IMPROVED FLIGHT TRAJECTORY PREDICTION ACCURACY BASED ON ENHANCED AIRCRAFT MODELS

Eric Conrado de Souza
Atech Negócios em Tecnologia S/A
Rua do Rócio, 313 – 2º andar, São Paulo, SP, (11) 3103-4600, FAX (11) 3103-4601.
ecsouza@atech.com.br

Amilton Tadeu Berne
Atech Negócios em Tecnologia S/A
Rua do Rócio, 313 – 2º andar, São Paulo, SP, (11) 3103-4600, FAX (11) 3103-4601.
amilton@atech.com.br

Suely Silva[*]
Atech Negócios em Tecnologia S/A
Rua do Rócio, 313 – 2º andar, São Paulo, SP, (11) 3103-4600, FAX (11) 3103-4601.
ssilva@atech.com.br

ABSTRACT

Future Air Traffic Control related operational procedures and systems will require greater airspace occupancy and safety features. These systems should provide increased aircraft position prediction accuracy intended for trajectory planning and conflict detection. This present note conveys remarks and preliminary results of ongoing investigation into improved models of the flight dynamics for future ATC/ATM systems. We review some requirements related to the trajectory prediction problem and illustrate significant results concerning the application potential and flexibility of use of flight dynamics modeling for trajectory prediction in air traffic control and management operations when contrasting these with real flight data.

Keywords: Trajectory prediction, Flight performance model, Prediction accuracy, ATC modernization, SIRIUS Program.

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1. INTRODUCTION

The outlook for worldwide passenger origin-destination air travel in the next 20 years corresponds to a growth of 1.8 to 2.8 times current scenario figures, depending on adopted border policies throughout (Pearce, 2014).[2] Similarly, the forecast estimates for the passenger air travel between Brazil and the U.S. (one important destination for Brazilian tourists) is expected to grow at an average of 4.4% per year up to 2035, according to the FAA Aerospace Forecast: FY 2015-2035, published annually. Domestic and international passenger transportation in the Brazilian airspace is expected to grow 109% in the 2012-20 time window (ABEAR, 2014). In order to achieve airspace capacity demands, while increasing safety measures of air transportation operations, knowledge dissemination processes amongst stakeholders and advanced ATM/ATC planning concepts and techniques are in the process of being revisited accordingly by the international ATM/ATC community. This effort aims to improve flight efficiency and accommodate operations management in a complex, future air traffic scenario. To support the aforementioned and other related operations on the ground and in the air, accurate aircraft trajectory prediction capabilities must be designed, developed, implemented, and deployed.

Trajectory prediction (TP) plays an important role in the context of modern Air Traffic Control and Management operations. Furthermore, TP represents a core functionality of many control and planning system services in current modernization programs, such as NextGen and SESAR. Shuster & Porreta (2010) corroborate the above claims: "Advanced decision support tools based upon TP will reduce controller workload, one of the key factors limiting airspace capacity."

It is expected that accurate prediction of flight trajectory and planning, through trajectory optimizations, will support a more rational use of airspace, will increase the efficiency of the air transportation management, and will contribute to reduced green-house related emissions. Moreover, these benefits will contribute to cost reduction for aircraft operators and ANSP and promote higher quality service for air transportation users. All the previously mentioned benefits are part of the SIRIUS project objectives, the solution pushed forward by Brazilian authorities to promote the needed infrastructure and support for future air travel demands. It is interesting to observe that, because domestic and international flights are tightly coupled almost everywhere, this is a global modernization effort, with worldwide implications, and is largely influenced by international trends and local (e.g., Brazilian) projected airspace demand referenced on current growth estimates.

The main goal of the present study is to disclose initial awareness about ongoing local research into practical trajectory prediction associated issues. A prediction engine based on the modeling of aircraft flight dynamics is considered. In this preliminary presentation, one principal concern is to discuss some of the challenges and effort connected to trajectory prediction accuracy evaluation with real flight data derived from the Brazilian ATC system[3]. Accuracy, however, is not the only chief concern here; the associated flexibility of use of the flight model as a trajectory predictor is likewise being investigated. We envision that this initial study will encourage further dissemination of knowledge in the present field of expertise. We also show preliminary results concerning the application potential of flight dynamics modeling for trajectory prediction in air traffic control and management operations.

The remainder of this paper is organized as follows: a brief overview of related trajectory prediction ideas and concepts are given in the following section. The following section introduces some prediction problem requirements which are being used in ongoing research. The next section, Flight Modeling, presents some details of the flight dynamics modeling employed as the prediction module. Prediction evaluation then follows in Section 5, where generated trajectories are contrasted

[2] According to IATA estimates.

[3] The SAGITARIO ATC system.

to flight tracks. The core contribution of this note is undertaken in the Comments Section. Final remarks are given in the last section.

2. TRAJECTORY PREDICTION

Torres wrote in his 2010 DASC conference paper about the importance of accuracy of predicted trajectories in modern tactical and planning air traffic systems: "Because of the foundational reliance on accurate gate-to-gate, four dimensional trajectory (4DT) predictions in TBO, trajectory predictors (TP) will have to meet stringent accuracy performance requirements."

Moreover (Torres, 2010): "A TP is not a monolithic algorithm but rather a collection of algorithms each specialized to solve a particular modeling problem to build a trajectory. Thus, it is envisioned that as existing TPs evolve towards meeting the requirements to support TBO, there is need to evaluate the impact of individual factors to trajectory accuracy to be able to focus algorithmic improvement efforts where they have more relevance." The above quote defines trajectory prediction and brings one important recommendation, namely, that the influence of specific factors should be identified and well understood and that effort must be concentrated for improvement based on these same factors, when required. This note is a first step towards this end goal.

