IMPACT OF FACTORS, CONDITIONS AND METRICS ON TRAJECTORY PREDICTION ACCURACY

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Abstract

As a central component of decision support tools, trajectory predictors require accuracy levels commensurate with desired DST performance. In this paper we decompose trajectory prediction accuracy as due to a collection of factors influencing trajectories under specific operational conditions. We discuss the use of "error signals" to report the impact of each factor from which multiple accuracy metrics can be derived. We illustrate how the definition of the derived metric will influence the magnitude and potentially the relative ranking of the effects of various factors. The paper shows that the influence of many factors is approximately linear and how the results of a sensitivity study can be used to approximate a scenario under a wider set of conditions. The results of such a sensitivity study can also be applied to investigate interoperability between DSTs using disparate trajectory predictors.

Introduction

The current vision of the future of the National Airspace System in the US, and the implementation of the European Air Traffic Management plan rely, in part, on the use of decision support tools (DST) to provide improved service to the user community under increasing traffic demand [1-3]. Furthermore, on both sides of the Atlantic, these strategies emphasize the measurement of system performance for the purposes of continual improvement.

The quest for improved decision support tools is driven by their promise to provide benefits in controller productivity and hence to accommodate forecast growths in air transportation while maintaining or improving the current level of service. Air traffic management research and development has provided a substantial collection of decision support tools that provide automated conflict detection/resolution [4-6], trial planning [7], controller advisories for metering and sequencing [8,9], traffic load forecasting [10,11], weather impact assessment [12-14], etc. Central to the function of many of these decision support tools lies the ability to properly forecast future aircraft trajectories. As a result, trajectory prediction and the treatment of trajectory prediction uncertainty continue as active areas of research and development (e.g., [15-23]).

Prior investigations of trajectory prediction performance have often been focused on the evaluation of DST performance [4,5,7,16,24,25]. This is natural, as the performance of DSTs relying on trajectory prediction will be tied to the quality of the predicted trajectory. Other investigations have focused on stand-alone trajectory prediction and methods for improving these (e.g., [15,17-20,22-24]). Investigators reported a wide variety of factors responsible for trajectory prediction uncertainty such as: wind modeling, undocumented procedures, ATC operations, aircraft performance, weight, track data, radar-based velocity estimates, departure uncertainty, etc.

In addition to there being a wide collection of factors influencing trajectory prediction accuracy, different measures of accuracy and TP-related DST-performance measures were reported. One commonly reported measure was a root-mean-squared along-track positional uncertainty consistent with a model of uncertainty presented in [4]. However, other measures included: vertical errors [26], time history of along-track errors [17], mean and standard deviation of arrival time prediction errors [16], probability of predicting an altitude within a tolerance of the actual during transition at a fixed look-ahead time [27], etc. These measures were typically related to the function and the conditions of interest to the decision support tool being investigated.

Regarding function of the DST, different measures of trajectory prediction performance will be relevant to different decision support tools. For example, short-term conflict alert may be concerned with positional uncertainty at a five-minute look-ahead horizon, medium-term conflict detection may be concerned with positional uncertainty over a 10-20 minute range, and metering tools would focus on the accuracy of arrival time forecast at a metering fix.

When we speak of the conditions of interest to a decision support tool, we are referring to the operational conditions under which the DST would operate. Examples of these include: phase of flight, dynamics of traffic (e.g., are there many turns and path-stretches), and weather situation. The conditions are likely to impact the choice of performance measures applicable to the trajectory predictor as well. For example, vertical prediction precision is applicable to tools operating in transition.

One of the consequences of different performance measures being reported in the research is the added difficulty in comparing results between research projects. Additionally, the measures of performance influence the choices made during DST development to improve those measures. These choices affect several aspects of trajectory prediction including: the fidelity of the prediction model and the quality of the data used to drive that model. As an example of the impact on fidelity of the model, a DST providing path-stretch advisories would likely require turn modeling, whereas this may be less important to a long-term sector load predictor. Applications concerned with descent, and using a "kinetic" aircraft model, could improve prediction through downlink of aircraft parameters [28]. This latter case represents improvements in input data quality.

