

# IMPROVING TRAJECTORY FORECASTING THROUGH ADAPTIVE FILTERING TECHNIQUES

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## Abstract

An adaptive Kalman filter is presented to provide improvements in short-term (5 to 20 minutes) trajectory forecasting. The approach treats the wind uncertainty as a random process with an autocorrelation function of known form. The filter estimates the current contribution of the wind uncertainty and estimates the future position given that future wind uncertainty will be correlated with the current wind uncertainty. The adaptation algorithm obtains the model parameters by looking at recorded data and can be applied in a real-time setting. Since the model adapts to measured data, the model does not require data exchange and should handle non-stationary processes that vary slowly.

A simulation was developed of the aircraft longitudinal equations of motion incorporating the effect of wind uncertainty. Simulation results show a potential reduction of trajectory forecasting errors between 70% at 5-minute look-ahead to 40% at 20-minute look-ahead. A sensitivity analysis revealed that the full longitudinal aircraft model is required for improvements below 5 minutes look-ahead, but a simplified model can be used for larger look-ahead times.

The filter was applied to a sample of radar data and reduced the trajectory forecasting uncertainty from 1.4 to 1.0 nautical mile at a 10-minute look-ahead. As an example, the impact of such a reduction on conflict probe performance was analyzed. Both missed and false alerts could be reduced and the buffer size could also be reduced to maintain a constant missed alert level.

## Nomenclature

$\underline{x}$	State vector
A, B, M	Matrices in state model
$\underline{u}$	Control vector

$\underline{y}$	Measurement
$\eta$	Elevator control
K	Control law or Kalman gain matrix
E[ ]	Expected value
$\underline{u}$	Speed perturbation
a	1/ wind perturbation time scale
$\tau, t$	Time
$\omega$	Frequency
w	Unity white noise
$a_1, a_2$	Terms in wind noise matrix
$\alpha$	Angle of attack
q	Pitch rate
$\theta$	Flight path angle
h	Altitude perturbation
$\Phi$	State transition matrix
$\beta$	Wind noise scale factor
Q	Wind noise co-variance matrix
R	Measurement noise co-variance matrix
v	Measurement noise
z	Measurement
H	Matrix relating measurement to state
P	Error covariance matrix
$\lambda$	Simplified longitudinal response parameter

## Subscripts & Superscripts

rms	Root mean squared
k	Time step
w	wind
$\wedge$	Estimate

## Introduction

Modernization of the current National Airspace System (NAS) is reliant on the development and deployment of automation and decision support systems (DSS). This is evidenced in descriptions of future concepts of operation for the NAS from both the FAA [1] and NASA [2]. The reliance on automation is not only limited to the USA, but is also evident in the strategy for the future European ATM system [3].

The drive to increased automation promises to deliver increases in efficiency, improvements in service quality, and better coordination and planning. However, the degree to which automation can deliver the promise is highly dependent on the ability of the automation to forecast the future state of the NAS. For example, the performance of conflict probe is largely based upon the accurate forecasting of future aircraft positions (e.g., [4], [5]). Future decision support tools such as the en-route/descent advisor (EDA) have also been shown to exhibit increased benefits with improved trajectory prediction [6]. While DST performance may also be affected by forecasting other aspects of the NAS (e.g., weather, outage status, load), this paper focuses on improving the accuracy of trajectory forecasts.

Errors in trajectory forecasting are the result of two basic causes: errors in modeling or errors in input data. Modeling errors include the omission of specific terms in the equations of motion (e.g., use of instantaneous turns, exclusion of the wind gradient modeling term, or errors in aircraft performance model). Errors in the input data include lack of intent, inaccuracies in obtained current aircraft position, errors in wind forecasting, errors in departure time, temperature errors and flight technical errors. Many of these errors are described in the literature (e.g., [7], [8], [9], [10] and [11]) along with the impact of the errors on trajectory prediction accuracy. Naturally, errors stemming from exclusion of modeling terms can be reduced through the inclusion of known terms in the equations of motion. Information exchange ([6],[12]) can be used to reduce input errors for certain cases when one participant possesses higher fidelity information (e.g., sharing intent, sharing weight information). However, errors in input data pose more of a challenge if the input data is only known to a certain degree of accuracy. One such term is the wind uncertainty.