Prediction is not a present necessity in ATC systems alone. Prediction for strategic operation, or the planning of airspace utilization, perhaps will show to be an even more critical requirement in future management systems relative to tactical control. In this regard, Nuic et. al. (2005) state that: "An efficient Air Traffic Management (ATM) system requires planning of traffic flows that rely on accurate estimation of aircraft performances."

Many are the factors that affect TP functionality and performance. Input to the predictor usually encompasses the following information:

- Flight plan and amendments: also termed Flight Intent data (Eurocontrol, 2010);
- Aircraft Intent data – speed regime, aircraft mass, thrust settings, etc.;
- Meteorology and atmospheric data;
- Aircraft performance data.

The output of the prediction process is a 4D trajectory with predicted future aircraft states including the corresponding intermediary and final estimated times of arrival (ETA).

A brief description about the aircraft type, onboard navigational equipment, the expected route waypoints, and anticipated cruise altitude and airspeed are all considered in standard flight plans. These are, however, 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, 2010). Intent data complements the flight plan with any type of information that can impact the future path of the aircraft and its exactness for TP is critical, (Schuster, 2010). Examples of intent data include the flight plan itself, controller issued altitude and time constraints, and aircraft guidance mode settings, (Vivona et. al., 2008). Speed profile intent, thrust and drag performance factors, aircraft weight, and maneuvering procedure of the aircraft over the trajectory prediction time horizon are also considered intent data. These may vary greatly based on the client application's operational environment and include pilot and controller preferences and objectives.

3. PREDICTION REQUIREMENTS

Trajectory prediction requirements deal with the specification about functional necessary conditions and performance measures concerning the estimation of aircraft position in terms of systems point-of-view and performance metrics, respectively. It has matured over the years; refer to the Eurocontrol (2010) reference report on this matter.

The TP system specifications require that a number of functionalities be implemented in order to provide service based information to other ATC/ATM systems. Transition take-off runway to en-route network of airways (SID charts), transition from en-route structure to touch-down runway

(STAR charts), strategic and tactical flight constraints, conditional routes, to name a few. Additionally, TP performance should be evaluated by statistical analyses on a significantly large sample of "truth data", usually in the form of radar tracks. S. Torres (2010) recently wrote that: "... to quantify trajectory accuracy is to compute the deviations of the predicted lateral and vertical position and time along the trajectory relative to a reference 'as flown' 4D path".

Notice that TP is an active area of research; consult Mondoloni & Kirk (2013) for a recent reference. Very recently the US-Europe transatlantic cooperation agreement has been ratified[4] because of the perceived acknowledged benefits attained with both NextGen and SESAR programs. TP is an ongoing research theme for these two modernization endeavors.

The kinetic approach to trajectory prediction is ideally suited to airborne FMS related decision support functionality since intent information is readily available. Ground air support systems require some intent data to be downlinked for TP, though. However, it is reported that: "An evaluation of the performance of kinetic versus parametric models in the context of traffic flow management (TFM) applications indicates that kinetic models exhibit better accuracy performance", (Torres, 2010). With the aid of digital data-link – like ADS-C and upgraded CPDLC – and 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. Satellite navigation technologies already provide planning execution aids for a more flexible flight realization. The advantages of information dissemination are evident, as seen in (Mondoloni, 2013), for example, where identified TP performance factors have been shown to improve in terms of accuracy, besides clear benefits towards Conflict Detection & Resolution and Traffic Flow Management.

In Schuster & Porretta (2010) flight measured wind data is claimed to enhance TP accuracy. More generally, real-time, airborne measured wind-field data could be transmitted to and combined with data collected by Aeronautical & Meteorological Information Services and then shared by the ground-to-ground network with Air Navigation Service Provider (ANSP) and Air Traffic Service (ATS) providers, etc. for improved accuracy of TP and flight planning and control processes. Interoperability issues arise and should also be appropriately addressed, (Mondoloni, Bayraktutar, 2005).

4. FLIGHT MODELING

Prandini and Watkins (2005) present, on page six of their HYBRIDGE report to the European Commission, an unavoidable problem related to prediction: "One of the difficulties in predicting the aircraft future position consists in modeling the 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."

The HYBRIDGE project (Glover and Lygeros, 2004) employs a six degree-of-freedom nonlinear dynamics model of civilian aircraft flight. Modeling simplifying assumptions or hypotheses include a flat earth model, i.e., the effect of earth surface curvature is negligible, trimmed flight conditions, and aircraft as a point mass model to list a few. The resulting aircraft model is a set of continuous-time ODEs[5] defined by:

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

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[6], altitude, aircraft true airspeed, heading, and aircraft mass. Jet engine thrust, roll angle, and wind velocity vector are

[4] http://www.intelligent-aerospace.com/articles/2015/06/faa-and-european-commission-expand-air-traffic-management-pact-cooperation.html

[5] Ordinary Differential Equation.

[6] Longitude and latitude.

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 conversion between aircraft calibrated speed 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).

Some intent information is coded into the model in the form of aircraft heading behavior. 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.

Various are the sources of uncertainty related to the flight dynamics model described above. Some of these are listed below:

- Aircraft mass at take-off (TOW);
- Aircraft speed at any given time of flight;
- Wind vector, direction and intensity, at any given time and altitude.

