COMMON TRAJECTORY PREDICTION CAPABILITY

FOR

DECISION SUPPORT TOOLS

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Abstract

Trajectory prediction capabilities are an essential building block for most if not all Air Traffic Management Decision Support Tools (DSTs). DST applications range from en route to terminal operations with advisories ranging from passive flow suggestions to active clearance/instructions. Many past DSTs have been fielded with their own unique trajectory prediction capability. The objective of this paper is to identify significant performance factors and design considerations for developing a Common Trajectory Prediction Capability. A system engineering approach is used to resolve key design issues and tradeoffs such as the balance between prediction accuracy and computational speed for a variety of DST applications. Controller intent uncertainty, the major source of prediction error, is mitigated by the control advisories of advanced DSTs that close the control loop. Key aspects of a common trajectory prediction module are presented including an approach to dynamically adapt the performance to support a range of DST applications. The characteristics of different aircraft performance models, the flight path integration logic and software implementation issues are also discussed.

Introduction

The future development of the Air Traffic Management system is based on the high level objectives to improve the four ATM key performance areas viz. Safety; Capacity; Efficiency; and the nugatory impact of the aviation industry on the Environment. Following a top-down strategy, these high level objectives are translated into Operational Improvements, which are realized through an Operational Concept. This Concept describes the characteristics of the air and ground components of the ATM system and how the human actors are assumed to interact with them. Typical examples of Decision Support Tools are Medium Term Conflict Detection functions, Arrival and Departure Management tools and tools that support Multi-Sector Planning functions. The performance of these tools is directly related to the accuracy with which the future evolution of the streams of traffic is predicted and the time required to compute the flight profiles.

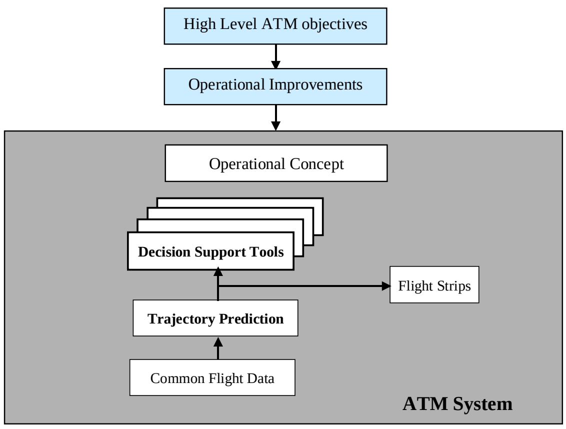

Figure 1 TP Context diagram

The Trajectory Prediction (TP) module is one of the kernel functions of the Flight Data Processing System. The importance of a common TP capability is emerging as a critical topic within the US and European ATM communities. Although performance factors and requirements vary with application, the physics of flight dynamics remains the same. In the future, co-operative ATM systems may use the trajectories computed by the on-board Flight Management System (FMS). However, it is expected that, for the short to medium term future, the ATM systems will continue to rely on ground-based trajectory calculation.

The context diagram in Figure 1 illustrates how the Trajectory Prediction module acts as a server to various clients like Flight Plan Processing and Decision Support Tools. The Trajectory Predictor module is a client to several server applications, e.g. the flight plan server, the radar track server, the environment server, the meteorological data server and servers providing aircraft operating procedures and aircraft performance models. For simplicity, these servers are considered to be combined in a Common Flight Data Server.

The Trajectory Prediction process

The Trajectory Predictor module computes the future flight path of aircraft on the basis of flight intent, an aircraft performance model and an estimate of the meteorological conditions. The information is delivered to the TP clients as a sequence of vectors describing the aircraft state over time. The data content depends on the information requirements of the client application. In addition to time, altitude, latitude and longitude, it could include airspeed reference, ground speed reference, an indication of the uncertainty and the confidence level, etc.