Errors in wind forecasting translate into errors in estimating the ground speed, and integrate into future positional uncertainty. Early investigations (e.g. [4], [12]) expressed the trajectory forecasting accuracy as growing linearly with a growth rate of between 7 to 15 knots. With this kind of growth rate, a twenty-minute prediction yields an error of 2.3 to 5 miles.

More recent investigations [13] have found wind uncertainty with expected rms values of 10 knots

with RUC-1 and 7.2 knots with augmented winds. However, the wind uncertainty was also found to contain a significant number of hours for which the rms errors were significantly larger (e.g., up to 30 knots). One therefore cannot assume that the wind errors encountered by an aircraft are stationary.

Within the air traffic management domain, efforts to improve the accuracy of trajectory forecasts due to wind uncertainty have led researchers to improve the wind forecasting (e.g., [13], [14]). For example, migration to RUC-2 was reported to reduce the rms vector error by 0.5 – 1.0 m/s (1-2 kts). Other efforts [12] have relied on the data linking of wind reports via ACARS to improve the DST knowledge of the winds. This latter effort provided improvements of 10-15% in along-track prediction error.

One may argue that migration to four-dimensional contracts may mitigate the need to improve trajectory forecasting, as aircraft will be capable of controlling to a desired trajectory. However, end states not relying on 100% equipage and transition to the end state are still likely to benefit from improved trajectory forecasting.

This paper presents an alternative approach for improving trajectory forecasts through application of known Kalman filtering techniques. The approach can be applied to ground-based decision support tools without requiring additional data exchange or collaboration on the part of the flight deck. The approach relies on knowledge of the dynamic response of aircraft to changes in the wind, and uses knowledge of the statistical properties of the wind to obtain the best estimate the future aircraft state. This approach is well defined in the literature (e.g., [15], [16]).

Since the statistics of the wind are known to be variable, an adaptive scheme is used to compensate for winds with variable statistical properties. This type of approach has been used in [17] to provide estimates of the wind experienced by a re-entering space shuttle.

## Longitudinal Aircraft Dynamics

Analysis of the impact of wind on an aircraft begins with a state-based description of the longitudinal linearized aircraft dynamics as shown below.

$$\dot{\underline{x}} = A\underline{x} + B\underline{u} \quad (1)$$

$$\underline{y} = M\underline{x} \quad (2)$$

Where, equation (1) can be expressed as:

$$\begin{bmatrix} \dot{u} \\ \dot{\alpha} \\ \dot{q} \\ \dot{\theta} \\ \dot{h} \end{bmatrix} = [A] \begin{bmatrix} u \\ \alpha \\ q \\ \theta \\ h \end{bmatrix} + [B][\Delta\eta] \quad (3)$$

References [18] and [19] can be used to obtain the matrices A and B. Each element of the state vector represents a perturbation away from an equilibrium value. We did not include the impact of the throttle, as we are applying the filter to situations for which flights are applying constant power. Also note that we are primarily concerned with the effects of wind on the aircraft trajectory forecasts; thus we elect to neglect the impact of high-frequency aeroelastic modes.

We model the closed-loop response of the aircraft by assuming an altitude-hold mode using the following control law. We neglect servo dynamics.

$$\begin{aligned} \Delta\eta &= [0 \quad -k \quad 1 \quad k \quad k_2] \underline{x} \\ &= K\underline{x} \end{aligned} \quad (4)$$

The control law is selected to provide increased damping of the phugoid and short-period modes while keeping the deflections reasonable.

### Wind Uncertainty Model

A simple model is selected for the wind uncertainty. We begin by assuming that the wind uncertainty can be expressed, in the aircraft reference frame, as a random process with a specified autocorrelation function. For the along-track error, we are only concerned with the longitudinal component of the wind uncertainty. The wind autocorrelation term is simply assumed to be Gaussian with an unknown time scale. This yields the following autocorrelation function for the wind error. Note that the wind uncertainty is assumed to be highly correlated close in time, with diminishing correlation as observations are further in time.

$$E[u_w(t)u_w(t+\tau)] = u_{rms}^2 e^{-a^2\tau^2} \quad (5)$$

This model is not meant to represent the *exact* autocorrelation function of the wind uncertainty. Instead, we are attempting to present a model of the wind error relevant to the trajectory-forecasting problem. For example, turbulent fluctuations would be concentrated at high frequency, but would likely not have an impact on the trajectory forecast. In Figure 1, we compare our model to the measured autocorrelation of a flight's speed perturbation from a mean. Clearly the model captures the salient features of the curve.

