AN ANALYSIS ENVIRONMENT FOR IMPROVED FLIGHT TRAJECTORY PREDICTION AND CONFLICT DETECTION INTEGRATION

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ABSTRACT

Flight trajectory prediction and conflict detection are two essential Air Traffic Control processes being addressed in this note. An analysis framework is devised in which a trajectory prediction engine provides flight position and time estimates for the conflict detection engine. In this framework, many other important features are considered, namely flight intent modeling, predicted trajectory processing for the conflict detection, and multiple flight scenario simulation. Additionally, attention is also devoted to prediction accuracy evaluation. Prediction accuracy is quantified according to specific defined metrics. Research results will aid future ATC related operations with greater airspace traffic and flight safety demands.

Keywords: Trajectory Prediction, Flight Performance Model, Prediction Accuracy, Conflict Detection, ATC Modernization.

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1. INTRODUCTION

There is widespread consensus, for some time now, that the current approach to Air Traffic Management (ATM) is unable to meet expected capacity, safety, and environmental demands, (Enea & Porretta, 2012). Many authors believe that accommodation of future demands by the ATM systems is only possible with increased automation and collaboration through interoperability of flight information between stakeholders, (Mondoloni, 2012). Hence, the need for modernized ATM related concepts and systems throughout.

ATM modernization is a global effort, with worldwide implications: local and international flights are tightly coupled almost everywhere. Additionally, Air Traffic in general is largely influenced by local (e.g., Brazilian) projected airspace demands and by international trends. As such, tactical and strategic system services in current modernization programs, such as NextGen, SESAR, and SIRIUS.

Trajectory Prediction (TP) is an important part in the ATM community vision for modern Air Traffic Control and Management operations and represents the core asset of many control and planning system services in these modernization programs. It is claimed that advanced Decision support Tools (DST) based upon TP are capable of reducing controller workload and, thus, for decreasing airspace capacity limitation, (Schuster & Porretta, 2010). Alternatively, DSTs, such as Conflict probe, Metering and spacing, Air traffic advisory, and Traffic Flow Management, already benefit greatly from trajectory prediction, (Eurocontrol, 2010), (Mondoloni, 2012). The DSTs have required specific levels of accuracy in terms of trajectory predictions, (Paglione & Oaks, 2007), and therefore pose on TP stringent accuracy performance requirements to provide prediction services accordingly to meet their needs. This dependence, it is thought, will become more outstanding with modernization and interoperability.

SESAR and NextGen are both based on full 4D Trajectory Based Operations, or TBO. The key element of Trajectory Based Operations is that airlines and the ATM system will agree about the trajectory that will be followed by an aircraft. Trajectory may also include additional constraints for improved predictability, thus aiding in workload reduction for air traffic controllers. It is envisioned that in the new ATM system airlines and ANSPs will optimize business and mission trajectories through a common 4D trajectory information network. This entails a systematic dissemination or sharing of aircraft trajectory data between various stakeholders involved in ATM operations. Operations range from strategic planning to tactical operations, from decision making to execution phases and are based on the most recent data available, (Nagle, 2009). These programs, and others being developed around the world, must be similar both in concept and in function since a global ATM modernization will require interoperability. With the dissemination of flight related information – such as aeronautical (AIXM), flight (FIXM), weather (WXXM), and the like – to various stakeholders, accurate prediction and planning is expected to generalize and become routine. This sharing is becoming reality with SWIM[†]; interoperability tests in a global scale have taken place. Refer to Koroishi et. al. (2016) for a detailed description about the Brazilian participation in these tests.

A deterministic prediction engine based on the modeling of aircraft flight dynamics is considered. In a previous presentation (Souza et.al., 2015), the principal concern was to present the challenges, the development effort and potential associated to trajectory prediction accuracy evaluation with real flight data derived from the Brazilian ATC system. Preliminary results in (Souza et.al., 2015) indicated the application potential of flight dynamics modeling for trajectory prediction in air traffic control and management operations. This presentation also considered preliminary accuracy evaluations of trajectory reconstruction of real flight trajectories.

The core paper objective revolves on presenting an analysis and systems development framework being devised in which a flight trajectory prediction engine provides accurate flight position

[†] System Wide Information Management.

and time estimates for a conflict detection module under development and intended to be employed for tactical operations together with the existing ATC system. The aircraft flight model in the Trajectory Predictor has evolved and matured to include extended modeling in a more robust implantation for TP. This evolution alone is responsible for improved prediction accuracy. Flight intent modeling also adds to increased accuracy. Accuracy, however, is not the only main concern here; the associated flexibility of use of the flight model as a trajectory predictor is further investigated.

The remainder of this paper is organized as follows: a brief exposition of the framework for analyses of trajectory prediction and conflict detection is given in the following section. The following section introduces specific details about the trajectory predictor implemented for this framework. This Section presents the flight dynamics modeling employed in the prediction module. Prediction accuracy evaluation is also considered by contrasting prediction with real flight data. General comments and discussion then follows in Section 4. Final remarks are given in the last section.

