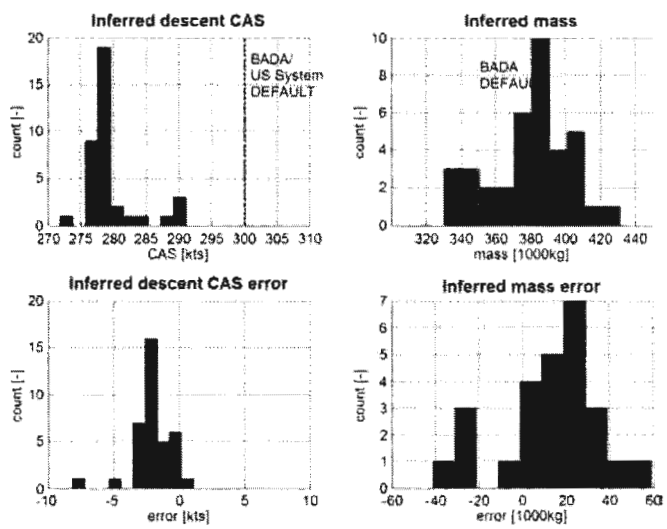

Figure 5. Inferred descent CAS and mass.

Figure 5 provides an overview of the inferred descent CAS and mass against the BADA and US system default values. BADA default values were used by both CINTIA and ATP-trad. Note that no default mass is provided for the US system as predictions performed by its kinematic trajectory engine do not depend on mass. The large difference between the default speed (300 KIAS) and the average inferred speed (280 KIAS) explains the shift in the mean TP performance. In terms of mass, the default value (350,000 kg) falls within the variance of the inferred mass (mean 380,000 kg, standard deviation 24,000 kg).

The variance in the inferred mass is quite large, and some values are likely to be unrealistic. For some of the 37 flights, Qantas provided aircraft recorded Quick Access Recorder (QAR) data that validated the inferred parameters. In terms of the inferred descent CAS the mean error is 2 kt too slow with a standard deviation of 2 kt. In terms of inferred mass however, the mean error is 11,300 kg too heavy with a standard deviation of 24,000 kg. The benefit of the inferred information is therefore most likely contributed to the inferred descent speed. Figure 5 shows the operations were quite consistent in terms of descent speed, an observation that was suggested in earlier sections of this paper, but now supported with the inferred descent speed information and verified by true operational data provided by Qantas QAR. Note that ATP does not infer descent speed and mass independently, but as a combined set of unknowns. In addition the accuracy of the inferred information depends on the difference between the support models used by the FMS and the inferring algorithm as illustrated earlier. As the inferred descent speed is quite accurate, this could indicate that in this scenario the predictions are more sensitive to descent speed than mass, and as such, the larger error in the mass is irrelevant. Further research into this observation will be conducted.

After application of the inferred information the remaining bias in ATP-trad is statistically insignificant, but a statistically significant bias remains present for CINTIA in all metrics, though significantly smaller than without the inferred information. These biases for CINTIA are most likely the result of the difficulty in modelling the level segment from GOATZ to SXC on the BUFIE procedure, as is mainly reflected in the ε_{TOD} metric bias shown by the trajectories it computes. Further experiments in which the vertical and horizontal profiles computed by CINTIA were shifted relative to one another to match the 12,000 ft constraint at GOATZ indicated that the TP adapted to handle the level segment would have produced ε_{TOD} results similar to ATP-trad. This "correction" could not be extended to the $\varepsilon_{ETA\text{-}MF}$ metric: as soon as the aircraft reaches 12,000 ft, CINTIA starts to decelerate the aircraft to intermediate descent speed (250 KIAS) and then continue the descent. The high variance for the $\varepsilon_{ETA\text{-}MF}$ metric can be explained by the strong correlation between the results and the wind errors due to the way CINTIA handles weather data: it accepts a single dataset composed of vertical bands between which weather conditions are interpolated and, for this research, the data used were taken close to the TOD. Note that some difference could also result because ATP infers information using BADA3 and CINTIA uses BADA4 and, therefore, there is limited (if any) calibration effect of the pseudo-mass as discussed previously.