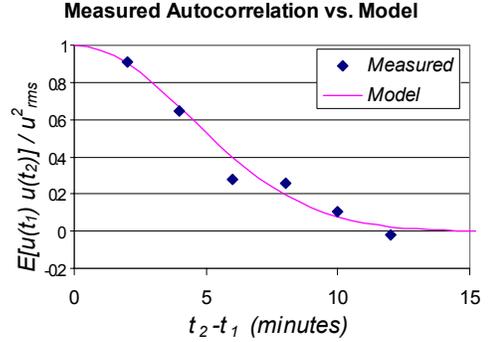


Figure 1. Comparison of measured autocorrelation function to model

### State-Vector Augmentation

Using the wind uncertainty autocorrelation function described in (5), we obtain the power spectral density (PSD) of the function and *approximate* the PSD with the following representation.

$$\left( \frac{\sqrt{\pi}}{a} \right) \frac{u_{rms}^2}{1 + \omega^2/4a^2 + \frac{1}{2}(\omega^2/4a^2)^2} \quad (6)$$

By applying spectral factorization techniques to the above, we can design a state-based model of the wind. The wind ( $u_w$ ) is modeled as a second order process driven by unity white noise ( $w$ ) as shown below.

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -a_1 & -a_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ w \end{bmatrix} \quad (7)$$

$$u_w = [b_1 \quad 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad (8)$$



## Results of Simulation

We determined the degree to which the filtering algorithm can improve a forecast of the future position of a flight by conducting simulations of a flight, using the equations in (10) as representative of “truth”. These equations were driven by unity white noise ( $w_k$ ). We verified that the autocorrelation function of the simulated wind corresponded to the desired autocorrelation function of the wind. A model of a “generic” jet transport was used. The first simulation assumed that the airspeed was being measured every 30 seconds.

Figure 3 compares the simulated versus estimated value of the altitude error. The simulation assumes a wind rms error of 10 knots and a characteristic time ( $1/a$  in (5)) of 1000 seconds. Even though we are only observing the airspeed, the Kalman filter can obtain the altitude for this scenario. The filter can also obtain other aircraft state variables.

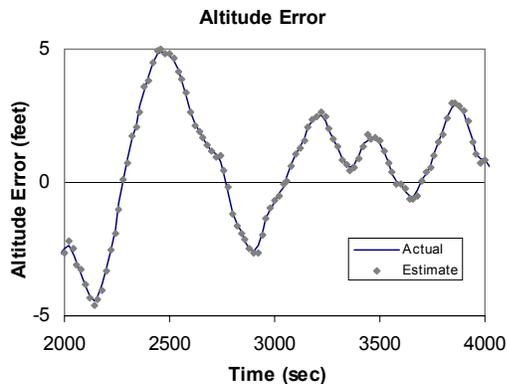


Figure 3. Simulated altitude versus estimate

Using the estimated state vector, we calculated the forecast position as described before. We compare the forecast to the position at the future time to obtain an along-track error. We also obtain the error based upon projecting the ground speed forward. Figure 4 shows these errors at a 10-minute look-ahead time for a candidate flight path. Observe that the filtered errors are typically below the projected errors.