2. THE ANALYSIS FRAMEWORK

The main contribution of this note is the description of the analysis framework for flight trajectory prediction and conflict detection being developed.

The trajectory analysis framework under development is composed of many modules. Similar implementations to the present framework can be found in the literature, though many distinct features are considered in the current development, see Weitz (2013). This analysis framework is being designed for practical convenient analysis of prediction accuracy and verification of flight conflict detection. Flight trajectories are fed into the conflict module can be originated from either the Trajectory Predictor or real flight data (tracks). Refer to Fig. 1 for the framework architecture: component and implementation (deployment) view. The framework is made up of the following components:

- Trajectory Predictor (TP), implementing:
    - Dynamical aircraft flight model
    - Numerical integration routine (implemented as a system library)
    - Flight Intent model.
- Trajectory Simplification (TS) process
- Conflict Detection module
    - Medium-Term Conflict Detection (MTCD) process
    - Conflict Detection Verifier: Visual and geometric
- Multi-flight scenario Simulator.

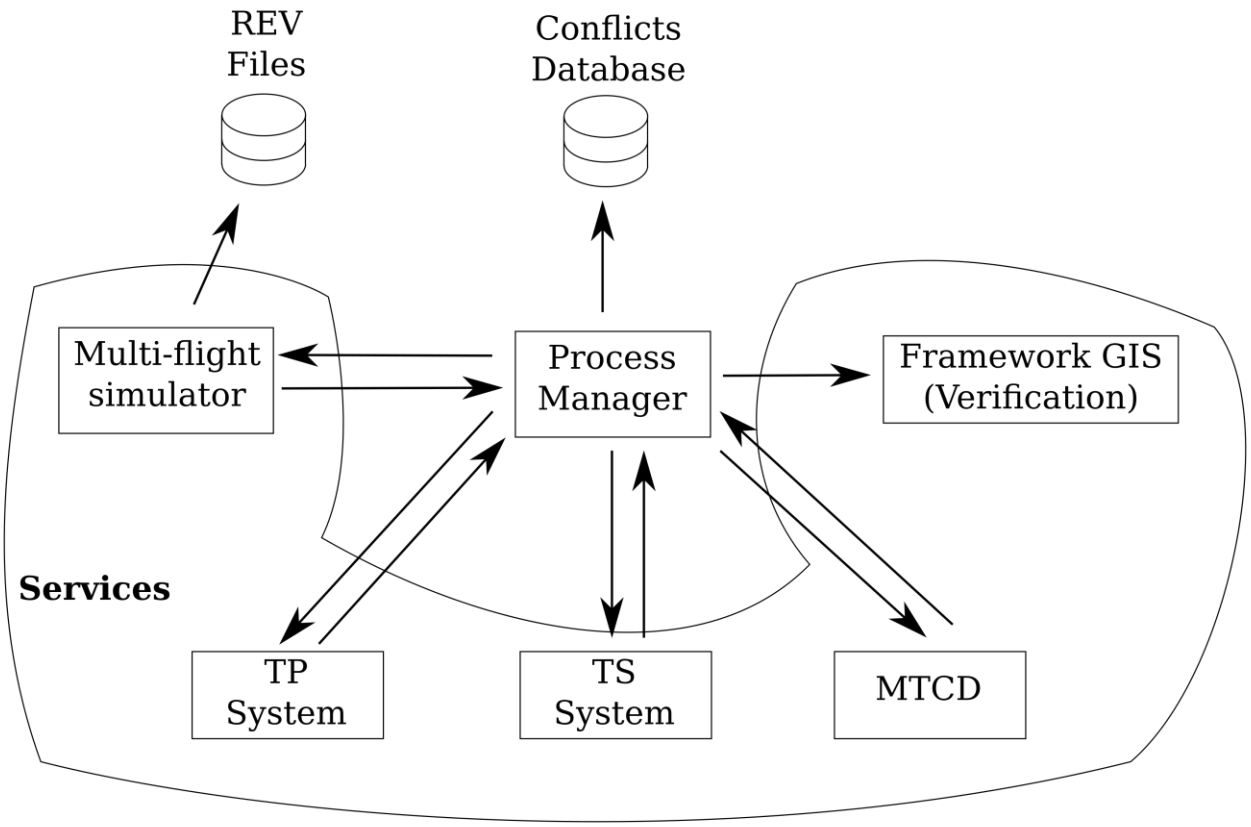


Figure 1: The Analysis Framework

The framework has, at its highest implementation level, a Process Manager, coded in Python, which coordinates calls to specific modules to be executed in sequence for the prediction and conflict detection process. The first module to be instantiated in the process, prepares data to be input to the Trajectory Predictor. The Predictor outputs prediction data in the form of 4D trajectories. The Process Manager provides these trajectories to the Trajectory Simplification Module, a middleware between prediction and the Conflict Detection module. Prediction data is, then, conditioned accordingly to the Conflict Detection module. Flight conflict results are verified either with a second algorithm, involving geometric interference (see below), or visually, with the assistance provided by a virtual Earth framework.