Decision Support Tools need predicted flight profiles with significantly better performance than applications in legacy Flight Data Processing Systems. In this context, “performance” refers to the *accuracy* and the *confidence* level with which the flight profiles are computed and the *speed* with which the computation is performed. A*ccuracy* is the measure of the difference between the observed and the predicted value of a trajectory state. The c*onfidence* level reflects the probability that a defined level of accuracy will be achieved at a given look-ahead time. The *speed* is related to the time that the TP needs to respond to a client request for a flight path calculation.

Trajectory Prediction uncertainties

Spread in aircraft performance

The trajectory prediction function needs to support the different aircraft types that operate in the target airspace. Besides commercial jet aircraft and propeller aircraft, these may also include helicopters and military fighters. The spread in aircraft performance in the vertical plane is significant. Figure 2 depicts the spread in vertical speeds during climb observed from some 10,000 commercial flights [1]. The 5th and 95th percentiles of the distribution of the vertical speeds for climbing traffic is shown. The dotted line in the centre represents the mean values. The distribution of the vertical speeds during descent shows a similar pattern.

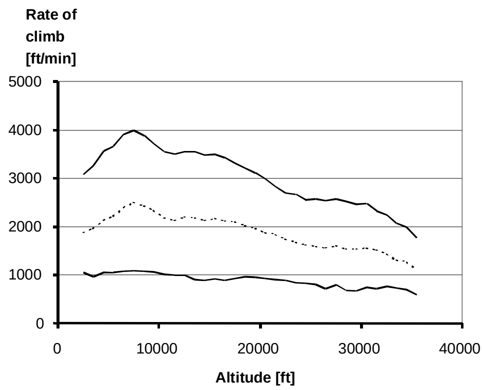

Figure 2 Spread in vertical speeds during climb.

Uncertainties in input data

This spread in performance is due to, inter alia, the spread in engine thrust and aerodynamic drag, the way the aircraft were operated, the aircraft mass and the meteorological conditions. Uncertainties in the different parameters directly affect the accuracy and the associated confidence level of the predicted flight profiles. The aircraft mass has an important impact on the accuracy of the predicted vertical speeds during climb and descent, the operational flight envelope, the acceleration performance and the selected speeds for take-off and landing. The uncertainty in the predicted wind speed vector directly affects the along track prediction error whilst the variation of the wind speed with altitude has an impact on the performance of the aircraft in the vertical plane. The uncertainty in the Outside Air Temperature (OAT) data may affect the output thrust of the engines and, thus, the vertical speed during climb. A thorough and quantitative treatment of the magnitude and impact of the uncertainties in the input data is beyond the scope of this paper. They are well identified in prior works that qualitatively describe all the vertical profile error sources and the specific flight test measurements of TP errors [2, 3, 4, 5].

Commercial aircraft are operated on constant Indicated Airspeed (IAS) or Mach number. Consequently, errors in the vertical plane of the flight profile will have an impact on the accuracy with which the progress in the horizontal plane can be predicted.

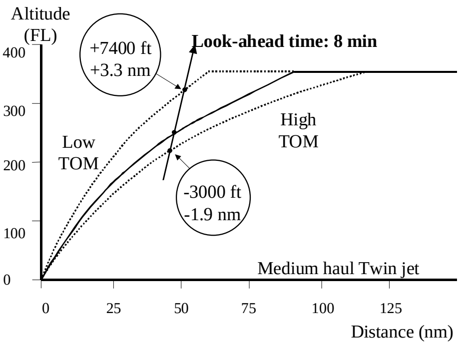

Figure 3 Impact of Mass uncertainty on vertical and longitudinal progress

This is illustrated in Figure 3. It depicts the extent of the error values in the vertical and the horizontal plane as a result of uncertainty in the Take-Off Mass (TOM) [6].

Uncertainty in pilot intent

Pilot intent comprises the information on how the aircraft is operated. This includes flight controlled by the Flight Management System. Uncertainties in pilot intent include, inter alia, the moment at which a transition to a new flight phase is initiated and the selected thrust setting, aircraft configuration, air bleeds and airspeeds. A detailed discussion on the impact of pilot intent uncertainty is outside the scope of this paper. Results from field evaluations of cruise-descent profiles are reported in [7]. The impact of uncertainties in pilot intent on the accuracy of predicted trajectories can be reduced by down-linking the intent information [3] or through conformance inferencing.[8].