With differences in modeling approaches and input data, different decision support tools will likely operate on inconsistent trajectories with different uncertainty characteristics. This fact can lead to some interoperability issues when various DSTs are combined at a system level. At a recent technical interchange meeting on the subject [29], various researchers reported this same interoperability concern resulting from DSTs operating on discrepant trajectories. This interoperability issue was also brought to the forefront during the PHARE demonstrations (e.g., [30]). While further interoperability issues can develop if the decision support tools do not consider their impact on each other, reconciling that impact becomes more challenging when the underlying trajectories are inconsistent.

In an effort to understand and document the effect of factors and conditions on trajectory prediction, one of the points of Action Plan 16 – Common Trajectory Prediction Capabilities – was to investigate the impact of various factors under relevant conditions. Using this as a starting point, this paper presents a sample of data from this sensitivity study. In particular, we focus on the following aspects:

1. Impact of metric selection – different metrics may exhibit differing sensitivity to certain factors.
2. Impact of operational conditions – the operational conditions will dictate the level of sensitivity to a particular factor.
3. Impact of factor – under any given condition and for any metric, a rank of the impact of factors will be presented.

One important aspect that is not considered in this paper is the notion that some accuracy improvements can require increases in computational expense. Thus, when dealing with interoperability concerns, an additional factor to consider would be the DST-specific timeliness requirements on trajectory prediction.

Trajectory Prediction Context

Reference [31] presented a useful model of the ATM control structures. This has been modified and duplicated within Figure 1 to depict decision support tool functions and the role of the TP within various DSTs.

The role of the trajectory predictor is to model, based on available information, the behavior of the region labeled the 'TP modeling domain'. While one approach would involve attempting to simulate every detail within the TP modeling domain, most trajectory predictors apply various levels of abstraction. In Figure 1, we refer to this abstraction as the prediction model (M). In order to obtain a predicted trajectory, the prediction model operates on the input data. These models require input data that we separate into two broad classes: intent and other input data. The reason for this segregation is due to the possible application of intent inferencing engines (e.g., [32]) to improve the intent information

Decision Support Tools take the output of the trajectory predictor and either present a forecast of a situation (e.g. a conflict, a sector overload), or iterate with the TP to obtain an advisory (e.g., a path-stretch maneuver to meet metering objectives). Errors in trajectory prediction will impact the outcome and eventual performance of the DST.