Each of the above mentioned framework components are described next.

2.1. The Trajectory Predictor

The Trajectory Predictor implements a deterministic prediction approach implementing an aircraft dynamical model and a flight intent model for flight guidance. Flight model and numerical integration routines are implemented in C language. The Predictor receives atmospheric and intent data along with aircraft parameters as inputs and outputs 4D trajectories. Evaluations of prediction accuracy analysis with real flight data of flights over Brazilian territory are being undertaken; some prediction results are presented in Section 4.

2.2. Trajectory Simplification process

Raw prediction trajectory data is large, and hence expensive to store and process. Simplifying trajectory data is important and can be done before processing. Simplification of generalized geometric contours is a recurrent problem in many fields of interest. For example, algorithms for drawing generalized profile sketches are used for simplifying map features in the

field of cartography, (Visvalingam & Dowson, 2001). The map feature simplification methods, however, do not apply directly to trajectory simplification, since the additional constraint of time must be dealt with, .i.e., when simplifying trajectory, trajectory velocity and direction should be preserved, refer to Long, et. al., (2013) for problem context. The trajectory simplification method employed in current framework implementation was largely based on the method for line or feature simplification. The method behind this process simplifies trajectories by eliminating iteratively those trajectory points which define an area, together with its adjacent points, below a pre-defined area threshold value. This method has been extensively used for line generalization.

2.3. The Conflict Detection module

This module represents a deterministic Conflict Detection algorithm of Medium-Term predictions, usually known as MTCD. The implemented algorithm computes the estimated time and trajectory locations when violation of minimum separation margins between two aircraft should take place. The violation of separation is determined when interference of one aircraft into the control volume surrounding another aircraft is detected. This interference is assessed when longitudinal, lateral, and vertical individual separations margins are trespassed simultaneously. The longitudinal and lateral conflict computations are geometric in nature, involving the projection of one flight path onto another and intersections of flight paths with safety polygons defined, by separation margins, around the flight path followed by the other aircraft. The computations required to assess vertical conflicts is based on the aircraft kinematics in the vertical plane. When conflict, between two or more flights, is detected, the MTCD process returns the estimated times and corresponding locations when this conflict is expected to occur. Fig. 2 depicts the MTCD process with a flowchart, indicating some general activities.

Conflict detection verification of MTCD results is performed by a geometric method implemented in Atech's visualization & capabilities framework consisting of a Geographic Information System (GIS) – based on NASA's Worldwind. Additional assistance to operator verification is done visually, with customized HMI support integrated to the GIS framework. This visualization framework, called 3D Visualization Framework, is currently under development at Atech. It is coded in Java; some methods were tailored to meet specific needs required by this project. This module is currently undergoing validation with real flight data.

2.4. The Multi-flight scenario Simulator

Simulation of Air Traffic Control Conflicts based on fast time simulations considering actual locations of a set of aerodromes and simplified preferential airways in the Brazilian airspace. Currently, simulation runs have been carried out for a scheduling of up to 120 reference flights. This simulator calls the framework trajectory predictor to create each and every flight instance in the simulation scenario. Simulation results are then analyzed and verified for possible flight conflicts. Specific conflict scenarios can be created or eliminated from the simulated scenario by iterating the scenario with modified flight evaluations. Similar research has been reported in (Fuxiang, Fengyun, Shengfei, Hong, 2006).

3. THE TRAJECTORY PREDICTOR

Trajectory Prediction is an active area of research, (Mondoloni & Kirk, 2013) and, as such, it is an ongoing investigation theme for the NextGen and SESAR modernization endeavors. The kinetic approach to prediction is preferred over the parametric approach due to its observed superior performance, (Torres, 2010).