The impact of the first two sources on prediction can be somewhat diminished with the help of an estimator coupled to the aircraft model itself. One noteworthy downside to this solution is the increase of modeling complexity and the need of extra tuning of parameters. Appropriate communication between Airline operators, ANSP and control centers of aircraft mass at take-off, in the first case, and continuous air-ground data link, in the second case, could represent simple and efficient solutions. Sensor network fusing data from ground stations, satellite, and airborne vehicles could mitigate wind uncertainty. Alternatively, one could employ a stochastic wind model superimposed to the deterministic average estimates obtained from historical records.

A set of deterministic, point-mass equations of motion, based on the dynamics presented above, was employed to model the physics of flight of an arbitrary airliner. Prediction, therefore, involves the solution of the continuous-time ODEs with initial values z_0, or Initial Value Problem, yielding the state $z(t)$ as a function of time. This is known in the literature as the kinetic approach to trajectory prediction. 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.

A numerical trial for a fictitious aircraft flight of approximately 4h40 in duration is depicted in Figs. 1-3. Observe that the aircraft is performing an arbitrary descent procedure, Fig. 2, and that it slows down to approximately 184knots (340km/h) before it speeds up again, Fig. 3. The zig-zag motion projected onto the horizontal plane, in Fig. 1, shows the effect of guidance laws in use together with the aircraft dynamical model. These prediction results also provide mass variation dynamics during flight (not shown below).

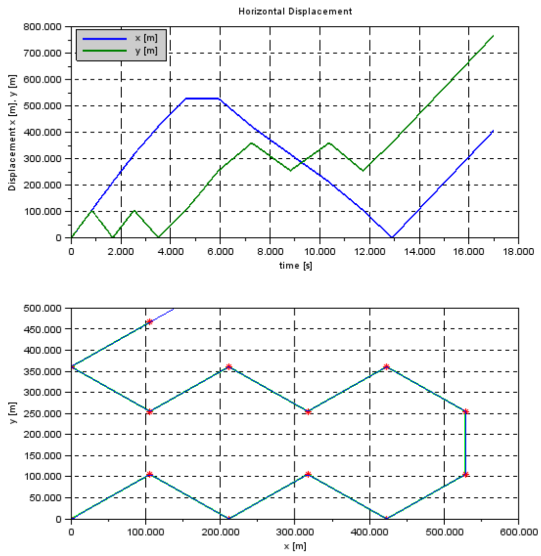

Figure 1: Horizontal displacement of a fictitious flight: Time curves and motion on the x-y plane. Graphics on the horizontal plane contain waypoints in red asterisks, routes in green lines and the generated flight trajectory in blue curves.

5. PREDICTION EVALUATION

The kinetic prediction engine is being evolved within a flexible, efficient development framework environment which can accommodate a great number of functionalities for both tactical and strategic operations and off-line analysis. A prototype system for improved and new ATC/ATM services will be fully available soon. A short description for this prototype system is given next.

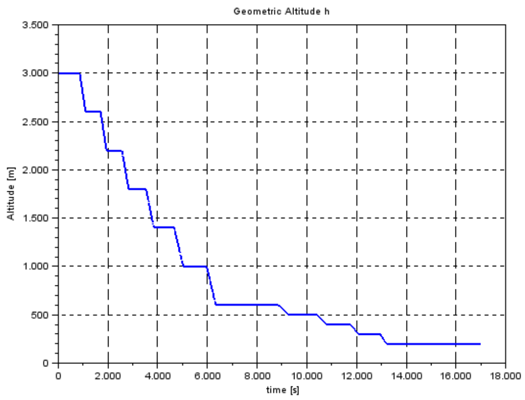

Figure 2: Aircraft flight vertical displacement w.r.t time.

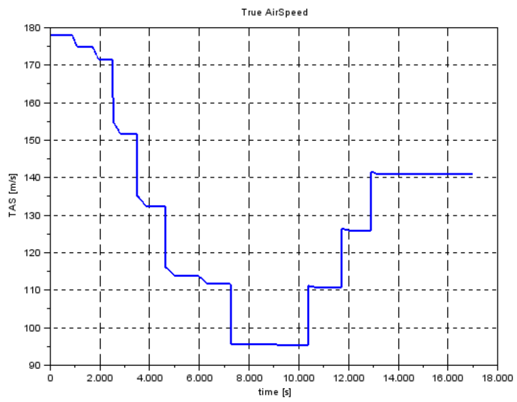

Figure 3: True Airspeed (TAS) for the fictitious flight simulation.

The ATC system configuration parameters and general settings data base, or DBS, is initially read and its contents are made available through the DDS bus to other network hubs:

- FDP system configuration settings;
- Air space structure for the FIR.

Route extraction then follows, yielding a sequence of way-points in three-dimensional space. Way-point values regarding position geographical coordinates and altitude are subsequently input to the predictor. In this study, the kinetic model based on aircraft flight dynamics was employed as a predictor engine, as illustrated in Figure. 4.

The aircraft flight dynamical model based predictor was implemented initially in a development environment, Scilab and Matlab, for algorithmic verification and validation purposes. High-order numerical integration methods were utilized to solve the aircraft flight equations of motion to yield numerical solutions with satisfactory accuracy in the short and medium term. Satisfactory implementation solutions are currently being implemented and tested in the framework environment, just mentioned, where the prediction algorithm will provide estimated flight data to be displayed in a virtual three-dimensional, georeferenced information system. This geographical environment is an integrating part of the extensive capabilities framework being developed at Atech. Figure 5 gives a snapshot of the current system, where general airspace components – such as airways, terminal areas (TMA), ADS-B tracks, and conditioned airspace – are displayed in evidence.