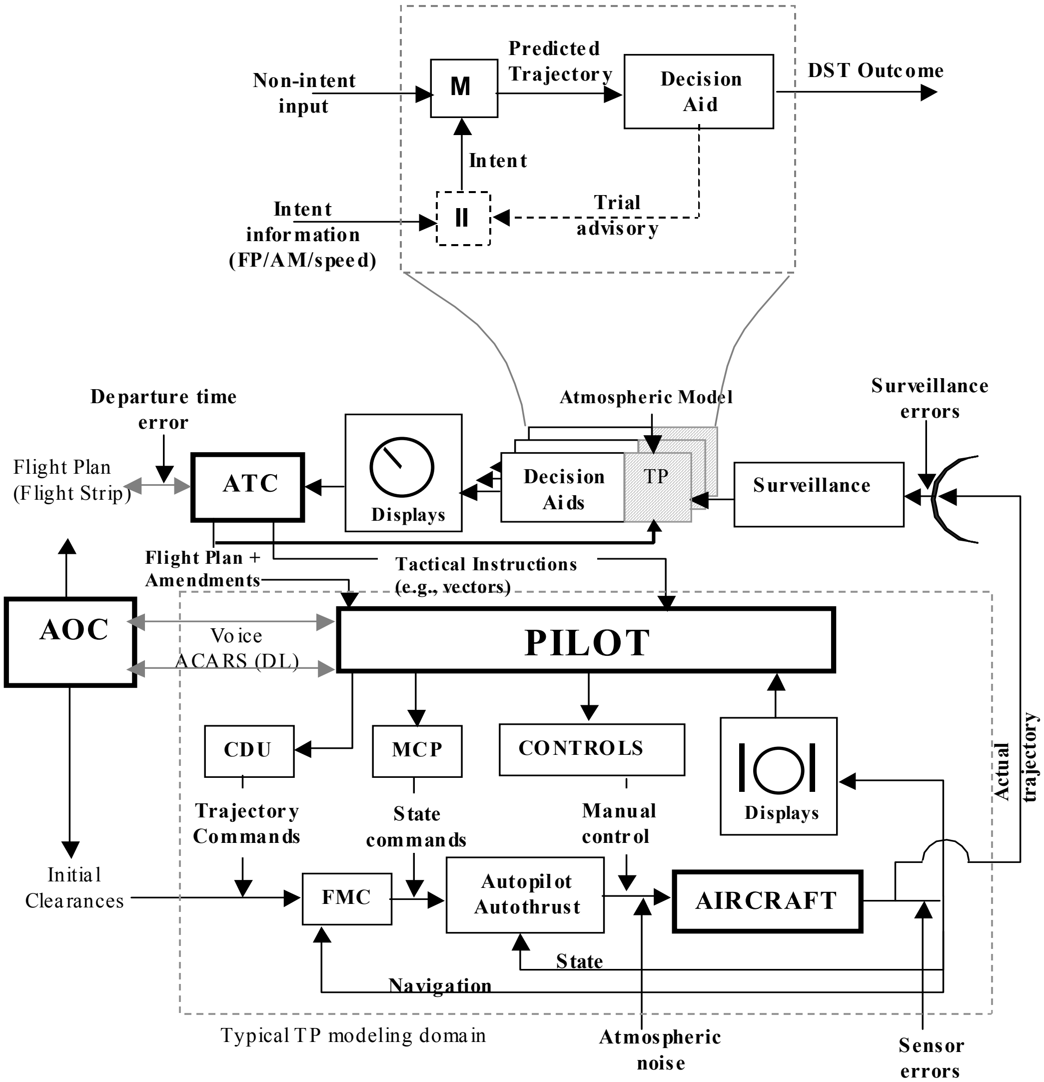

Figure 1 ATM Control Structure [31] and ground-based DST Model

Since trajectory prediction has been decomposed into three parts, the error contribution due to each part can also be classified in the same manner. Trajectory prediction errors stem from: modeling errors, intent errors or other input data errors. This broad classification can sometimes be useful when reconciling differences between TPs where certain elements are known to be common.

When we refer to trajectory prediction errors for a specific DST, we are typically comparing the *predicted trajectory* for a specific DST to the *actual trajectory* to be experienced by an aircraft. Discrepancies between these two types of trajectories typically affect the performance of the DST.

When multiple DSTs are offering advice and information to ATC, discrepancies can occur between the predicted trajectories of two DSTs. These discrepancies lead to interoperability issues between the DSTs.

As an example, consider the application of two DSTs with different trajectory predictors. While these may operate on the same intent information, they may have different models (e.g., kinetic/kinematic) and require different sources of information. The individual performance of each DST will be determined by differences between the actual trajectory and the respective predicted trajectories. However, interoperability issues will arise due to discrepancies between the two predicted trajectories. Furthermore, since intent is consistent between the models, other input and modeling differences likely drive interoperability.

Decision Support Tools

Our initial investigation of trajectory prediction fidelity was limited to flight segments above 10,000 feet. In this section, we discuss the applicable types of decision support tools.

One of the primary services provided by Air Traffic Control is that of separation assurance. This service is supported with conflict detection and resolution tools. These span the range from basic conflict alerting function [33], to conflict detection functions [4-6], to conflict resolution tools in various stages of development (e.g., [12,34]). These tools operate in various ranges of interest from one minute out for conflict alert to up to 20 minutes for medium term conflict detection. Predictions are based on a range of trajectory predictor types and data. Shorter-term tools base their predictions on filtered and extrapolated aircraft state vectors, while longer term predictors require higher-order models of intent and requisite data to support those. Intent-based tools exist with either kinetic or kinematic models of trajectory prediction.

Other types of functions provided by DSTs (within the domain of interest) include sequencing, metering, weather impact assessment, and traffic load forecasting [8-14]. Tools providing metering and sequencing have a range of approximately 20 minutes and use kinetic trajectory models. Metering tools have been integrated with conflict resolution functions using identical trajectory prediction [9]. Traffic Flow Management (TFM) DSTs (weather impact, and traffic load forecasting) deal with longer time-horizons from a half-hour to three hours out. Predicted trajectories for TFM applications do not use kinetic models and recently have focused on quantifying the temporal uncertainty [11,21].