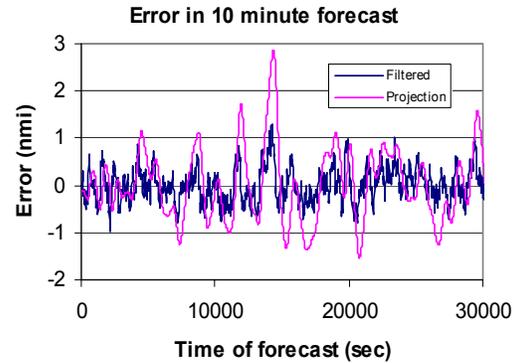


Figure 4. Filtered vs. Projected forecast error

We repeat the above for a variety of look-ahead times and plot the root-mean-squared (rms) errors in Figure 5. Application of the filtering technique results in a significant reduction in the rms error across all look-ahead times. Naturally, the magnitude of the reduction will be dependent on the characteristics of the wind uncertainty (i.e., wind error rms and spectral density function).

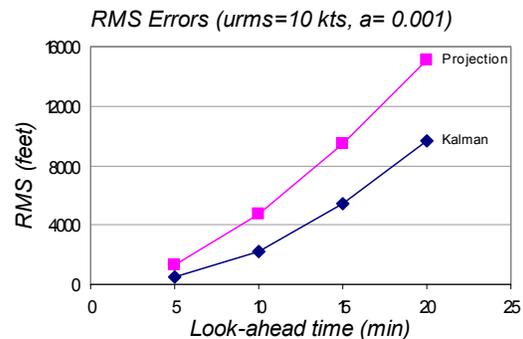


Figure 5. Impact of filter on forecast error versus look-ahead time

## Parametric Analysis

The approach described for forecasting the future aircraft position relies on two separate models: an aircraft dynamics model and a model of the wind uncertainty. Modeling errors for each of these may occur for a variety of reasons:

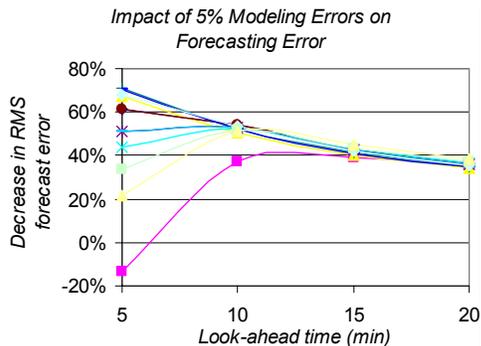
- The model is only an approximation of the physical processes (e.g., the noise will not exactly follow the estimated PSD).
- The data within the model can only be known to a limited degree of accuracy (e.g., the weight of the aircraft, some of the aircraft stability derivatives).

- The physical processes are not all stationary; in particular the wind error parameters will change with time.

One method for dealing with the last two modeling errors is to incorporate an adaptation scheme into the filtering algorithm. Briefly, this adaptation scheme varies the model parameters and selects the “best” parameters. Since the filter is already performing some optimization, the adaptation, in essence, is seeking the “best of the best”. The adaptation algorithm is described in more detail in the next section.

The aircraft model described in the prior section requires a large number of parameters for the purposes of computing the aircraft longitudinal response to perturbations. Examples of these parameters include stability derivatives, feedback gains, average wind rms, and wind time scales. Given the large number of parameters, it is not reasonable to adapt each parameter in the model. We therefore conducted a sensitivity analysis of the forecast to errors in each parameter.

The results of this analysis indicate that the effect of modeling errors depends on the time scale of interest. Figure 6 illustrates the range in fractional reduction in error as a function of look-ahead time. Each curve represents a 5% modeling error in one parameter (e.g., weight, lift curve slope, etc.). Even with modeling errors, for a 20-minute look-ahead, a 35-40% reduction in forecasting error was possible. However, at a 5-minute look-ahead, modeling errors had a significant impact on the *relative* performance of the filter although the absolute error is small (see Figure 5).



**Figure 6. Impact of 5% modeling errors on the relative forecasting error.**

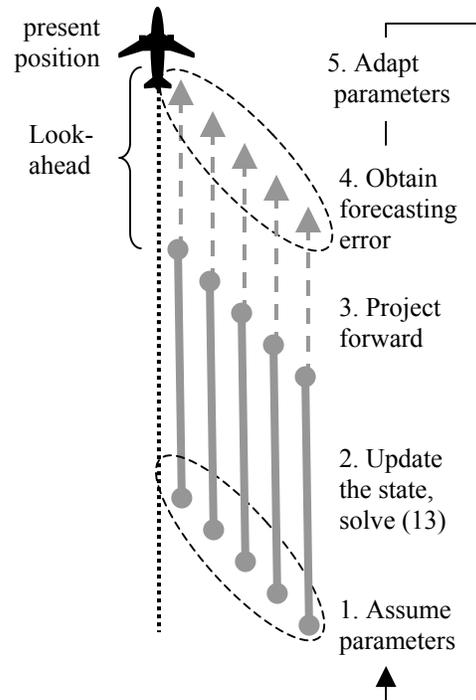
For shorter look-ahead horizons, precise modeling of the longitudinal dynamics of the aircraft is