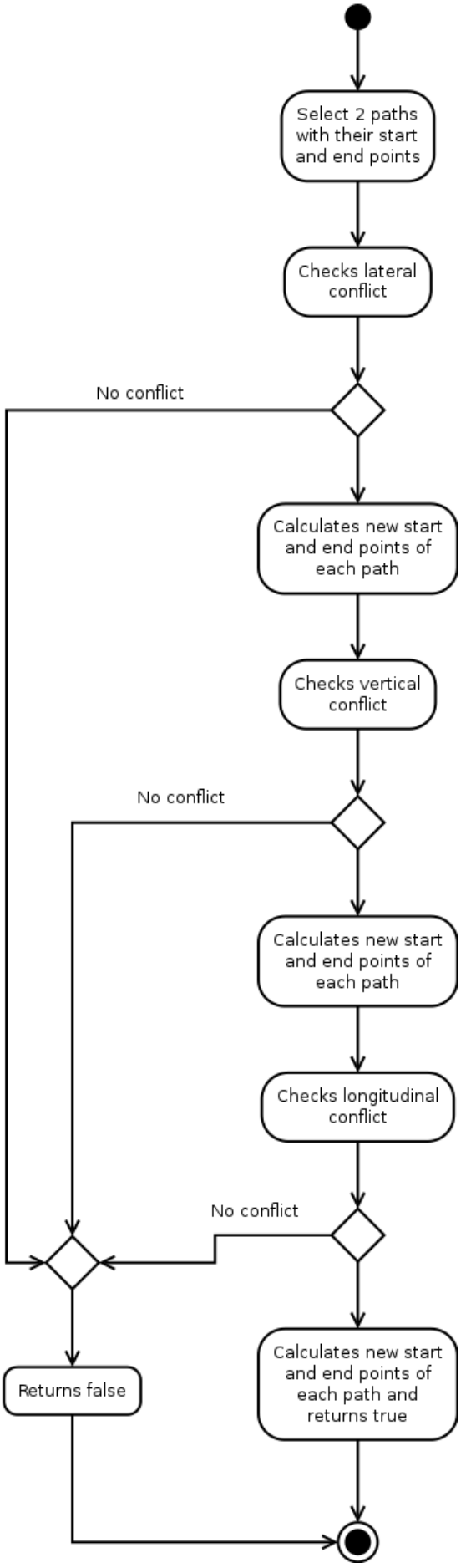


Figure 2: The MTCD process Activity Diagram.

3.1. The Aircraft Dynamical Model

A kinetic approach to trajectory prediction is considered: a set of deterministic, point-mass equations of motion, based on the flight dynamics presented below, was employed to model the arbitrary airliner. The Flight Model implemented in the Trajectory Predictor is a six degree-of-freedom nonlinear dynamics model of civilian aircraft flight in trimmed flight, see Glover and Lygeros (2004). The resulting aircraft model is a set of continuous-time ODEs defined by Eq. 1:

$$\dot{z}(t) = f(z(t),u(t),t), \qquad z_0 = z(t_0), \quad (1)$$

where f is a general non-autonomous mapping between the aircraft state z, input u, time t and the time rate of state $\dot{z}$. A minimal realization of the state vector z usually comprises aircraft position written in the Cartesian representation of the Earth geographical coordinates[‡], altitude, aircraft true airspeed, heading, and aircraft mass. Jet engine thrust, roll angle, and wind velocity vector are considered model inputs and are lumped together in the input vector u.

Atmospheric modeling is integrated to the above aircraft flight model. This modeling provides parameters for conversion between aircraft calibrated and true airspeed figures, provides atmospheric states' values for the computation of lift & drag forces acting on the aircraft model and provides intermediate states for determining mass variation dynamics. See also Porretta et. al. (2008).

3.2. Flight Intent Modeling

Standard flight plans are insufficient information for satisfactory trajectory estimation because flight plans do "not contain enough information to build from it an unambiguous rendition of the flight path in 4D", (Klooster et. al., 2010). Besides a brief description about the aircraft type, onboard navigational equipment, the expected route waypoints, and anticipated cruise altitude and airspeed in the flight plan, intent data complements the flight plan with information that can impact the future path of the aircraft with critical impact on prediction, (Schuster et. al., 2010). Intent data include not only the flight plan itself, controller issued altitude and time constraints, and aircraft guidance mode settings, but also speed profile intent, thrust and drag performance factors, aircraft weight, and maneuvering procedure of the aircraft over the trajectory prediction time horizon. These may vary greatly based on the client application's operational environment and include pilot and controller preferences and objectives.

Flight intent data modeling based on low-frequency motion components of real flight data. Additional intent information is coded into the model in the form of aircraft guidance laws. Feedback loops are also in place to reject disturbances and regulate cross-track and heading deviations to zero w.r.t. a nominal trajectory given by the expected flight route. No aircraft flight velocity scheduling look-up table was employed: the flight control system was used to regulate aircraft velocity based on intent modeling. An ad hoc aircraft input saturation compensation strategy was also devised and employed for control under engine saturation.

The Intent model describes "how the aircraft is to be flown". The intent model is as necessary as the aircraft flight mode for a successful prediction process. As in the previous presentation of this research (Souza et.al., 2015), prediction trajectories were created by inputting a sequence of route waypoints to the predictor engine. These waypoints are based on flight history (tracks) and contain more than just geographical coordinates of aircraft position: altitude and speed are also provided to indicate main aircraft motion over the flight period considered. In the previous presentation (Souza et.al., 2015), these waypoints were transformed into continuously differentiable class functions to be used by the guidance and control laws in the flight model for input tracking and aid the trajectory reconstruction process. The prediction results presented here, on the other

[‡] Longitude and latitude.

hand, require only discrete waypoints as intent input, and not specific class functions, and are less dependent on flight history information. Intent modeling with data from departure and approach procedures will also be considered in future developments to enhance the flight intention information being input to the Predictor, as mentioned above.

Other sources of uncertainty related to the flight dynamics model described above will be addressed in a forthcoming presentation.

3.3. The Prediction Process

The prediction process involves the fast-time solution, or simulation, of an Initial Value Problem (IVP) with initial values z_0, yielding the state $z(t)$ as a function of time. The time horizon for this estimate varies from problem to problem. For example, gate-to-gate prediction would involve a time horizon of many hours; while conflict detection would require flight state estimation of 20 to 40 minutes of look-ahead-time from current aircraft position.