Trajectory Prediction Metrics

Measuring trajectory prediction performance begins with the comparison of trajectories. Most trajectory error metrics are *derived* from a vector random signal that is the evolution of the differences between state vectors. As discussed in [35], these comparisons can be spatial or temporal and may require synchronization. Figure 2 illustrates a temporal comparison. The bottom curve represents one measure (e.g., ε_j=along-track error) as a function of look-ahead time (t) based upon a forecast at t_0. When comparing a noisy source (e.g., radar) to a forecast, it is useful to project onto the more stable trajectory (i.e., the forecast).

In order to derive statistics for these curves, a set of such error signals would be generated in one of two manners:

1. A set of many signals could be generated by allowing the prediction time t_0 to vary along the flight
2. A set of many flights would be evaluated under the same set of circumstances (e.g. with t_0 being fixed at an event such as top-of-descent)

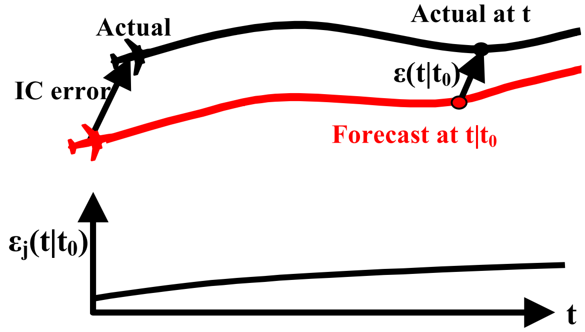

Figure 2 Comparison of actual to predicted trajectory

While the first case appears to be the common approach for trajectory predictions in cruise, if the error signal is dependent on the initial prediction time (t_0), the second set would provide more useful measures. For example, during climb the altitude error is not just a function of look ahead, but depends on when the prediction was made. The resulting efficacy of DSTs using these forecasts will be affected as well. Figure 3 illustrates the altitude profile error during climb.

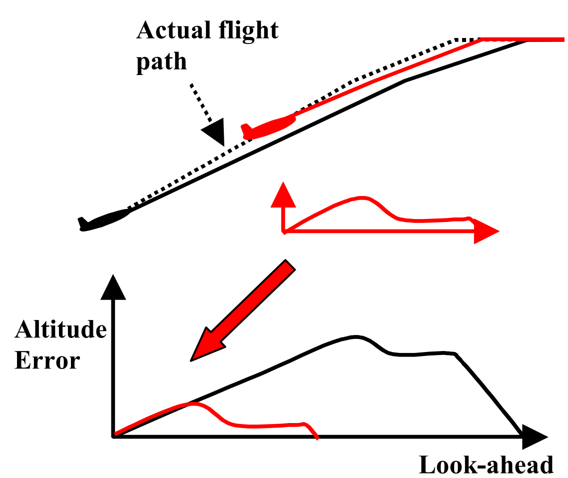

Figure 3 Altitude error as a function of look-ahead

When deriving means from these sets, the first set would yield time averages, whereas the second would provide ensemble averages (for N flights) as calculated in the following manner.

$$\varepsilon_j(t_{LA}) = \int_0^T \varepsilon_j(t_{LA} + t_0 \mid t_0)\,dt_0$$

$$\left\langle \varepsilon_j(t \mid t_0) \right\rangle = \frac{\sum_{k=0}^{N} \varepsilon_j(t \mid t_0)_k}{N}$$

Once the type of data set and the underlying measure (along-track, cross-track, time at a point, vertical error) has been established, the standard metrics can be derived from that set (average, rms, standard deviation, peak, etc.).

Another consideration when developing metrics for trajectory prediction has to do with large, infrequent errors. These include substantial errors in intent that, while infrequent, are of sufficient magnitude to affect statistics considered above. Certain reported measures capture these effects; for example, [27] looked at the frequency with which flights exceeded a vertical error bound. Depending on the frequency, trajectory prediction may still be suitable and should not be discounted based upon statistics skewed by these infrequent events.

Infrequent errors can be geographically and temporally dispersed, as for many intent errors, or can be geographically and temporally correlated. This can occur as a result of large wind and temperature errors occurring as demonstrated in [36]. Frequency of large errors is insufficient to capture the impact, as large errors could affect 5% of the flights across the year, or affect all flights 5% of the time. Operational suitability of a TP is likely to be affected by the type of error being reported.