Uncertainty in controller intent

The uncertainties in Controller intent are probably by far the largest source of error in flight profile prediction. The controllers are tasked to ensure separation and mitigate congestion. To solve these ATM problems they will modify the planned flight profiles. One of the factors contributing to the uncertainty in controller intent is the unpredictability of the actions taken by the individual persons: the specific techniques for conflict resolution and de-congestion vary per controller.

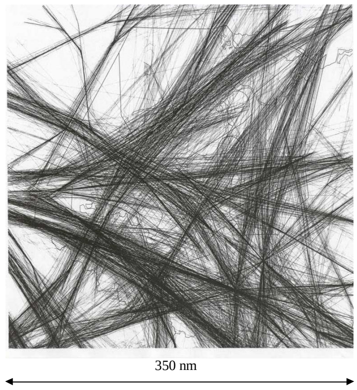

Figure 4 Radar tracks in Maastricht UAC

Reference [9] reports on the comparison between aircraft trajectories predicted on the basis of active flight plans in the Maastricht Upper Airspace Control Centre and radar track observations of the profiles actually flown. Figure 4 shows the recorded radar tracks in plan view. Although all flights are planned via a fixed, underlying route structure, this can only be recognized with difficulty.

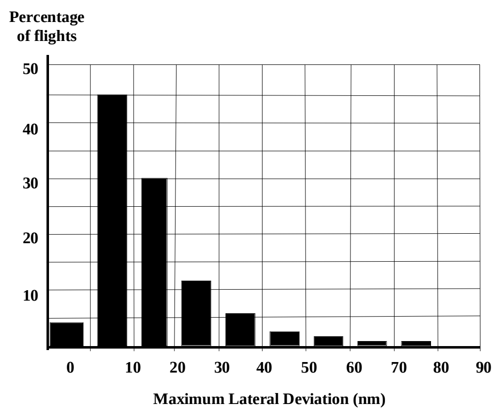

Figure 5 Maximum lateral deviations

Figure 5 presents the distribution of the maximum lateral deviations between the predicted routes and the observed tracks through the control area.

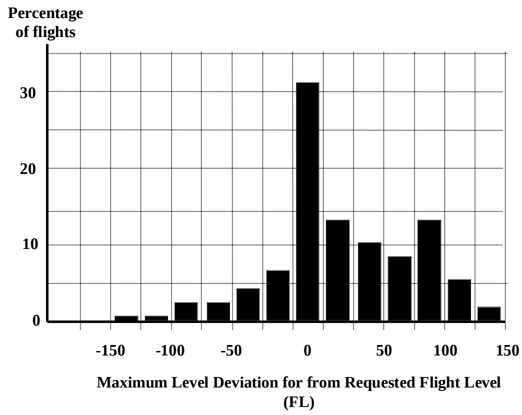

Figure 6 Maximum vertical deviations

Figure 6 presents the distribution of the maximum differences between the requested cruise levels and the observed ones. In this analysis only level flights were considered.

Although certainly not all the differences can be contributed to uncertainty in controller intent, they do illustrate the severity of the problem.

Uncertainty in longitudinal progress

From an application point of view, it is practical to express the uncertainty in the longitudinal progress as a unit of distance per minute look-ahead time. The lowest, realistic uncertainty along track amounts to 0.13 nm/min-look-ahead-time with a confidence level of 65 %. This results from the assumption that the aircraft speed can be measured and maintained with an accuracy of at least 1 %, the wind vector errors can be predicted with an uncertainty better than 7 kt rms and that the uncertainty of the temperature has a standard deviation of 2 ^{0}C. The analysis of radar track observations of aircraft in stable, horizontal flight conditions confirms this. From a data sample of more than 1300 flights performed in the airspace of Maastricht UAC, an uncertainty of 0.2 nm/min.-look-ahead-time with a confidence level of 1 SD was deduced [10]. Similar results were found in [11]. It can be expected that the uncertainty will increase rapidly, when level or heading changes are also included.