Another interesting observation is that ATP-trad in inferred mode shows no significant bias in ETA error while the original IPI information did. This finding would indicate that the bias in the IPI is not the

result of any intent error (assuming that the FMS is fully aware of its intent), but maybe the result of a bias in the forecast assumed by the FMS (note that all flights came from a similar direction with similar prevailing wind conditions). Also, ATP-trad has a smaller standard deviation in ETA error than the original IPI data. For the current sample size this improvement over the FMS is just significant at a 95% confidence level. The improvement is likely the result of better knowledge of speed intent and initial conditions combined with a more accurate, detailed forecast weather model available to ATP. Interesting to note is the small error in TOD position after applying the inferred information. The bias appears even smaller than for the FMS derived TOD. The noise related to determining the "actual" TOD position as explained previously makes judgment of these small figures difficult. In any case the improvement is substantial.

ATP-path is clearly the best performer of the different TPs. This TP was used in the study published in [Bronsvoort et al., 2012] where the theory was first applied to a sample of more than 400 FANS-equipped Boeing 737-800 flights and where the improvement over the original FMS IPI data was proven statistically significant. The identical performance of ATP-path and the FMS in terms of TOD position is not a surprise, as ATP-path uses the geometric path established from the IPI. The improvement of ATP-path over the FMS in terms of the other two metrics is related to the use of the inferred mass and predicting ahead what the speed variations of the aircraft will be as result of holding the path at idle thrust (path-on-elevator) when using a more accurate and detailed forecast than available to the FMS. For the investigated sample an average speed deviation of 4 kt too slow with a standard deviation 1.5 kt was observed. The reduction in ETA error between ATP-path and ATP-trad is not that large when compared against the performances of the other TPs. A larger sample would be required as to claim the improvement as statistically significant.

Thus, the benefit of the inferred information is mostly a shift in the mean due to the consistent Qantas operations. If other airlines with different operating procedures (even for the same aircraft) were to be added, the inferred operation will likely not only result in a significant reduction in bias, but also a significant reduction in variance.

APPLICATION

The previous section showed the significant improvements to ground-based trajectory prediction when enhanced with aircraft derived information from FANS. Once again, it needs to be emphasized that FANS is standard equipment on any wide-body aircraft being made today. The two work horses of short- to medium-range fleets, the Boeing 737NG and Airbus A318-A321, are easily capable of being

fitted with FANS. In case of the B737NG airlines must only purchase the FANS-1 Service Bulletin (SB). The SB will include activation of the FANS applications already in the FMS and will also identify other equipment changes needed for the aircraft, if any (depending on airline standard equipment). Qantas and former Continental Airlines (now United Airlines), have activated FANS on their Boeing 737-800 fleet. The process for A318-A321 is slightly different as on top of the FANS A+ SB some additional equipment is required. A few airlines like Silk Air, Gulf Air, and China Eastern have equipped their A320 fleet with FANS. Currently, about 20% of arrivals into LAX specify in their flight plan being data-link (FANS) equipped. In Australia there is a similar percentage, but this grows significantly when one considers the FANS capable Boeing 737-800 fleets of Qantas, United, and others, as the equipment is not yet used by ATC.

With a growing number of aircraft capable of down-linking trajectory information, this section continues to discuss some possible applications within the domains of NextGen, SESAR, and the Australian ATM Strategic Plan (AATMSP).

NextGen Applicability

While the operational TP in ERAM cannot make direct use of inferred intent from ADS-C today, on-going work in support of the FAA's NextGen Program is exploring major enhancements for a future release of ERAM's TP. The project has already developed a kinetic-based TP model in the laboratory and was scheduled for comprehensive evaluations in late 2013 supported by the data from this study. This paper's demonstration in utilizing airborne intent in a ground-based TP is one of several motivations for developing such an upgrade for ERAM and offers decision makers further reason for making the investment [Torres et al., 2012].