Prediction results are, amongst many others, used to feed the conflict detection service in tactical operations. Improvements in prediction for shorter look-ahead times require a higher-order aircraft model. In contrast, a lower-order model is sufficient for longer time horizons. Therefore, the numerical integration routines used for solving the IVP are based on a 4^{th} order Runge-Kutta integration method with an adaptive timestep size control for integration performance accuracy and runtime efficiency. Similar methods for numerical integration in trajectory prediction have been documented in the literature (Hadjaz et.al., 2012).

Figure 3 provides a schematic diagram of the sub-components of the Trajectory Predictor.

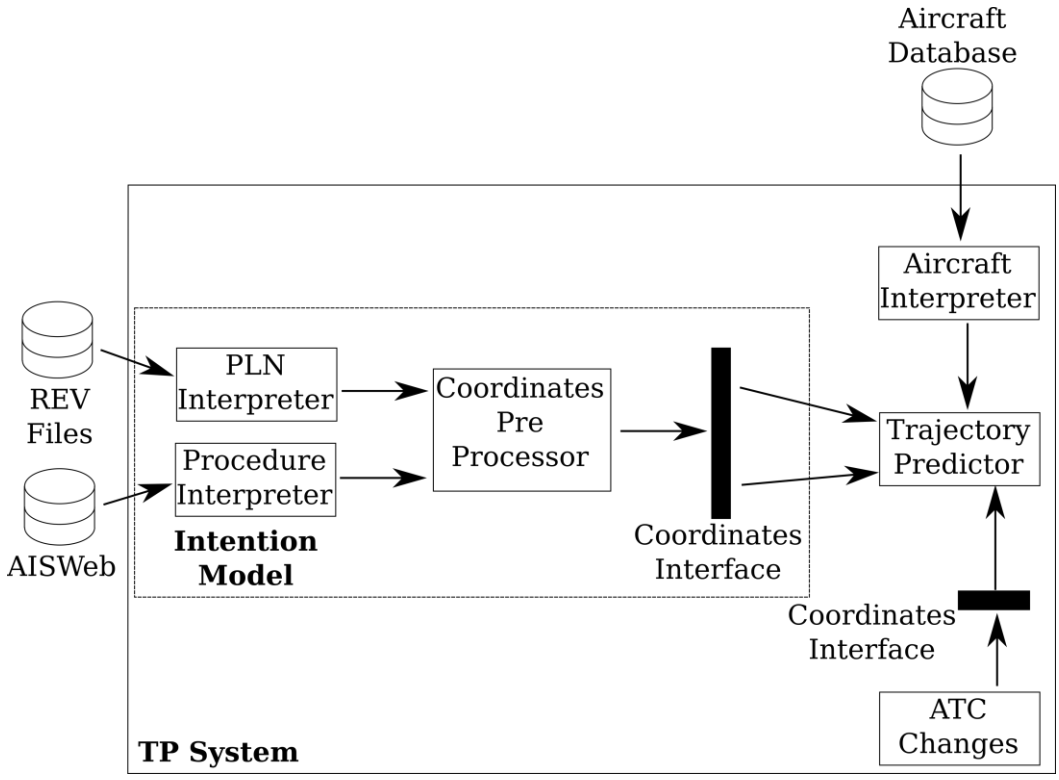


Figure 3: The Trajectory Prediction Process.

4. TRAJECTORY PREDICTION ANALYSIS

Predicting the aircraft future position is regarded as a difficult endeavor. This difficulty is related specially to the estimation of perturbations influencing its motion. The actual motion of the

aircraft is in fact affected by uncertainty, due mainly to wind, but also to errors in tracking, navigation, and control.

Flight intent modeling is based on flight plan information and, more prominently, on a limited set of flight data for that flight in the past and from flight procedures. From the analysis of flight data, one is able to determine aircraft rate of climb and descent, speeds, airline policy, etc. and introduce these measures into the Trajectory Predictor in the form of a flight intent model. When predicting aircraft location into the future, these intent measures could represent the best description of flight intent along with other prediction parameters.

A selection of flights was made with the intent of showing prediction performance. Three flights were selected for this study. The first flight, referenced with callsign XXX1111, departs from Goiania (SBGO) towards São Paulo (SBSP) at 11h50 (EOBT) with an estimated time of flight of 1h15 (EET) and a cruising flight level of FL390 at 450kn. The second flight, YYY2222, departs from Confins (SBCF) towards Manaus (SBEG) also at 11h50 (EOBT) with an estimated flight time of 3h32 (EET) and a cruising flight level of FL340 at 462kn. This flight involves two FIRs and analysis here will cover only the FIR Brasilia branch. The third flight, ZZZ3333, departs from Guarulhos (SBGR) towards Ribeirão Preto (SBRP) at 11h55 (EOBT) with an estimated flight time of only 00h41 (EET) and a cruising flight level of FL240 at 342kn.