Common TP design considerations

Integration with DSTs

The designers of Decision Support Tools need to accommodate the limitations in the accuracy of the predicted trajectories. The performance of DSTs with a “basic” functionality level, like URET, MTCD and operational Arrival Mangers, is directly affected by the prediction errors that increase with the look-ahead time. Reference [12] reports that, on the basis of the “best possible” trajectory prediction data, at 20 minutes look ahead time, two out of three detected conflicts would not have materialized in real life. In a live operational environment the situation will be significantly worse. The designers of basic conflict detection tools reduce this “false alert rate” by decreasing the probability that all conflicts at the target look-ahead will be detected. This is achieved by lowering the required “Confidence level” [11, 13].

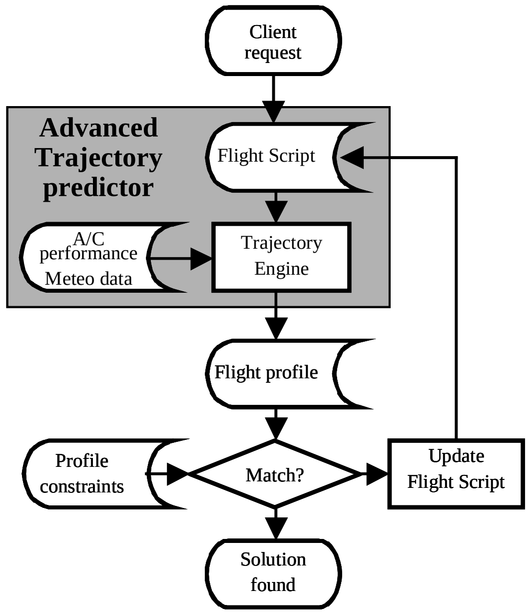

Figure 7 Constraint matching for advanced DSTs

Instead of coping with reduced confidence levels, superior performance requires a reduction in TP uncertainties, the most significant source being intent error. One system engineering approach is to leverage advanced DST capabilities that "close the loop" on intent by providing controllers with active advisories for sequencing and spacing. Many critical intent errors are associated with congested airspace. Sequencing and spacing actions (for managing congestion) often result in undocumented flight plan deviations. Even less flight plan intent is maintained in terminal operations. However, advanced DST capabilities for merging and spacing not only provide controllers with advisories for managing congestion, they also provide insights into flight intent needed to improve TP and conflict probe performance. This approach is depicted in Figure 7.

The Trajectory Predictor computes the flight profile on the basis of a “Flight Script”. This is the data container that comprises the flight specific input data, like the present aircraft position, the flight plan, the current and considered ATC clearances and instructions, etc. The “Trajectory Engine” is the process that translates the flight script into the predicted flight profile. This consists of a sequence of vectors describing the aircraft state over time. The data content depends on the information requirements of the client application. Besides time, altitude, latitude and longitude, it could include airspeed reference, ground speed reference, confidence indication, etc. Subsequently, the computed flight profile is compared against the profile constraints, managed by the DST. If the match is insufficient, then the intent information in the flight script will be updated and a new flight profile will be computed. This process is often referred to as the “closed-loop” approach. Typical examples of advanced Decision Support Tools that use this approach are the Arrival Management tools CTAS [14] and Zone of Convergence (ZOC) [15] and the Conflict Resolution Assistant, CORA [16].