important if one seeks to improve trajectory forecasts. However, for longer look-ahead times, the longitudinal dynamics may be simplified further by just considering the speed response as a damped exponential driven by the wind term (equation 14). We verified that this model produced rms errors identical to the full longitudinal model for look-ahead times above 5 minutes.

$$\dot{u} = \lambda u + \dot{u}_w \quad (14)$$

## Adaptation Algorithm

Many of the parameters described in the preceding section are not known for flights in the airspace. Furthermore, even if known, certain parameters (e.g. wind autocorrelation time scale  $a_w$ ) will likely change as a function of time. The purpose of the adaptation algorithm is to obtain a set of parameters providing the best solution given all available information. We define the “best” solution as that which minimizes the rms error of the desired forecast.



**Figure 7. Illustration of adaptation process**

Figure 7 illustrates the adaptation process that we applied to the prior filter. We are applying this filter to flights in progress for which we have stored recent position and velocity information. This approach requires that the user specify a desired look-ahead

time for the adaptation. The algorithm then proceeds as follows:

1. Assume values for all parameters used by the filter.
2. Use stored flight data to solve for equations (13) from a large time in the past up to the present time minus the look-ahead time.
3. As the state in 2 is updated, project equation (11) forward without the random term ( $w_k$ ). Integrate the ground speed to obtain the forecast position.
4. Obtain the forecasting error as the rms of the difference between the forecast position and the observed position.
5. Perturb the parameters in such a way as to minimize the forecasting error.

We experimented with a variety of algorithms (Powell’s method, steepest descent, random search, and exhaustive) for selecting the parameters that would minimize the forecasting error. Ultimately, the exhaustive search provided the best solution without large computational penalty. Given the simplification provided by equation (14), the number of parameters in the model was reduced to three ( $\lambda$ ,  $u_{rms}$  and  $a_w$ ). We additionally added a constraint on the  $u_{rms}$  parameter to ensure that the measured value was consistent with the assumed value.

Once the parameters of the model are determined, we continue to update the state up to the aircraft present position. We then obtain a forecast of the aircraft position, a look-ahead time from now, by propagating the state transition matrix forward (equation 11).

All of the equations of motion described so far refer to speeds that are perturbations from a mean. However, that mean may also be a variable function of time. As a result, every time the process illustrated in Figure 7 is performed, we renormalize all data using a current estimate of the average ground speed. Since the position data is also subject to measurement noise, we obtain the current average ground speed as that which minimizes the sum of the square of the errors to the measured positions.

The approach proposed here is based entirely on measured past data obtained for an individual flight. This method is therefore suitable both for real-time applications and post-processing applications.

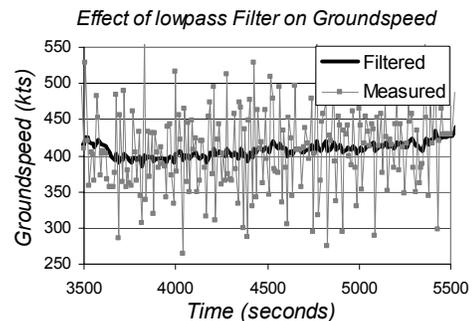
## Application To Radar Data

We obtained a sample of radar data for a collection of flights in the New York ARTCC. From this data, we extracted a subset of flights meeting certain conditions:

- A continuous segment of data exceeding 30 minutes was available for the flight.
- The flight did not encounter any large turns or vectors during the 30 minute segment.
- The flight was maintaining a constant altitude during the time segment.

After the above selection criteria, we obtained 10 flights with a total of 1975 data points on which we could evaluate our filter.