In addition, the FAA is investigating enhancements to improve the operational system's trajectory predictions and in turn provide ATC better strategic aircraft-to-aircraft conflict predictions. As documented in a recent study [Crowell et al., 2011], the FAA and industry researchers developed and tested a prototype algorithm that detects in-trail overtaking conflict predictions. The prototype makes better use of radar surveillance speed estimates to reduce errors under this common operational situation. However, the resulting benefits are constrained due to the limitations of existing aircraft intent. The authors believe that the aircraft speed profile that can be inferred through FANS ADS-C would significantly enhance this algorithm and reduce a long-standing source of error in the operational system. Applying inferred intent to improve the core trajectory prediction in the US ground automation will impact many functions in operation today like conflict prediction, as illustrated here, and future capabilities such as conflict resolution,

automated coordination, and arrival sequencing tools like path arrival management (3D-PAM).

SESAR Applicability

SESAR Step 1, time-based operations, relies on the capability of the ATM system to build a reference business trajectory at a level of time accuracy such that it can be flown in most cases. Introducing time constraints into present ATC operations aims at getting the traffic better organized, especially when converging to extended terminal areas.

As concluded in previous work by these authors, however, the time accuracy of present ground-based TPs does not allow the immediate introduction of time-based operations [Bronsvoort et al., 2011]. Airborne enhancements are foreseen as being essential to a successful implementation of Step 1 in two ways:

- The use of the airborne controlled/required time of Arrival (CTA/RTA) capability to guarantee that an aircraft meets a given time constraint over a point
- The use of airborne-derived data to improve the accuracy of the ground TP

Concerning the second item, an enhancement to ADS-C, Extended Predicted Profile (EPP), is being developed and includes climb/cruise/descent speed schedules, take-off and top of descent weights and a list of a maximum of 128 4D points from present position to destination.

The temporal accuracy of the data-link enhanced ATP-trad and ATP-path for SXC is close to what was achieved during the 2010-2011 Boeing 737 RTA trials into Seattle for a comparable fix on the arrival procedure (9.4 seconds standard deviation for the RTA trials versus 14.8 seconds (0.8%) for ATP-path) [Bell, 2012]. Most wide-body aircraft are yet unable to control to an RTA for a point on descent, but are equipped with FANS. This technique might therefore assist to handle initial mixed equipage scenarios.

As FANS was first introduced in the early 1990s, it has taken more than 20 years to reach the equipment levels earlier quoted in this section. Without an ADS-C EPP mandate, fitting this equipment could be similarly slow. This problem is compounded by little knowledge of what equipment levels are required to provide a benefit to operations. The i4D+CTA Step A Validation studies showed that even with 40% of aircraft equipped, controller workload remains negatively affected [SESAR JU, 2012]. Therefore, the work presented in this paper is of critical interest to SESAR Step 1, as it shows what improvements can be achieved on ground TP accuracy, both longitudinally and vertically during the descent, using a source of airborne data, FANS 1/A, already available today. The authors believe that the

work presented in this papers can assist in providing a transition concept towards more advanced technologies and a potential method to handle mixed equipage.

Australian Applicability

Both SESAR and NextGen propose that aircraft will be assigned times at waypoints that they must achieve within set limits (RTA functionality). Any speed change by an aircraft in attempt to meet the assigned time will cause increased workload to ATC, as the impact of such a change is assessed. A concept relying on airborne equipment to meet time constraints therefore still requires continuous monitoring by ATC. In addition, problems will result from slow equipment fitting as mixed equipage will need to be handled for many years.