Factors Affecting Prediction Accuracy

We conducted a parametric analysis of trajectory fidelity by first determining the relevant factors that determine trajectory prediction accuracy in the portion of flight above 10,000 feet. These were initially obtained by first brainstorming all the factors affecting: cross-track, vertical and longitudinal uncertainty. A joint team of FAA-MITRE and NASA engineers with trajectory prediction experience categorized these factors and ranked them in terms of perceived importance. This initial list was subsequently reviewed, as part of activities under AP-16, by a team of experts from Eurocontrol. The high-impact factors are detailed below.

1. Intent error – vectors: Deviations from the expected route of flight and the turn back to the route have a significant effect on cross-track and along track error.
2. Intent error – TOD: Knowledge of the top-of-descent location is limited due to errors in predicting when a clearance will be provided, automation input latency and latency in pilot execution.
3. Intent error – Interim altitudes: Automation may not have knowledge of interim altitudes and does not have access to the duration of the level off.
4. Intent error – Speed: Uncertainty in the speed intent will affect aircraft climb/descent rates and the along-track location.
5. Intent error – Altitude crossing restrictions: Knowledge of altitude crossing restrictions can help prediction, but prediction of when the descent is initiated remains uncertain.
6. Aircraft performance: Models of aircraft performance are subject to modeling errors due to simplification, erroneous data or due to variations between airframes.
7. Wind: For a given true airspeed, errors in the along-track wind will affect the ground speed and hence the predicted position. During a climb and descent, errors in the wind will affect the altitude profile of a flight.
8. Aircraft weight: Knowledge of the weight of an aircraft allows TPs to better predict climb and descent profiles.
9. Wind gradient modeling: Certain predictors do not include the effects of wind gradient on climb or descent. Neglect of this term can have a significant effect on the altitude profile.
10. Turn modeling – Certain predictors do not include the effect of modeling turns. This will affect both the cross-track and along track error.

Many more factors were initially considered (e.g., flight technical error). However, the above listed factors were determined to be the ones with the largest influence. For this reason, we only investigated the above factors.

Impact In Descent

As an example of the trajectory fidelity investigation, we discuss the impact of various factors in descent. The impact of a specific factor is evaluated by first generating a baseline trajectory for an aircraft under specific conditions. These conditions include: atmospheric conditions, aircraft type, aircraft weight, number of turns, cruise flight level, bottom of descent location, etc. The specific factor is then parametrically perturbed to compute a perturbed trajectory. The baseline and perturbed trajectory are then compared to yield an error signal in altitude and along-track as shown in Figure 4 for a 10% change in speed. This shows a co-temporal example; a co-spatial case would have distance on the abscissa.