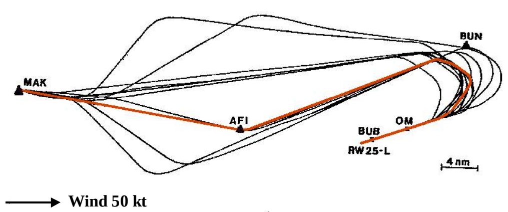

Figure 8 Managing uncertainty in controller intent

The flight profiles depicted in Figure 8 from [17]. are an illustration of what is achievable. The data result from real-time flight trials using a B757 flight simulator from British Airways. For each of the flights presented, the transit time from start at MAK, FL 100 to touchdown was identical. Shortly after the start of the exercise the controller would send a tactical clearance to the aircraft simulating a potential conflict with other traffic. Subsequently, the ZOC Arrival Manager would generate the tactical advisories to facilitate the touch down at the target time. Although the wind conditions were adverse (50kt from 270 degrees) all flights landed within a 10 second margin from the target time. The air-ground communication during the exercises was standard R/T.

TP performance requirements for advanced DSTs

The Arrival Management task requires a DST or a series of DSTs which operate with target delivery time accuracies that vary with the remaining distance to key convergence point(s) (e.g. for merging and metering). Ultimately, advanced Arrival Management tools need to deliver the aircraft at the touchdown point with accuracy in the order of 10 sec.[6]. To achieve this accuracy, the “closed-loop” method requires a calculation granularity that is significantly smaller (e.g. the example system of [17] uses 2 sec. accuracy during the last 20 nm). The generation of the “best next advice” to the controller sometime requires the calculation of up to 60 alternative trajectories per radar information update cycle. Besides accuracy, reduction of the trajectory calculation time also becomes paramount.

Architecture of an Advanced Trajectory Prediction Engine

To meet the requirements of the basic and advanced DSTs and the Flight Data Processing System by a single, common Trajectory Predictor it is required to be able to control the balancing of system accuracy and speed during the calculation process in a convenient way. The CINTIA (Control of inbound trajectories for individual aircraft) trajectory predictor [18] is an example of such a component. Its architecture is shown in Figure 9. Four sequential processing steps can be identified, viz. the parsing of the Flight Script; the definition of the integration step, the calculation of the step in the vertical plane and the calculation of the step in the

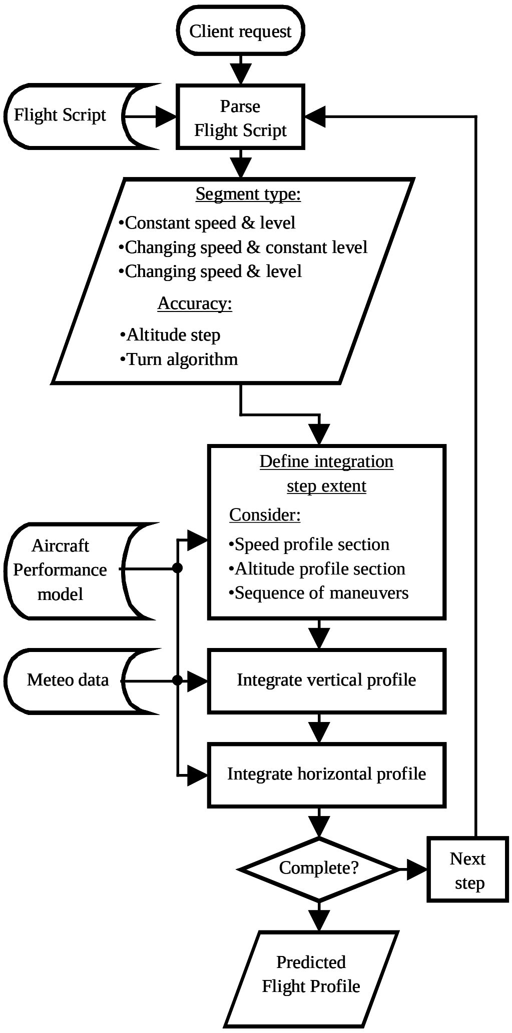

Figure 9 Advanced Trajectory Engine

horizontal plane. The total process is repeated until the complete flight path is computed.

Structure of flight script

The flight script describes, in detail, the pilot intent and how the transition between the sequential flight segments will be performed. Typically, in an advanced Trajectory Predictor, the flight script has four independent sections describing the speed profile; the altitude profile; the sequence of maneuvers and the general flight information and calculation instructions.