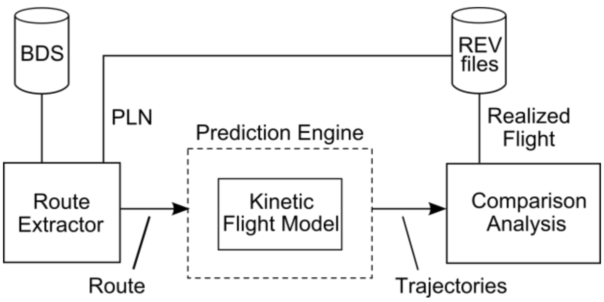

Figure 4: Trajectory prediction process and analysis.

Besides the uncertainty associated to flight modeling, some of which were briefly mentioned above, other sources of uncertainty are present, such as those related to ATC systems operations and flight intent. The effect of waypoint fly-by or fly-over maneuvers is negligible since RNAV navigation is in effect over the Brazilian continental FIRs. The flight dynamics model used for the kinetic predictor was devised with the capability to implement either fly-by or fly-over modes.

Unit conversion and coordinate transformation from geographical to Cartesian coordinate systems can become additional sources of error if not dealt with accordingly. Although there are many coordinate transformations available in the literature, the same projection technique should be used for trajectory performance evaluation as the one

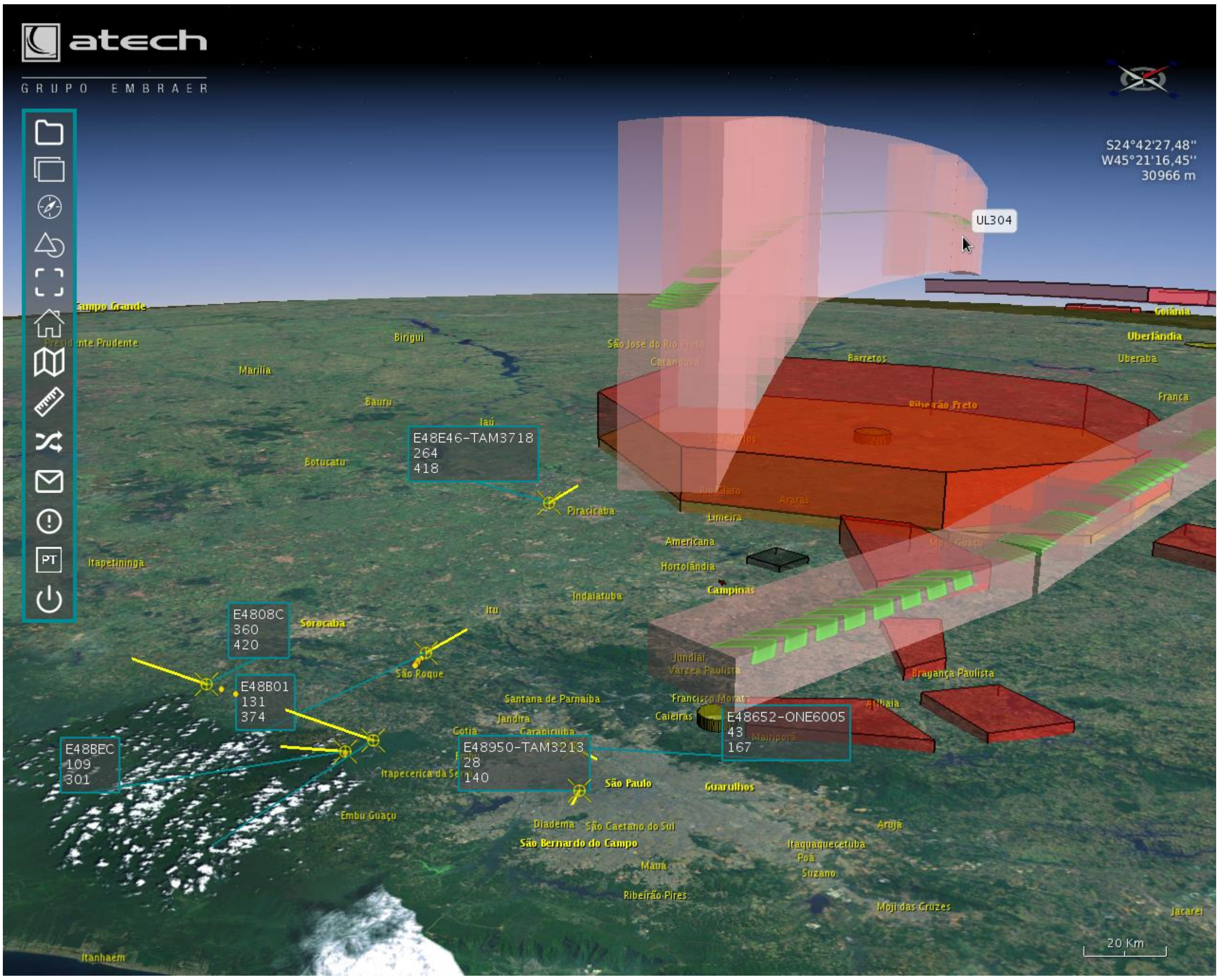

Figure 5: Capabilities framework being developed at Atech. Some airspace structure is being displayed, in 3D mode, in the form of airways, TMAs, conditioned airspace, and ADS-B tracks.

employed in the ATC system when REV files were generated.

Tracking data is yet another source of uncertainty when performing trajectory comparison. Track history from REV files were filtered for tracks with high values of quality factor property to be used in this performance evaluation.