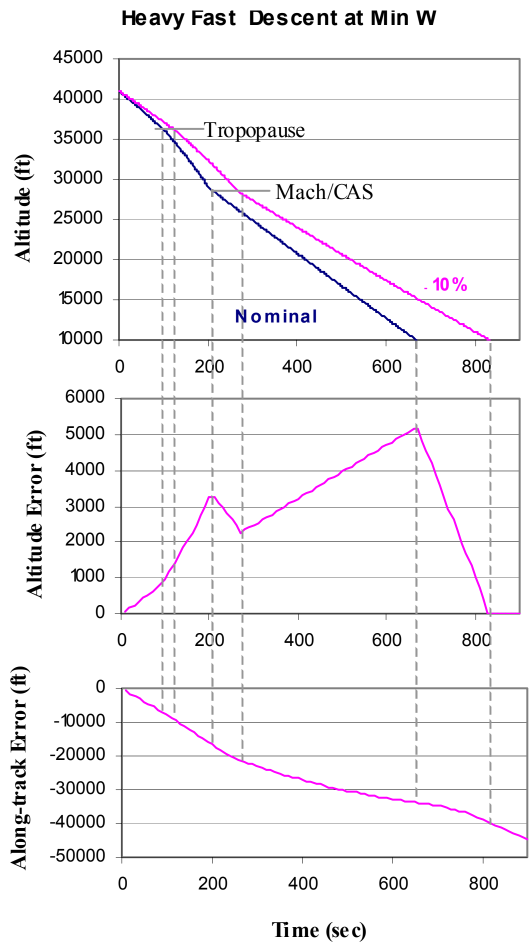

Figure 4 Example calculation of error signals

As part of the fidelity investigation, we compute error signals for multiple conditions and for the factors previously discussed. From the error signal, we can derive some commonly reported metrics and report these errors for each parameter being varied according to the magnitude of that variation. Here we present four cases for each factor as shown in Table 1. For example, we computed the impact of errors from –10% to 10% in the weight of a flight and wind bias errors from –20 to 20 knots.

Table 1 Parameter values for each factor

Factor	Errors			
TOD – NMI	2	5	10	25
Co-temporal level-off – MIN	1	2	3	4
Co-spatial level-off – NMI	5	10	15	20
Acft perf - % drag error	-5	-2.5	2.5	5
Weight - %	-10	-5	5	10
Wind Grad – kts/1000'	-3	-1.5	1.5	3
Turn Model – NMI of PS	5	10	15	20
Vector intent – NMI of PS	5	10	15	20
Wind Bias – KTS	-20	-10	10	20
Speed Intent - %	-10	-5	5	10
Color in Charts				

The figures that follow show the difference in the impact of each factor on various metrics. Each color on the bar chart represents the magnitude of the factor errors reported in Table 1. Figures 5 and 6 show the co-temporal peak altitude error for a large jet under two descent conditions: heavy/slow compared to light and fast. Two level-off factors were considered, one below the M/CAS transition (1) and another above (2).

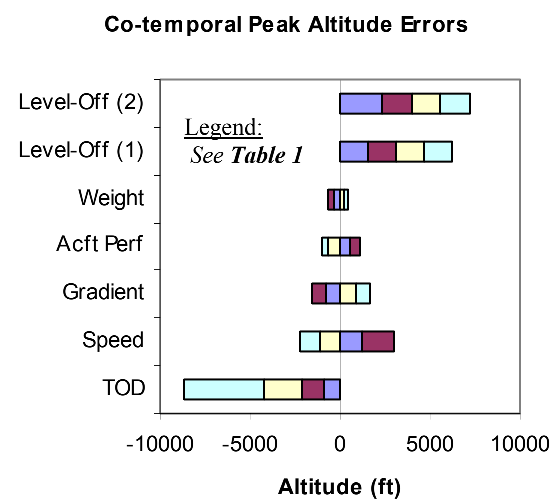

Figure 5 Co-temporal peak altitude errors in descent for a slow and heavy large jet

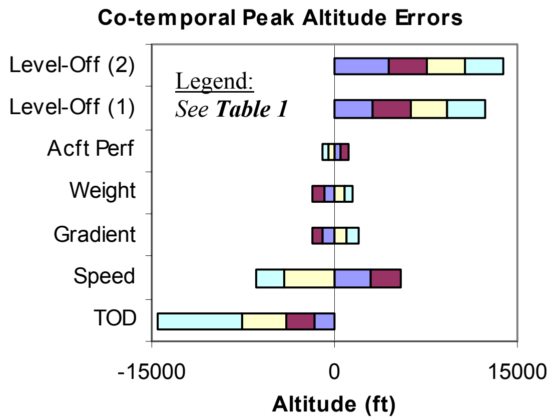

Figure 6 Co-temporal peak altitude errors in descent for a fast and light large jet

We note that the conditions here (base weight and descent speed) have a substantial impact on the magnitude of virtually all errors (except wind gradient and aircraft performance). For example, the impact of a 25 NMI top-of-descent (TOD) error changes from a peak altitude error of 8625 feet to 14566 feet due to the baseline conditions. We note that the relative magnitude of these factors remains similar, with slightly more emphasis on weight error for the lighter case.