For every integration step the Flight Script is parsed. This process defines the type of segment to be computed in the next step and the calculation algorithms to be used in function of the accuracy level required. A description of the Flight Profile Description Language developed to code the flight script can be found in [18].

Integration using dynamic time steps

Controlling the extent of the integration step performs the balancing of the requirements for accuracy and calculation speed. For maximum calculation efficiency the trajectory integration step should be as large as possible whilst ensuring the target accuracy and confidence levels. If required, intermediate data points can be computed through linear interpolation. This holds that the integration step size varies in function of the complexity of the flight segments. Cruise segments flown at constant speed indication and constant level can be accurately computed with a large time step whereas a turn requires a very small time step. The target accuracy of the computed flight profile is controlled through the information contained in the “calculation instructions” in the flight script. These comprise e.g. the maximum altitude step, the turn algorithm to be used, etc. These data may vary over the flight path so that the calculation accuracy can be optimized in specific areas of the flight path.

As an example Figure 10 presents the number of calculation steps per minute elapsed time for a 120 nm cruise-descent flight path computed by the CINTIA TP. The peak in calculation steps around the 1200 sec flight time results from the calculations of the base turn and turn to the intercept leg.

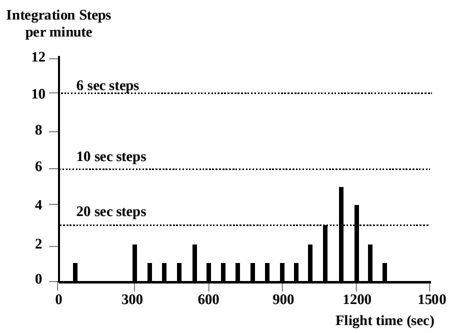

Figure 10 Integration steps

The diagram illustrates that a reduction in calculation of a factor 4 is quite feasible whilst minimizing potential degradation in accuracy.

Impact of turn algorithms

Depending on the level of fidelity used, the dynamics of the turn may be calculation intensive. The impact of the turn algorithm used on the accuracy of the computed flight path depends largely on the extent of the change in heading. For the prediction of en-route flight profiles, which often have small heading changes, it is quite acceptable to assume instantaneous turns. Operation in Terminal Areas is different. Here, sometimes large turns are required, in particular for aircraft arriving via a down-wind leg. In [3] the “instantaneous turn” method is compared with a “circular-arc” turn algorithm, which assumes that the maximum bank angle of 25 degrees is achieved instantaneously. An along track error of 1.4 nm and an off-track error of 1.5 nm are reported for a heading change of 80 degrees at 400 kt True Air Speed. Depending on the client application, the latter algorithm may still not be sufficiently accurate. Figure 11 depicts the difference in accuracy between the “circular-arc” turn and a turn computed assuming a gradual increase/decrease of the bank angle with a roll-rate of 3 degrees per second.

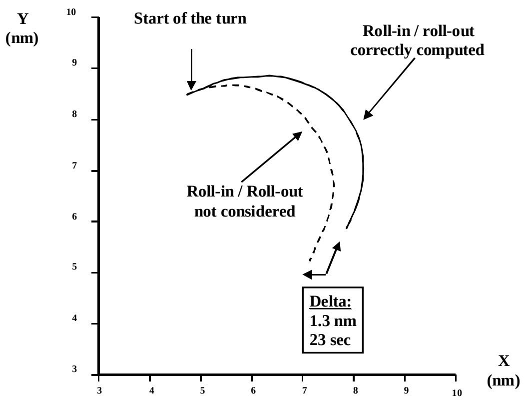

Figure 11 Impact of roll-in/roll-out on calculation accuracy

The operational scenario assumed a base turn from down wind with a heading change of 140 degrees. The wind is 30 kt from 270 degrees. During the turn at 2000 ft, the aircraft decelerates from 250 to 210 kt. CAS. The actual roll rate depends on the aircraft type and how it is operated. For such a turn, considering the effect of roll-in/roll-out is important as the aircraft encounters a tail wind at the start of the turn and operates at a lower speed in a head wind at the end.