5.1. Input Data to Prediction

Flight data used to input the prediction engine were taken from a small available database of *flight recordings* of real, performed commercial flights. These flight recordings are a collection of flight related data stored in the, so called, Revisualization or REV files, which are read for flight plans (PLN) historical reports and for radar-tracking system reports. Flight data taken from real flights were used to evaluate the performance of the kinetic prediction engine described previously.

A selection of flight instances was assembled from the pool of flight plans read from REV files. This selection involved both PLN and flight tracks reports. Flight instances were based on flight “indicative” and, more effectively, the SSR code, besides EOBT and ADEP. To date, our selection criteria considered only nominal flights without non-typical issued instructions or actions involving inflight detours or rerouting by the controlling authority. The reason for this criteria adoption is simply to facilitate analysis, on current research stage, by avoiding ambiguity in the execution of these rerouting instructions.

Despite the above criteria and the lack of precision provided by controller issued instructions, altitude clearance during cruise flight phase are not being ruled out from this initial selection, however. Track data history analysis has shown that it is possible to reduce ambiguity in altitude clearances. Further investigation will pursue the use of data from any flight plan, however complex it may be.

A selection of flights was made with the intent of showing prediction performance. Three flights were selected for this study. The first flight, referenced as 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. Flight trajectories projected onto the Cartesian horizontal plane are shown in Figure. 6. Notice the influence of RNAV navigation on the geometry of flight trajectories. Trajectories are characterized by a more rectilinear form or feature, in contrast to a trajectory with sharp corners given by the flight route which is built by the linearly interpolation of the navigational aids (navaid) themselves. Maximum flight track distance from the corresponding navaid is smaller than 2NM, well below the RNAV-5 stipulated threshold currently valid over the continental Brazilian territory and in accordance with present legislation.

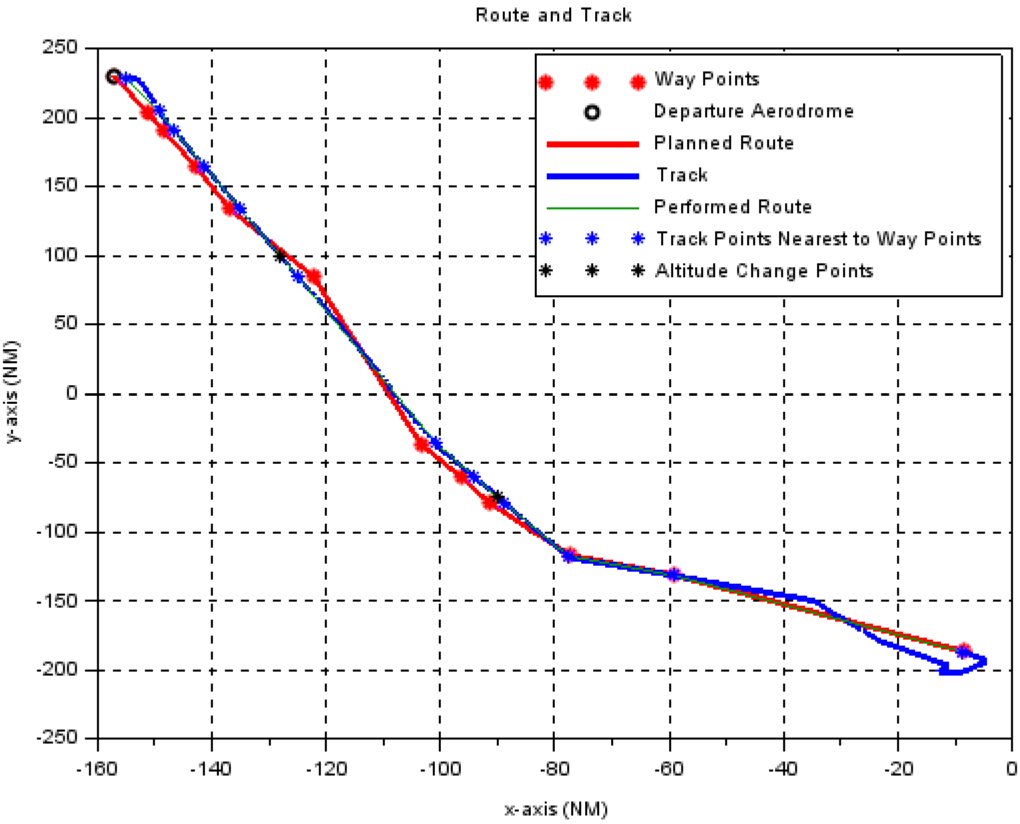

Figure 6: Route and Flight Track analysis for flight XXX1111.

For some selected flights, it was not uncommon to find altitude (Mode C) and speed data to be characterized by an unexpected variation which hampered further use in the current criterion described above.

Flight level (Mode C) data is given with a one hundred feet accuracy resolution. A finer unit of measure would ease prediction comparison. We're currently looking into this issue.

The radar system records Ground Speed (GS), i.e., speed relative to ground which is generally perturbed by wind. In order to obtain True Airspeed (TAS), which is used directly as a reference aircraft speed in the dynamical flight model, wind data must be provided for that location, date and time, and flight altitude.

5.2. Prediction Results

In current ATC systems, Flight routes are subsequently generated by the ATC system Route Extractor from PLN information as a sequence of waypoints linking departing to destination airports. The resulting routes, one for each PLN, are used to input the Trajectory Predictor (TP) which is responsible for computing the time estimates for aircraft "rendezvous" with route waypoints at flight level. Time estimates for aircraft over each route waypoint are now available and serve as reference for intent input to the predictor engine.