The positions obtained from radar data are subject to substantial measurement error (average distance to radar = 146 nautical miles). Naturally, the ground speed obtained from numerically differentiating these positions provides a very noisy signal. Prior to implementing our filter, we reduced the measurement noise by passing the ground speed through a first-order low-pass filter. We argue that the high-frequency terms are dominated by the measurement noise and are not relevant to the trajectory forecasting problem. Figure 8 illustrates the ground speed before and after filtering. This filtering scheme continues to ensure that the overall approach can be applied in a real-time environment.



**Figure 8. Impact of low pass filter on speed**

Once we obtained the filtered speeds, we synchronized the data for use in our approach. Our method is greatly simplified by assuming a constant time step between data points. Yet the radar data is received asynchronously. We therefore translated the asynchronous data into synchronous data through interpolation of positions.

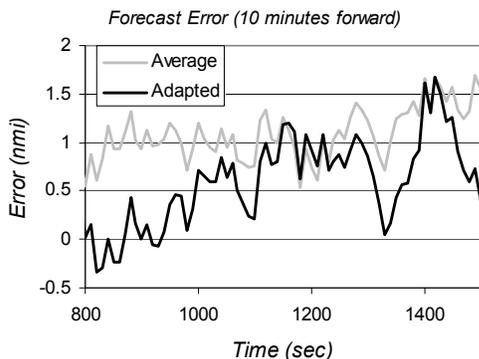
One of the required elements in this approach is an estimate of the measurement noise autocorrelation (the  $R_k$  term in equation 13). We obtain an estimate of this term by assuming that changes in the ground speed from one time step to the next are largely the result of measurement noise. The effect of the wind is assumed to be a smaller effect occurring over multiple time steps. We validated our approach to obtaining the measurement noise by deriving the implied positional uncertainty from the unfiltered data, and compared this error to the positional error described in [20].

We applied the filter to each flight in our data set. The first half of each flight was used to train the filter and obtain an initial guess at the filter parameters. The filter then continued to adapt as the flight progressed. Our analysis using the radar data only involved a look-ahead time of 10 minutes since our data was limited to about 30-40 minutes of data per flight.

For each flight, we obtained the error in forecasting the future position using two methods:

- Projecting current average ground speed forward for the look-ahead time
- Using the adapted filter approach to obtain the forecast position at the look-ahead time.

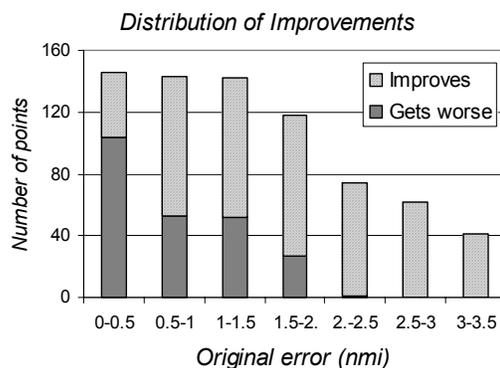
Figure 9 displays an example of the positional error obtained using these two methods. The curves represent the error in the current forecast that will be encountered 10 minutes from the current time. In this case, notice that the adaptive filtering approach produces a smaller error, on average, than extrapolation of the average ground speed.



**Figure 9. Reduction in forecast error through application of adaptive filter**

When averaged across all forecast data points, the error using the extrapolated average ground speed is 1.4 nautical miles at a look-ahead of 10 minutes. This figure is commensurate with an 8.4 knot growth rate in the error, consistent with prior studies. This error is reduced by 0.37 nautical miles ( $\pm 0.06$  nautical miles at 95% confidence) through the application of the adaptive filter.

Since the filtering approach reduces the forecasting error, on average, there are some points for which the error will be worst than without the filter. However, the adaptive filter tends to result in the worst error when the original error is small. Figure 10 illustrates this effect. As the original error (obtained by extrapolating the average speed), decreases, a higher percentage of points experience an increase in the error through the adaptive filtering technique. This situation might occur when the wind is not subject to many random variations.