In an efficient trajectory prediction function all three algorithms should be considered, i.e. *instantaneous* turns for small heading changes, *circular-arc* turns for intermediate heading changes and *roll-in/roll-out effects* should be considered for large heading changes. Similar considerations apply for the changes in airspeed that can occur during the turn maneuver.

Choice of aircraft performance model

For ATM applications, the aircraft behavior may be simplified to a differential system with three degrees of freedom [19] consisting of :

- ❖ A set of equations of motion based on seven dependent state variables, namely position (3), speed (3) and mass (1);
- ❖ Three dependent, non-derived control variables, namely geographical heading, angle of attack and power setting;
- ❖ A set of two scalar relations describing aerodynamic lift and drag.

The exact solution of this set of equations of motion requires significant data processing resources and an extensive set of performance data. In a practical ATM situation, many uncertainties in the input data exist. Therefore further simplified approaches may be considered that significantly reduce the time required to calculate the trajectories without leading to an important degradation of the overall accuracy.

The aircraft performance model defines the performance of the aircraft in the vertical plane, the acceleration/deceleration capabilities and the operational flight envelope within which the aircraft can be safely operated.[1]. There are two main approaches to aircraft performance modeling for ATM applications: the *kinetic* and the *kinematic* approach.

Following the *kinetic* approach, the aircraft behavior is computed from the newtonian equations of motion that use independent models for the thrust

[1] The model is completed by a description of the instantaneous fuel flow from which the aircraft weight data can be updated and the emissions of greenhouse gasses can be estimated. Independent models exist for the estimation of aircraft noise.

and drag forces that affect the centre of gravity. The aircraft manufacturers use accurate kinetic models for the generation of the aircraft performance manuals, e.g. the INFLT and OPAL programs of Boeing Aerospace and PEPC of Aerospatiale. The performance tables of these models often contain more than 1 Mbyte of data. For ATM applications, a compressed version of the tables can provide sufficient accuracy. The aircraft performance model used in the trajectory predictor in the CTAS tools is a good example of what is achievable [20].

In the *kinematic* approach, the aircraft behavior is directly described through a set of look-up tables or polynomial functions without attempting to model the underlying physics. The GAME database (General Aircraft Modeling Environment) is an example of this approach [21]. GAME provides a large set of function definitions that, in most cases, facilitate the integration process in the vertical plane by a single function call.

The Base of Aircraft Data, BADA [22], is a “pseudo kinetic” method developed to support enroute ATC simulations. The aircraft behavior is computed using a simplified set of equations of motions, but these refer to pressure altitude rather than geographical altitude. The thrust and drag estimates are computed through polynomial approximations. The simplicity of the functions used does not cater for the discontinuous effects of engine “flat rating” with altitude and the compression effects on the aerodynamic drag at high speeds.

The target accuracy for the kinetic model used in the CTAS tools is 5% for the vertical speeds in climb and descent [20]. Figure 12 shows the summary of average approximation errors in the vertical speed for the GAME and the BADA performance models using the PEPC manufacturers performance data as a reference. The data relate to constant CAS climbs of an A319 aircraft and cover the complete operational flight envelope. The white areas in the figures represent achieved error levels of less than 5 %. The Figure shows that the GAME kinematic model has an approximation error similar to the kinetic model used in CTAS. The BADA method shows a lower accuracy level.

A comparison in calculation performance between the BADA and the GAME approaches has been made using the same Application Program Interface [23]. For all aircraft state calculations, the GAME model was at least three times faster than BADA. The calculation performance of the CTAS model was not assessed. However, as the CTAS model uses a more complex set of equations than BADA, it may be expected that the calculations take longer.