In this study, the flight plan routes were fed into the kinetic predictor which generated the corresponding sets of estimates for the same sequence of routes' waypoints. Waypoint estimates from the kinetic predictor was then contrasted to the waypoint flight times derived from multi-radar tracking data for comparison.

Aircraft mass and wind feeds were estimated for use in the kinetic predictor model. At this point a naive estimate was adopted based on historical records, though more elaborate online identification process could be used.

Departure and arrival route procedures can be considered and implemented within the prediction modeling solution through the modeling of SID and STAR charts data, for example. Flights with ATC vectoring during arrivals were specifically avoided due to difficulty in reproducing intent with the flight dynamical model.

Trajectory evaluation was initially tested for the cruise phase. Climb and descent phases were subsequently evaluated. This strategy was adopted in order to better understand the flight dynamical model sensitivity to parameter tuning for a constant speed, leveled flight before considering a relatively more complex model tuning scenario, involving climb, descent, and turn maneuvers.

5.3. Prediction Performance Analysis

The kinetic approach to prediction addresses many important flight configuration parameters and is sensitive to inputs and parameters. The effect of aircraft mass on climb and descent rates is noteworthy. Wind velocity plays an important role in prediction. It affects aircraft motion on all three translational axes directly and, as a consequence, prediction entails accurate wind estimation.

Figures 7 through 9 illustrate the qualitative comparison of the predicted trajectories against truth data given by performed flight XXX1111; the first of the three case studies presented previously. These trajectories were created by inputing a small sequence of twelve (12) flight track data, somewhat evenly distributed over the flight period considered, to the predictor engine. 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. A standard prediction process would, of course, receive route waypoints as input; not track data as in this demonstration trial. These twelve waypoint coordinates were then transformed into continuously differentiable class functions to be used by the guidance and control laws in the flight model for input tracking. Comparison of predicted horizontal motion for flight XXX1111 w.r.t. flight track data is seen in Fig. 7. Notice that for the final portion of flight, related to approach and landing at ADES, predicted trajectory and track data diverge significantly. This can be explained by flight guidance being performed through a STAR chart, and this intent information is not implemented in the predictor engine. Similar divergence effect of predicted and real trajectory curves is observed in Figs. 8 and 9, where altitude and TAS are plotted with time.

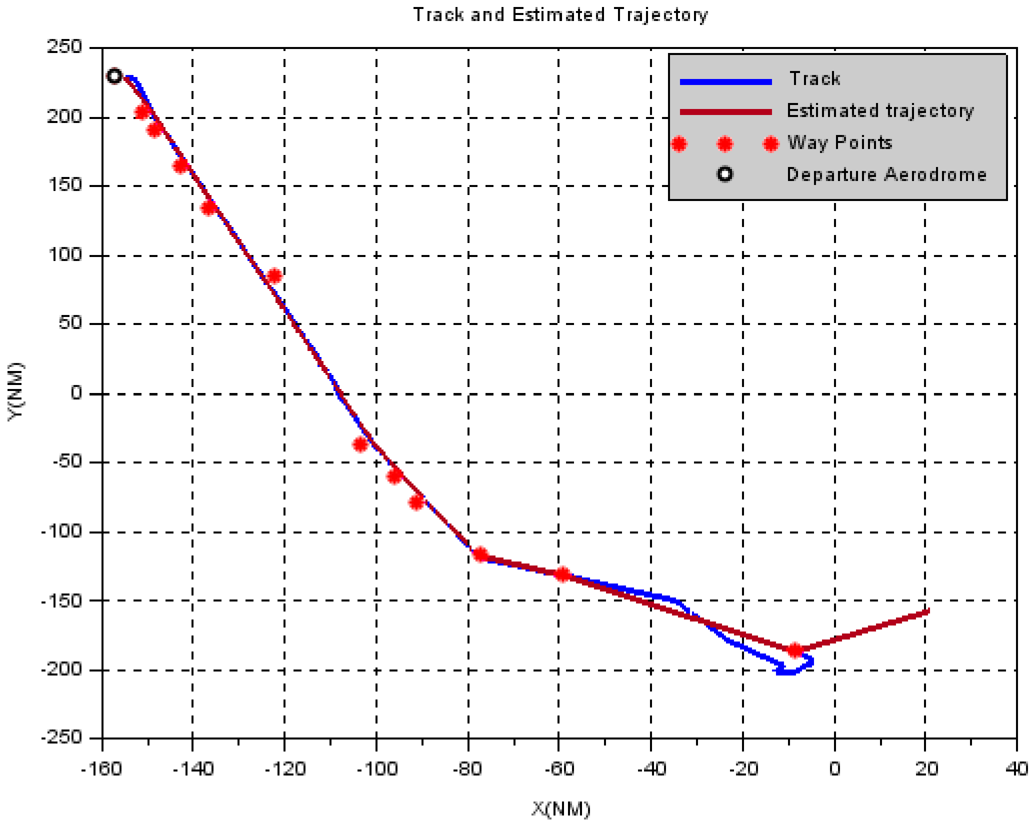

Figure 7: Comparison of the horizontal motion for flight XXX1111 trajectory (radar tracks) and predicted trajectory. Notice, once more, that the predictor was intended to reproduce flight trajectory in this evaluation.

It is understood that there is no need for normalization of trajectories, as suggested in (Torres, 2010), before the utilization of metrics for the comparison analysis since the trajectories under scrutiny come from the same center, do not originate from distinct sources, and are generated under the exact same conditions (i.e., in a research investigation and procedures). Refer also to (Mondoloni, Bayraktutar, 2005).