**Figure 10. Distribution of improvements as a function of original error magnitude**

### Impact of Reduction

The observed reduction in trajectory forecasting error can be translated into improved performance of decision support tools. As an example, we investigated the improved performance of a conflict probe using a look-ahead time of 10 minutes and a positional uncertainty of both 1.4 nautical miles and 1.0 nautical mile with the adaptive filter. A Monte Carlo simulation of flights potentially subject to conflicts was developed and the statistics of the conflict detection were investigated. We only investigated the impact on crossing conflicts.

Without any buffers on the conflict probe, the improved trajectory forecasting results in a reduction of the missed alert rate from 9.5% to 6.4%. The false alert rate similarly decreased from 6.8% to 5.1%.

If a 3-nautical-mile buffer is placed on the conflict probe, the missed alert rate is reduced to a low level in the original case (0.17%). The conflict probe using the adaptive forecast encounters a very low missed alert rate of 0.02%. Using the adaptive filtering technique, the buffer size on the conflict probe can be reduced to 2 nautical miles while maintaining the same missed alert rate. This simultaneously leads to a reduction in the false alert rate from 31% to 23%.

## Conclusions

We have presented a technique using an adaptive Kalman filter to provide improvements in short term (5 to 20 minutes) trajectory forecasting. Results of simulation using this technique show improvements in trajectory forecasting from 70% with a 5-minute look-ahead to 40% at 20 minutes. While shorter look-ahead times have a higher percentage improvement, the errors and corresponding error reductions are smaller at these shorter look-ahead times.

Use of this method for look-ahead times at or below 5 minutes requires a model incorporating longitudinal aircraft dynamics. For longer look-ahead times, the longitudinal aircraft dynamics can be simplified into a lagged response to wind disturbances.

An adaptation model was developed and applied to actual radar data with promising results. The filter relied entirely on historical data and could be applied in a real-time setting. With a look-ahead time of 10 minutes, the measured forecast position error could be reduced by about 30% from an rms value of 1.4 nautical miles down to 1 nautical mile.

While the adaptive filter reduces the *average* error in position forecasting, there are instances for which the error is increased. Fortunately, these correspond to times during which the uncertainty is low and a method could be developed to turn off the filter during these periods.

Improvements to the short-term trajectory forecasts can provide benefits to ATM tactical decision support tools such as metering tools and conflict probe. Results of a Monte Carlo simulation showed that the reduction obtained could be used to provide improvements in missed alert, false alert and required buffer size. The reduction in the false alert rate would lead to reduced controller workload in

unnecessarily displacing aircraft, and to trajectory benefits for flights (time and fuel). Further benefits of improved trajectory forecasting are well documented (e.g., [4], [5], [6], [9]).

The proposed method could also be applied to airborne tools for self separation. Unlike the ground system, the aircraft would be able to locally measure some of the adapted parameters and may provide better results.

The approach described herein can provide some trajectory forecasting improvements via processing of existing data. This approach does not require the development and deployment of sensors, nor the exchange of data between airborne and ground systems.

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## Key Words

Trajectory forecasting, Kalman filter, adaptive filter, wind uncertainty, decision support tools

## Biographies

**Dr. Stéphane Mondoloni** is chief scientist at CSSI Inc. in Washington, DC. For the past ten years, he has been developing simulation models and conducting analyses for the Federal Aviation Administration and the National Aeronautics and Space Administration. Recent tasks have focused on conflict detection and resolution, aircraft trajectory optimization, airspace complexity and evaluation of alternative operational concepts. He received his Ph.D. in 1993 from MIT in Aeronautics and Astronautics.

**Diana Liang** works for the Office of System Architecture and Investment Analysis for the Architecture and System Engineering Division. She is responsible for the development of the NAS Architecture Tool and Interface called CATS-I, directing analyses in support of NAS Concept Validation, and the development of Modeling Tools and Fast-Time Simulations to support that validation. This work includes several models she is developing jointly with NASA and cooperative efforts with Europe via Eurocontrol. Prior to working for ASD, Ms. Liang worked in the Office of Energy and Environment for two years as the lead for the Emissions and Dispersion Modeling System (EDMS), updated the FAA's Air Quality Handbook and reviewed Environmental Impact Statements related to emissions. Ms. Liang holds a BS in Computer.