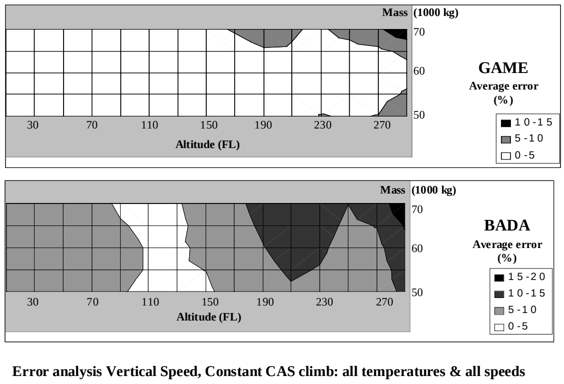

Figure 12 Comparison of GAME and BADA vertical speed accuracies for constant CAS climb

Performance inference

The uncertainty in aircraft performance can be partially mitigated through Performance Inferencing. The use of observed radar history in combination with intelligent Conformance Monitoring can significantly improve the uncertainties in aircraft data, meteorological conditions and, sometimes, pilot intent [24], while controller intent remains as another issue. Due to the simplicity of the approximation functions, it may be expected that a kinematic performance model, like GAME, will be more efficient than the kinetic models.

Software Implementation strategies

When pure calculation performance is paramount, the use of modern object oriented software development techniques is not so obvious. During the development of the CINTIA trajectory predictor, anecdotal evidence was developed, indicating that careful software design and the use of “traditional” programming languages lead to an improvement in calculation efficiency by a factor eight [25].

For the integration of the Trajectory Prediction function with the DST clients often pure software solutions are chosen, based on “middle ware” architectures. There is anecdotal evidence that using modern hardware architectures consisting of

Multiple Symmetrical Processors driving large shared memories can be significantly more efficient [25].

Conclusions

The objective of the paper is to assist the development of a Common Trajectory Prediction Capability to support ATM Decision Support Tools. The efficiency of such tools depends to a large extent on the performance of the Trajectory Predictor, i.e. the accuracy of the predicted aircraft state in function of the look-ahead period, the confidence level of the estimated accuracy and the time required to compute the predicted flight profile.

The impact of the uncertainty of input data that affect the accuracy and confidence levels of the predicted profiles are discussed. The use of performance inferencing techniques to improve the input data quality is very promising and should be developed. The use of downlinked aircraft data may further improve this process.

Controller intent uncertainty is a major source of prediction error. This can be mitigated by the use of control advisories generated by advanced DSTs that close the control loop. This approach requires the higher accuracy requirements of advanced DSTs to be addressed through the design of the trajectory prediction function itself.

Key aspects of a common trajectory prediction module are presented including an approach to dynamically adapt performance to support a range of DST applications. Maximum TP performance is achieved by providing flexible means to balance dynamically the accuracy and calculation speed requirements. This requires special attention for the optimization of the interaction between the Trajectory Prediction Engine and the data structures contained in the Flight Script and between the Trajectory Prediction Engine and the Aircraft Performance model. The example of the CINTIA TP illustrates that cruise-descent profiles with an extent of one hour flight , can be accurately computed within 1 mSec.

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Keywords

Trajectory prediction, Decision Support Tool, Intent, Performance balancing, Flight Script, Trajectory Engine, Aircraft Performance Model, Software implementation.

Biographies

Sip Swierstra is responsible for the Centre of Expertise for Trajectory Prediction at Eurocontrol Headquarters in Brussels, Belgium. After graduating as an electronics engineer he joined Eurocontrol in 1973. He has been working on aircraft performance modeling, trajectory prediction and the application of these techniques in advanced ATM tools, in particular the Arrival Management concept “Zone of Convergence”.

Steven Green manages NASA's en route ATM research. An instrument-rated pilot, he received a M.S. degree (Aeronautics & Astronautics) from Stanford University, and joined NASA Ames in 1985 to pursue ATM research. One of the four CTAS "founders," he led the development and field testing of the CTAS Descent Advisor and pioneered NASA's concepts for integrating FMS and ATM automation through data link. Mr. Green co-chaired RTCA's FMS-ATM-AOC Integration Work Group. Currently, he is the co-lead for NASA's Distributed Air-Ground Traffic Management (DAG) effort, and is developing Regional Metering enhancements to the CTAS TMA.