Therefore, in Australia a concept is researched in which aircraft are permitted and expected to operate consistently without unexpected changes to their operation. The concept envisions aircraft to conduct a continuous descent in the airline-preferred path managed mode. In path managed mode the aircraft can conduct a continuous descent along a consistent descent profile with the uncertainty contained in the temporal dimension of the trajectory. ATC is subsequently supported by accurate ground-based trajectory prediction to manage this temporal uncertainty through metering at strategically chosen points along the aircraft's trajectory [McDonald and Bronsvoort, 2012]. The ATP-path system is specifically designed to support this concept, and its capability was demonstrated in this paper.

CONCLUSION

This paper demonstrated that significant improvement in ground-based trajectory prediction can be achieved with use of FANS trajectory information. Results demonstrated how critical elements of trajectory information useful to ATC such as descent speed schedule and aircraft mass can be inferred using FANS and applied in a format accepted by different ground-based TPs.

The method was applied to Qantas Airbus A380 operations in Los Angeles conducting optimised profile descents. Results from the data-link enhanced TPs were compared against baseline predictions provided by current operational systems and TPs without the use of data-link. Because of the consistency of the Qantas A380 operations, improvements mainly emerged in reduction, or even elimination, of the bias in the baseline predictions, as the inferred speed schedule replaced the default values used by these systems. Even though most of the aircraft in the sample conducted a descent according to a similar descent speed schedule, the inferring algorithm was able to detect the cases where a faster or slower descent was anticipated.

This finding suggests that even when the operations are inconsistent, the method might further improve on the variance in the trajectory prediction error. The ability of the inferring algorithm to estimate the aircraft mass was found to be less accurate, but the predictions appeared not as sensitive to this.

Some of the investigated data-link enhanced TPs proved to be more accurate than the original downlink predictions on which the inferred information was based. This finding is partly due to the ground-based TP combining the down-linked trajectory data in an effective way with an extensive weather forecast. Results of this paper, therefore, provide arguments for a combined air-ground solution to trajectory prediction rather than sole reliance on airborne trajectory data.

FANS is standard equipment on most wide-body aircraft and fitting options exist on the major single-aisle aircraft fleet. Therefore, as the infrastructure to obtain the required data are already in place, both in the air as on the ground, the approach proposed in this paper is immediately feasible with minimum investment and systems changes. Use of FANS intent capability provides an interim solution to improve operations today until the data-link standards proposed under SESAR and NextGen are deployed and reach sufficient equipage levels.

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ACRONYMS

AATMSP	Australian ATM Strategic Plan
ADAPT	Aircraft Data Aiming at Predicting the Trajectory
ADR	actual descent rate
ADS-B	Automatic Dependent Surveillance Broadcast
ADS-C	Automatic Dependent Surveillance Contract
ATA	actual time of arrival
ATC	air traffic control
ATM	air traffic management
ATP	Airservices Trajectory Predictor
ATS	air traffic system
BADA	Base of Aircraft Data
CMS	common message set
CNS	Communication Navigation and Surveillance
CPDLC	Controller Pilot Data Link Communication
CTA/RTA	controlled/required time of arrival
DEF	default information
EDR	estimated descent rate
EPP	extended predicted profile
ERAM	En Route Automation Modernization
ETA	estimated time of arrival

FANS	Future Air Navigation Systems
FMS	flight management system
Fpm	feet per minute
HCS	host computer system
INF	inferred information
IPI	intermediate projected intent
JEDI	Java En Route Development Initiative
KIAS	knots indicated air speed
KZAK	Oakland Oceanic Airport
LAX	Los Angeles International Airport
QAR	Quick Access Recorder
SB	service bulletin
STAR	Standard Terminal Arrival Route
SXC	Santa Catalina
TBO	trajectory based operations
TOC	top of climb
TOD	top of descent
TP	trajectory predictors
TRACON	terminal radar approach control
ZLA-ARTCC	Los Angeles air route traffic control center

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BIOGRAPHIES

Jesper Bronsvoort is an Aerospace Engineer at Airservices Australia, Melbourne. He works on several initiatives involved in the transition to Trajectory Based Operations in Australia. He holds a BSc degree (2006) and an MSc degree (2011) in aerospace engineering, both from Delft University of Technology, The Netherlands. Currently he is a PhD candidate at Universidad Politechnica de Madrid, supported by Airservices.