4.1. Prediction Accuracy Analyses

This section is focused on the performance analyses using spatial and temporal metrics. A few metrics were selected and used for the comparison of TP performance evaluations against flight track data. Trajectory prediction in the context of medium-term conflict detection should consider typical look-ahead-times of 20 to 40 minutes. However, in order to validate prediction accuracy, prediction performance will be evaluated with longer flight parts.

Ryan et.al. (2004), and more recently Paglione & Oaks (2007), have presented useful definitions of metrics and related criteria, for metrics application, to the problem of trajectory accuracy evaluation. Metrics for quantifying the error of the predicted trajectory to a reference trajectory, flight tracks typically, can be categorized in two groups: Spatial Errors: Horizontal (HE), Along-Track (AE), Cross-Track (CE), Altitude Errors (AE). There are also two general criteria with which to employ these metrics: the spatial-coincident and time-coincident approaches.

Error analyses results are illustrated in Figs. 4-7. The trajectories for Flight XXX1111 and ZZZ3333 considers a descent phase; Flight YYY2222 does not have its descent phase analyzed. Flights XXX1111 and YYY2222 intent were deliberately under modeled, i.e., poor modeling was considered for their prediction. Flight ZZZ3333 had its flight intent modeled with care for all flight phases. The motivating objective behind this comparison is to show some level of accuracy performance the kinetic flight model is able to deliver by reproducing real flight trajectory with a small number of input waypoints as the main representation of intent. Flight XXX1111 showed poor prediction performance during descent; see Fig. 4 for the prediction results on the horizontal plane and Fig. 7 for vertical prediction performance. Flight YYY2222 displayed poor prediction performance, due to deliberate poor intent modeling, in all phases, see Fig. 5, 7. Flight ZZZ3333 outperformed both previous flights because of adequate intent performance, Fig. 6, 7. This deliberate strategy for illustrating gain in prediction accuracy performance is reflected in the order of magnitude of the errors. Peak prediction errors for XXX1111 and YYY2222 range from 20 to 30 NM, respectively; see Figs. 4, 5. Errors for ZZZ3333, in contrast, which conveys adequate intent modeling, peak to 1.5 NM at most.

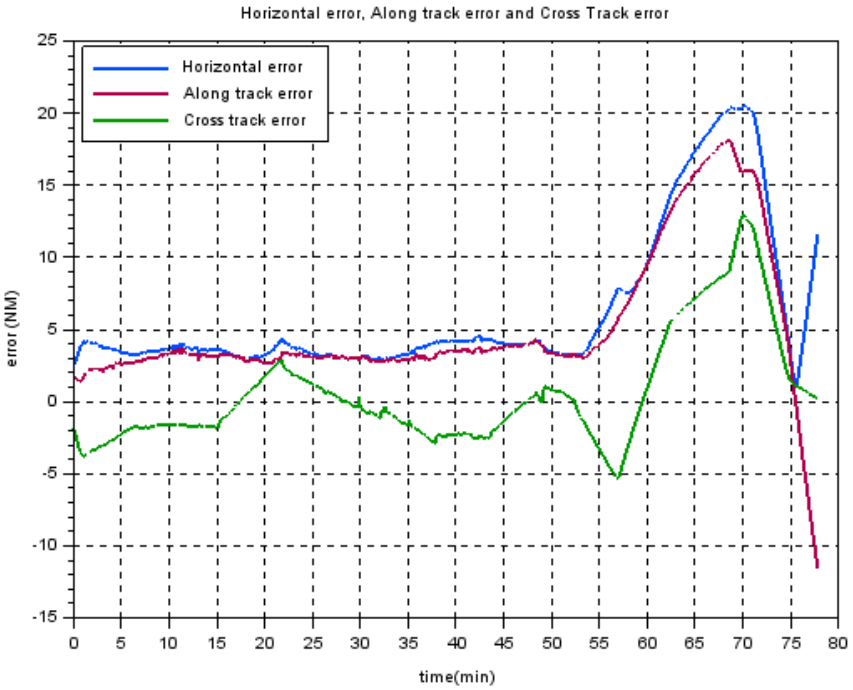


Figure 4: Horizontal prediction performance for flight XXX1111: horizontal, along-track, and cross-track errors.