5.4. Spatial Performance Analysis

This section is focused on the performance analysis using spatial metrics. A few spatial metrics were selected and used for the comparison of TP performance evaluations against flight track data:

- Distance Errors (DE);
- Altitude Errors (AE).

Heading errors (HE) are also a means to evaluate prediction performance. Temporal performance metrics, such as the Time-of-Arrival errors (TAE), are also being currently considered in this research, though a presentation of the evaluation results and the corresponding in-depth discussion accompanying it will be postponed to a forthcoming opportunity. One interesting subject reserved for a future discussion stems from the search effort for a practical definition to trajectory accuracy in the context of *Free Flight*, see (Navarrete, 2006) and the references therein. In the case of gate-to-gate based operations, the flight and taxi duration time could be used as a definitive measure to quantify temporal trajectory performance, amongst other metrics. A relatively more interesting situation would be to measure performance for arbitrary segments of trajectories.

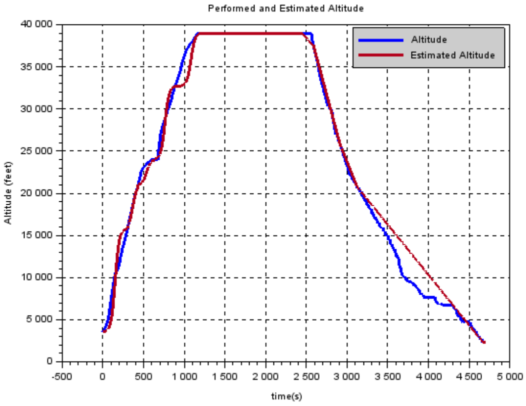

Figure 8: Altitude comparison of flight XXX1111 and predicted trajectories.

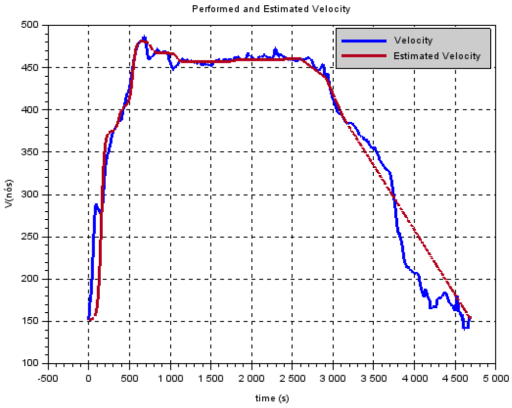

Figure 9: True Airspeed (TAS) comparison of flight XXX1111 and predicted trajectories.

A Distance Errors (DE) metric is introduced as an alternative, for this analysis, to along-track and cross-track errors metrics generally employed for spatial accuracy evaluation. The quantitative comparison for the DE and Altitude Errors (AE) metrics is given in Table 1. We remark that the errors listed in Table 1 are relatively large, when considering model theoretical trajectory and flight tracks. This claim is explained by the fact that the predictor was used to reproduce track data inputs to the flight model implementing the predictor engine itself. Additionally, the fact that a small number of points was used to reproduce real trajectory must also be taken under account. Predicted trajectory for the YYY2222 flight considered only five (5) input points to the flight model; while thirteen (13) input points were used to reproduce flight ZZZ3333. Inputing the high-frequency component observed in flight TAS data, as seen in Fig. 9 for example, would not only be impractical but would be without purpose. The quality of points provided is of great importance: they should indicate when a varying in flight state is happening and this choice of points was not always considered in these trials.

Notice, moreover, 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: Distance (DE) and Altitude (AE) RMS errors for the three flight instances.

Flight *Indicativo*	***DE (%)***	***AE (%)***	**Flight duration**
XXX1111	0,599	1,00	01h17
YYY2222	0,219	0,89	00h30
ZZZ3333	1,000	1,00	00h41

The error values disclosed in Table 1 should be considered of qualitative nature only. This is due to the fact that many versions of flight modeling are currently being investigated for application to trajectory predictor. Moreover, each flight model 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.

Figures 10 and 11 illustrate prediction results for flight ZZZ3333 in terms of flight altitude and true airspeed. A simple visual analysis for these two figures will review very poor flight state reconstruction with the predicted trajectory. This is somewhat deliberate and aims to call attention to the fact that intent information in the form of waypoints provided to the predictor dynamical model was of limited quality and, perhaps, quantity; thus preventing the predictor from computing a satisfactory flight state profile. In essence, the dynamical flight model is unable to predict real flight tracks unless enough data concerning the how the aircraft is supposed to be operated. The flight dynamics incorporated into the aircraft performance model paramount though insufficient for useful prediction.

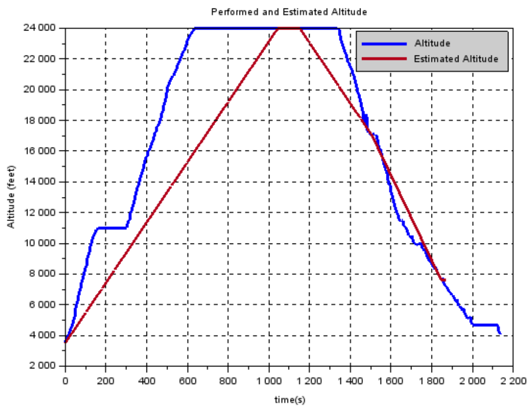

Figure 10: Altitude comparison of flight ZZZ3333 and predicted trajectories.