Greg McDonald is an Air Traffic Controller with in excess of 30 years experience in all facets of the craft. Since 1998 has been involved in the Australian ATM Strategic Plan and implementing efficiencies for airlines including AUSOTS flex tracks. His work managing the Tailored Arrivals program for Australia has lead to his interest in improving ground based trajectory prediction to efficiently manage the increasing air traffic.

Mike Paglione is the Branch Manager of the FAA's Concept Analysis Branch at the FAA W. J. Hughes Technical Center, Atlantic City, NJ. Before taking the current

management position in 2012, he had served as a FAA engineer and project lead for 13 years. He has extensive experience in air traffic control automation algorithms, simulation problems, analysis of decision support software, applied statistics, and general systems engineering. The Concept Analysis Branch (ANG-C41) conducts research to validate new aviation concepts' technologies, investigate system capacity issues, and evaluate the performance of both emerging and existing systems within the National Aviation System (NAS). Mr. Paglione has supported the development, testing, and evaluation of FAA air traffic management software and also served as a NextGen program manager. He was FAA's Rutgers University Fellow from 1994-1996, Accuracy Test Lead for the FAA's User Request Evaluation Tool, Program Manager for the Joint University Program from 1999 to 2004, Lead for the Automation Metrics Test Working Group (a cross organizational team developing and implementing metrics for the En Route Automation Modernization Program, ERAM), and a program manager supporting a NextGen project investigating improvement to the separation management functions in the en route automation. He holds B.S. and M.S. degrees in Industrial and Systems Engineering from Rutgers University.

Christina M. Young received the B.S. degree in Industrial Engineering from Rutgers, The State University of New Jersey. She worked on FAA research projects under a fellowship grant while earning graduate degrees: M.S. in Statistics and Ph.D. in Industrial and Systems Engineering. Since completing her doctorate in 2010, she has worked on NextGen projects at the FAA William J. Hughes Technical Center at the Atlantic City Airport in NJ. Dr. Young is part of the Concept Analysis Branch (ANG-C41), which conducts research to validate new aviation concepts technologies and evaluate the performance of both emerging and existing systems within the NAS.

Andrew J. Fabian has been working since 2008 on NextGen projects at the FAA William J. Hughes Technical Center at the Atlantic City Airport in NJ. He started as a student intern while in pursuit of the B.S. degree in Mathematics and the B.S. degree in Computer Science from Rowan University, both of which he received in 2009. He continued as an intern and earned the M.S. in Computer Science from Rowan University in 2011. Mr. Fabian is now part of the Concept Analysis Branch (ANG-C41), which conducts validation studies of new aviation technologies and analyzes performance of both emerging and existing systems within the NAS.

Jean Boucquey graduated from Université Libre de Bruxelles in Belgium with a B.S. degree in Computer Science in 1984. He obtained a M.S. degree in Computer Science from the same university in 1986 and a special M.S. degree in Business Administration from Solvay Business School, in Brussels, Belgium in 1988. From 1992 on, working for EUROCONTROL, he has been active in ATM system prototyping and simulation with a constant focus on improving and adapting trajectory prediction. Currently working in EUROCONTROL's Directorate SESAR and Research, he supports and provides expertise to several SESAR operational, system and long term research projects in the fields of Trajectory Management, Trajectory Prediction and Complexity Assessment and Resolution. He is, amongst others, member of the ACM (Association for Computing Machinery), AMS (American Mathematical Society) and the AAAI (Association for the Advancement of Artificial Intelligence)

Carlos Garcia Avello, Mechanical engineer from Université Catholique de Louvain, Belgium, has been working on R&D activities in the fields of aircraft performances modeling, trajectory prediction, ATC simulation and the development of ATM advanced automation (complexity management, arrivals/departures management). He retired from EUROCONTOL Agency, Brussels.