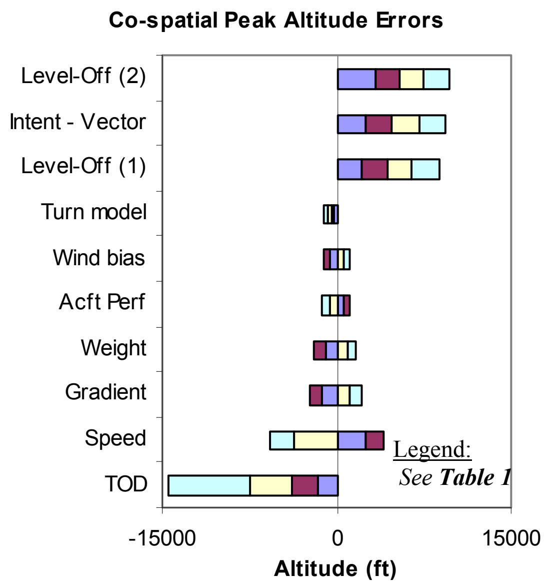

Figure 7 Co-spatial peak altitude errors in descent for a fast and light large jet

In the case of the co-temporal metrics measured from top-of-descent, certain errors are zero (lateral errors, wind-biases and the neglect of turns). However, these appear when we consider the same metric using a co-spatial synchronization as shown in Figure 7 for the light and fast condition. Note that the ordering and relative magnitude of the sensitivity to each factor is similar regardless of the use of co-temporal or co-spatial synchronization.

Regarding the intent errors (e.g., top-of-descent, level-off, vectors), while these appear significantly larger than other factors, these are reported in the preceding figures as the error contribution, *when the intent error occurs*. Since intent errors only occur some fraction of the time, the eventual average contribution of these errors will be reduced.

One commonly reported metric is the along-track error as a function of look-ahead time. Figure 8 illustrates the impact of factors on a 10-minute look-ahead from top-of-descent. Looking at the ranking of the factors, the impact of wind is significantly greater than for altitude errors. Also, proper modeling of turns increases in impact for this metric.

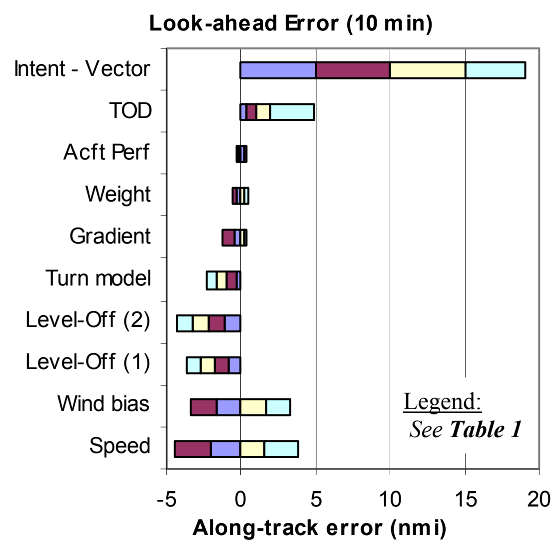

Figure 8 Along-track error at 10-minute look-ahead for a fast and light large jet

We also investigated the impact on metering fix arrival time prediction as shown in Figure 9. As expected, the results are similar to the along-track error case. However, in this scenario the bottom-of-descent was fixed to ensure the metering fix was being reached. In the prior scenarios, the top-of-descent was used as a reference point (except for the cases with an error in the top-of-descent).

For most of the accuracy metrics investigated, the error contribution due to a factor scales approximately linearly with the error in the input factor. Thus, a 10% error in weight yields about twice the resulting error as a 5% error in weight. However, along-track and time errors due to omission in the climb gradient did not scale linearly.

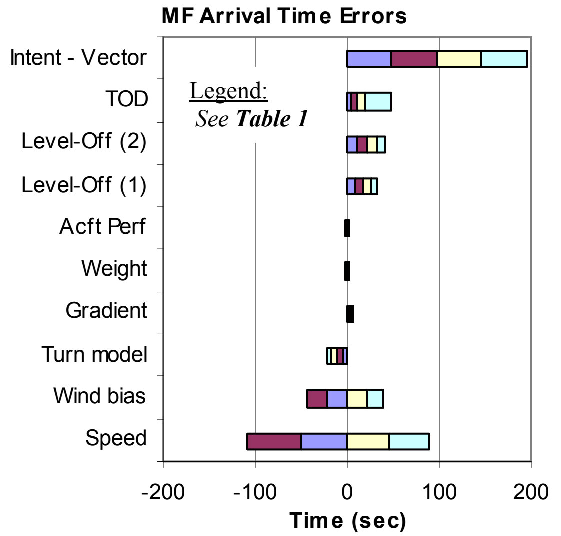

Figure 9 Metering fix arrival time error for a fast and light large jet

Application to a Scenario

Once we have parametric data (as error signals shown previously) for a variety of aircraft types operating under a variety of conditions, we can obtain errors for specific metrics derived from these signals. Using the linearity of the metrics with the error in the factor, we can approximate the contributions due to specific cases. For example, knowing that we have a 9% error in weight, we can estimate the contribution due to that factor.