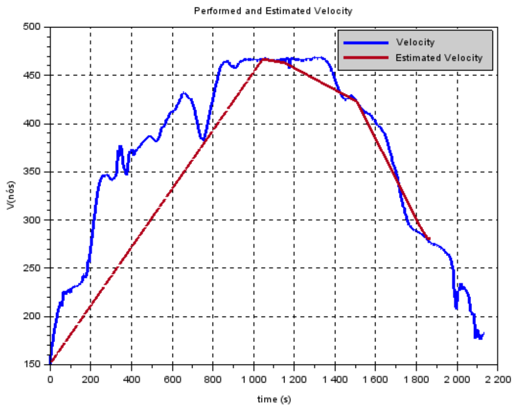

Figure 11: True Airspeed (TAS) comparison of flight ZZZ3333 and predicted trajectories.

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.

Flight YYY2222 is basically a straight line flight, Fig. 12, and prediction on the horizontal plane, measured by the DE metrics, yields a relatively satisfactory performance. Altitude error, measured with AE metrics, is comparable to the other flights because flight level intent was not provided accordingly, see Fig. 13.

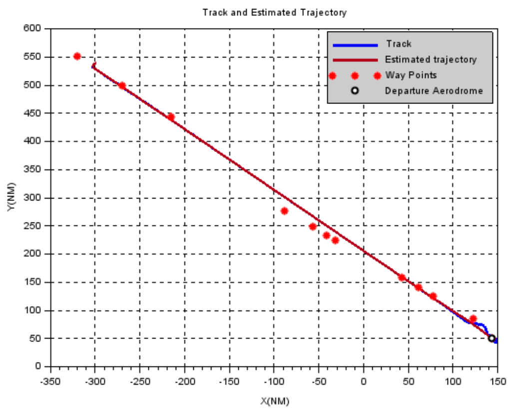

Figure 12: Comparison of the horizontal motion for flight YYY2222 trajectory (radar tracks) and predicted trajectory.

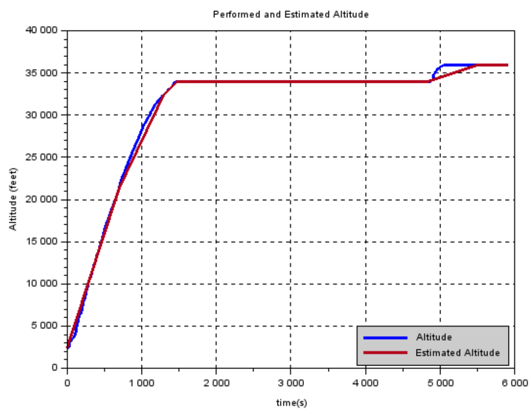

Figure 13: Altitude comparison of flight YYY2222 and predicted trajectories.

6. COMMENTS

The influence of the selected numerical integration technique on the predicted trajectory accuracy and on prediction computational cost can be significant. Appropriate tuning of numerical integration tolerances is recommended to achieve desired accuracy at the expense of computation load on the system. This is paramount when designing ATM/ATC systems decision support tools to address controller workload under new airspace capacity demands. And according to Schuster & Porreta (2010), and others, this is one key limitation that must be overcome.

It is easily observed that the quality of input data directly affects trajectory prediction accuracy, and this has been reported elsewhere (Mondoloni, 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. These can be explained by the fact that required altitude and heading are clearly defined in the flight plan, whereas the accumulation of small aircraft speed deviations because of wind will impact the overall ATE and TAE.

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 [look-ahead-time] 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."

Prediction results are, amongst many others, used to feed the conflict detection service in tactical operation. 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.

Because of the versatility of use, the results also indicate that the kinetic prediction solution being researched in this study shows significant potential for real applications and are expected to achieve the same degree of safety-critical measures as those observed with currently employed prediction engines in the field.

7. CLOSING REMARKS

This note on trajectory prediction evaluation represents an initial effort on devising a thorough systematic and consistent method for achieving required prediction accuracy for future ATC requirements and demands.

The trajectory prediction evaluation process with real flight data requires a great deal of data conditioning and pre-analysis prior to the comparison evaluation itself of distinct trajectories.

Some measure of effort was experienced and dedicated to harvesting and formatting data appropriately for the evaluation analysis just described. This is being addressed in ongoing research intended towards improving the methods employed for a consistent and high-quality TP process.

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 fulfill new operational expectations. Atech is committed to maintain the high level of system critical safety under these new operations.

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10. LIST OF ACRONYMS

ABEAR	Associação Brasileira das Empresas Aéreas
ADEP	Departure Aerodrome
ADES	Destination Aerodrome
ADS-B	Automatic Dependent Surveillance – Broadcast
ADS-C	Automatic Dependent Surveillance – Contract
AE	Altitude Errors
ANSP	Air Navigation Service Provider
ATE	Along Track Errors
ATC	Air traffic Control
ATM	Air Traffic Management
ATS	Air Traffic Service
CPDLC	Controller-Pilot Data Link Communications
CTE	Cross Track Errors
DBS	Data Base System
DDS	Data Distribution Service
DST	Decision Support Tool
EET	Estimated Elapsed Time
EOBT	Estimated Off-Block Time
FAA	Federal Aviation Administration
FDP	Flight Data Processing
FMS	Flight Management System
HE	Horizontal Errors
IATA	International Air Transport Association

LAT	Look Ahead Time	TFM	Traffic Flow Management
ODE	Ordinary Differential Equation	TOW	Take-off weight
REV	Revisualization	TP	Trajectory Predictor / Prediction
TAE	Time of Arrival Errors		
TBO	Trajectory Based Operations	UTC	Coordinated Universal Time