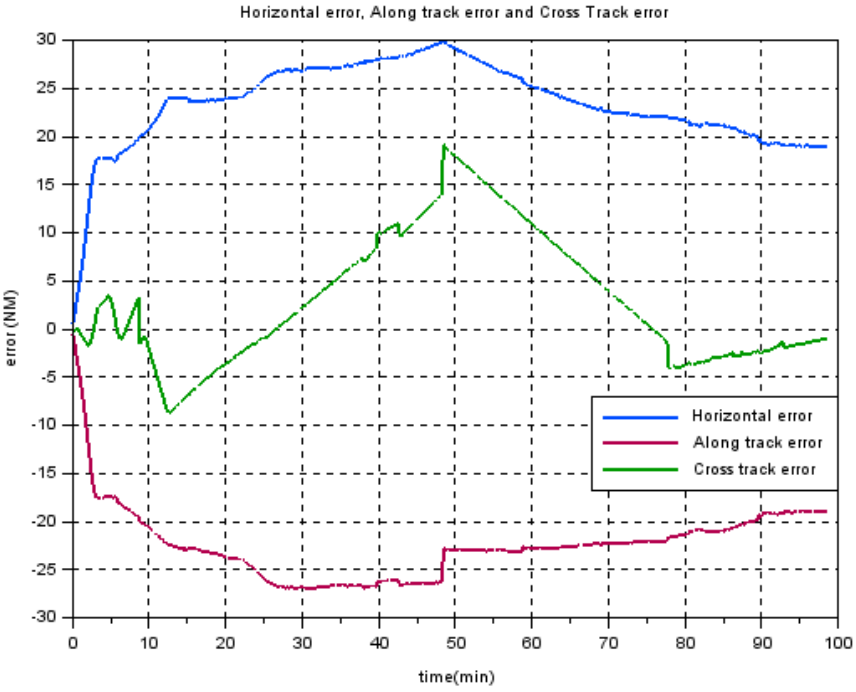


Figure 5: Horizontal prediction performance for flight YYY222: horizontal, along-track, and cross-track errors.

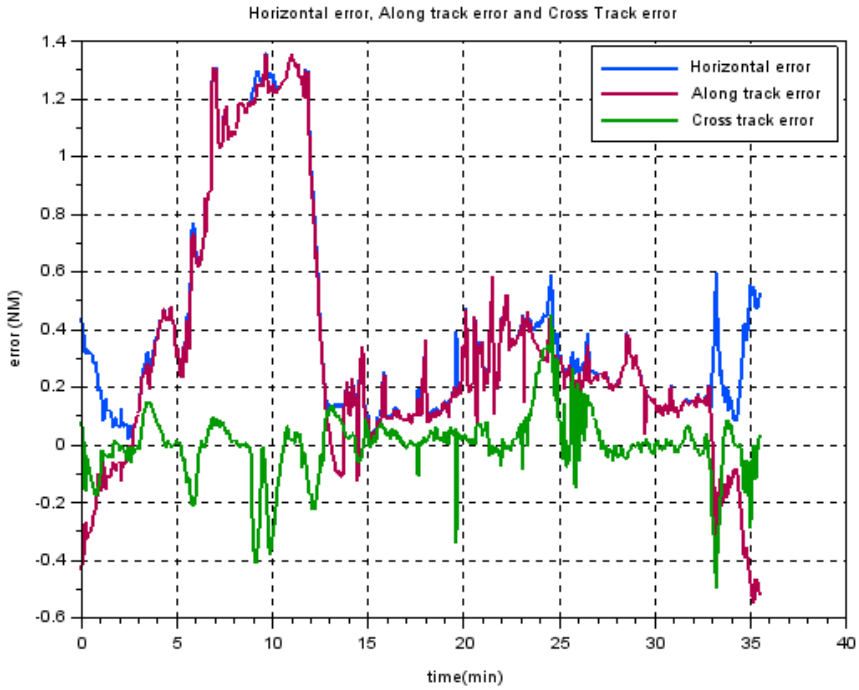


Figure 6: Horizontal prediction performance for flight ZZZ3333: horizontal, along-track, and cross-track errors.

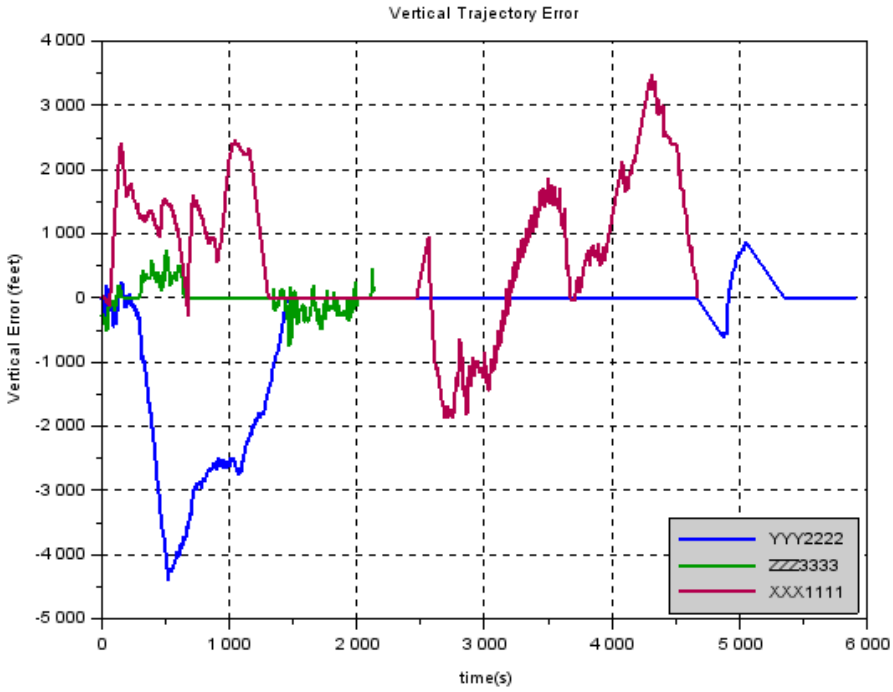


Figure 7: Vertical prediction performance for the three flights.