In Figure 10, we simulated a case of 700 flights sampled across the NAS using a single day's weather. Each flight was subject to errors in each factor sampled from a distribution. The errors were computed from an ensemble-averaged signal. We assumed that altitude level-offs would be imposed on 27% of flights and vectors on 23% of arrivals per observations of operational data. We obtained distribution on duration and magnitude of vectors from the same operational data in transition. Various aircraft types were modeled and the nominal speeds were sampled from descent speed distributions for the specific aircraft models. We also show in Figure 10 the approximation that can be obtained by scaling the uncertainties obtained in Figure 8. More accuracy can be obtained by combining information from a variety of aircraft types in proportion to the data in the sample. This is particularly evident for the error due to aircraft performance, as this is likely to be sensitive to the aircraft type. Also, the magnitude of the vectors observed in our sample data was smaller than the values used in our parametric study. Our wind bias approximation could have been improved through scaling based upon the proper distribution of headings for all flights, rather than assuming a uniform distribution.

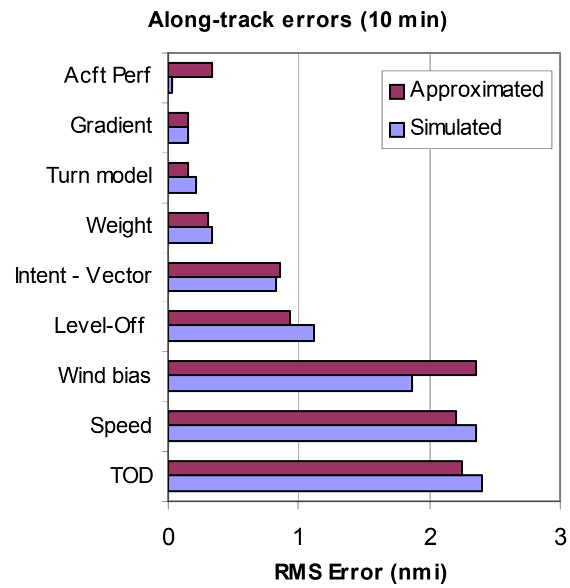

Figure 10 Along-track errors at 10 minutes from TOD for a sample of descents

We have shown here an example illustrating the evaluation of the expected accuracy of trajectory prediction due to certain factors. The same methodology can be applied to investigate the interoperability question of disparate predictors. In this case, the error signals are comprised of the difference between one predictor and a separate predictor.

These differences can arise when predictors have modeling differences (e.g., the gradient term or the turn modeling is not included), the predictors may or may not have access to adequate intent information (e.g., down linked speed intent or top-of-descent information), or some information is simply not used by one of the predictors. For example a predictor may not use aircraft weight information, but substitute some value as a proxy in a lookup performance table. In this case, the weight uncertainty effect would have to be estimated based upon the uncertainty associated with using the proxy for aircraft weight.

Conclusion

When evaluating trajectory prediction accuracy for decision support tool applications three areas have been discussed: factors, operational conditions, and metrics. We have discussed some of the error factors that can drive the accuracy of trajectory prediction in the en route domain. Improvements in TP accuracy have largely been focused on these factors. By drawing upon results from a trajectory fidelity investigation, we have shown how the operational conditions being evaluated can drive the magnitude and the relative importance of each factor considered. Furthermore, the application of different metrics to evaluate performance can result in different priorities for model or data improvement.

We have presented an example of the sensitivity of prediction accuracy due to various factors under specific conditions. By reporting an error signal from specific events, many metrics can be derived and combined to estimate the errors under a set of disparate conditions.

In addition to applying this method for investigating prediction accuracy, the interoperability of various predictors can also be investigated.

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