The time-coincident criterion to metric use was applied (Ryan et.al., 2004), (Paglione & Oaks, 2007), yielding the results of Table 1.

Notice that RMS errors increase with flight duration considered in the analysis; the longer the flight, the greater RMS related errors will be accumulated, in general. Hence, RMS figures for each flight instance should not be contrasted to each other directly. Similarly, in the TP context, a

temporal metric would indicate flight performance for distinct aircrafts flights reaching intermediate waypoints or a final destination as a function of their adopted trajectories.

Table 1: Horizontal (HE), Along-Track (AE), Cross-track (CE), and Vertical (VE) RMS errors for full flight analysis for the three flight instances. Time-coincident criterion for metric was used.

Flight Callsign	HE (%)	AE (%)	CE (%)	VE (%)	Flight duration
XXX1111	0.300	0.277	0.465	0.973	01h17
YYY2222	1.000	1.000	1.000	1.000	00h30
ZZZ3333	0.013	0.014	0.009	0.111	00h41

The error values disclosed in Table 1 should be considered of qualitative nature only. Moreover, each flight intent model, for flights XXX1111 and YYY2222 specifically, can be fine-tuned for improved performance with respect to a specific metric employed for error computation. The amount of flight intent information supplied to the predictor model is also of great significance when interpreting these numbers, since they are relative to the quality of intent information used in the prediction. Hence, no importance should be given to the analysis of absolute error values at this moment and comparison should be based solely on the relative measure of computed errors.

Error results for Table 1 should also be considered in light of flight duration times. Observe that altitude error, captured by the HE metric, for flights XXX1111 and ZZZ3333 are the same. The scale for the altitude axis and flight duration must be taken into account when analyzing the AE numerical values obtained in the comparison table. Although XXX1111 is much better reproduced by the predictor, it is a longer duration flight. The same error value was achieved by flight ZZZ3333 much earlier in flight due to poor altitude profile reconstruction by the lacking of quality intent data.

5. COMMENTS

The results presented here improve, in terms of accuracy, over those preliminary results presented in (Souza et. al., 2015). Flight intention data considered here is more carefully modeled and the Trajectory Prediction itself is founded on a more robust implementation, less dependent on flight history. In the previous study, results were based trajectory reconstruction with the flight dynamical model. This is one important difference with respect to current prediction module, where prediction per se is taking place. Moreover, the flight model considered currently is able to cope with input saturation. A heuristic for replanning, even, of flight intent with the objective of reducing undesirable effects of saturation is being designed and tested.

It is easily observed that the quality of input data directly affects trajectory prediction accuracy, and this has been reported elsewhere (Mondoloni & Liang, 2003). The uncertainty related to the wind-field estimation greatly impacts along-track and time-of-arrival errors; this has been observed previously, (Mondoloni & Bayraktutar, 2005). In contrast, the wind influence on cross-track and altitude errors are less apparent.

Therefore, in order to mitigate differences between true, or observed, aircraft behavior from theoretical prediction one must provide a satisfactory uncertainty model. Whatever the approach to uncertainty modeling may be, the following comment serves as a guiding lemma for establishing the scope of trajectory prediction algorithms w.r.t. look-ahead times, (Thomas et. al., 2003): "... it is likely that with the increase in uncertainty at such long LATs the rate of both false alarms and misses will be prohibitively high and will not produce a useful tool when it comes to planning for projected conflicts."

Once again, as in the preliminary study (Souza et. al., 2015), the kinetic approach to TP enables greater flexibility in terms of parametrization of a wide range of different flight conditions and intent scenarios; proving itself adequate to modern air traffic modernization operational demands. This increase in flexibility does, however, demand more knowledge about these same

conditions and scenarios and how to best employ this knowledge to correctly parametrize the flight model. In many cases, the underlying predictor flight model is significantly sensitive to this parametrization. We do recognize, nevertheless, that through a collaborative environment for the flow of information, this demand for flight related knowledge will be supplied and that modernization of ATC/ATM systems will be ready to fulfil new operational expectations.

6. CLOSING REMARKS

This note on trajectory prediction evaluation and conflict detection represents a continued effort on devising a thorough systematic and consistent method for achieving required prediction accuracy for future ATM requirements and demands.

As emphasized previously, we stress that some measure of effort was experienced and dedicated to harvesting and formatting ATM flight data appropriately for the performance evaluation analyses just described. This is still being addressed in ongoing research intended towards improving the analyses methods employed for a consistent and high-quality TP process.

Future research and project development include implementation parameters tuning refinements and code optimization, towards improved framework system performance. Additional methods for flight state estimation and wind data treatment are also to be considered. Finally, an extensive testing and validation program, of individual modules and the entire framework as a whole, is also to be continued.

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