Enhanced Wind Magnitude and Bearing Prediction

Onboard algorithm

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***Abstract*—The article deals with the aircraft onboard wind prediction if there is no up-to-date accurate weather forecast available. The simple method for extrapolation of measured wind dynamics is presented. Also the algorithm for blending average wind trends with measured data is presented.**

Keywords - wind prediction, RUC analysis, wind trends

I. INTRODUCTION

The proposed Enhanced Wind Prediction Algorithm (EWPA) is intended to be a tool for the onboard wind magnitude and bearing prediction in case of absence of a suitably accurate meteorological forecast in the Flight Management System (FMS). The further motivation for this study and for an algorithm development is the fact that studied meteorological forecasts [5] have a lower accuracy than onboard measured data in vicinity of the aircraft.

The key question which the enhanced algorithm development tries to answer is: “Is it possible to improve actual onboard predicting algorithm even without a valid up-to-date wind forecast available onboard?”

As an answer to this question the following approach has been designed and tested. Since the actual prediction algorithms deals only with wind magnitude and bearing data for a level flight, the proposed one focus also only on these quantities. However, any other variables (such as temperature, humidity, etc.) can be predicted in a similar manner.

In absence of up-to-date wind forecast onboard, the algorithm currently used in FMS utilizes an actual wind measured by sensors as the measurement prediction (e.g. prediction of the future wind behavior). The values of the wind measurement prediction are directly projected to all points along the (planned) flight path. This approach does not consider the dynamic change of the wind during the flight path and thus does not evaluate wind behavior dynamics. This is a serious limitation of the described approach, because the wind dynamics is an important factor, as stated in [3]. The proposed approach combines the local development of onboard measured data together with average wind trends, which characterize the wind behavior in broader horizon/more distant segments of the trajectory. The average trends of the winds are supplemented with the information about their standard deviations. The identification of the typical trends together with their description can be derived from any suitable weather database, which collects data for sufficiently long time period. In case of the presented study, the RUC databases have been used [5]. The methodology used for the analysis of weather data and resulting wind characteristics are described in [3].

II. MEASUREMENT PREDICTION MODEL

The EWPA is initially intended to be a tool for the CRUISE phase of the flight designed with the respect to the possible embodiment of the other phases of the flight. The design was constrained also by computation performance of the FMS [1].

Prior the flight, the preprocessed average weather characteristics are loaded to the FMS. During the flight, the data about the wind magnitude and bearing are periodically measured and stored with a given frequency. The set of the last measurements is used for determination of the parameters of the simple dynamic model for the measurement prediction (prediction of the future wind evolution) in local vicinity of an aircraft.

The following text describes the steps of EWPA:

- The prediction of the wind measurement magnitude values based on on-board measured data.
- The blending of the measurement predictions with the typical weather trends along the trajectory.

The prediction of the wind bearing values is based on the same algorithms and therefore only the magnitude part of the algorithm is presented.

A. Wind Magnitude Prediction

The measurement model is used for the magnitude measurement prediction. The first order dynamic model was chosen as a suitable and simple description of the wind magnitude behavior. The nature of the wind behavior is tended to be steady than continuously changing [3]. This way of behavior is introduced by the saturation limit of the wind measurement model. The function of the measurement model can be constructed as:

$$Mag_{Measure}(d) = K\left(1 - e^{\frac{-d}{D}}\right) \qquad (1)$$

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Where:

$Mag_{Measure}\ldots$ the value of the predicted wind magnitude,

$K\ldots$ the value of the measurement model saturation,

$D\ldots$ the distance from the actual aircraft position d_0 to the point of the model saturation (eq.4),

$d\ldots$ the distance from the actual aircraft position d_0 to the point for which the prediction is processed.

For the determination of the measurement model parameter D the parabolic regression is fitted to the wind data. The parabolic interpolation allows simple description of the dynamics of the wind development and its computational demands are not high at the same time. The equation of the parabolic interpolation is:

$$y = ad^2 + bd + c \qquad (2)$$

where:

$d\ldots$ the distance from the actual aircraft position d_0 to the stored wind sample,

$a,b,c\ldots$ the parameters of the parabolic function,

$y\ldots$ the value of the interpolated data.

In the next step, the resulting parameters of the interpolation are used to determine the tangent to the curve in the point of the last measurement d_0 (Fig.1). The angular coefficient of the tangent line k is:

$$k = 2ad_0 + b \qquad (3)$$

The angular coefficient k of the tangent line is used for determination of the parameter of the measurement model (eq.1).The setting of the saturation limit K (eq.1) can be determined based on the statistical analysis of the wind data as the average value of the wind magnitude change in the chosen distance horizon.

Once the saturation limit K is selected, the distance D is then evaluated as:

$$D = \frac{K}{k} Mag_{d_0} \qquad (4)$$

Where Mag_{d_0} is the value of the wind magnitude at the point d_0 and D is the distance from the current aircraft position d_0 to the point where the tangent line defined by angular coefficient k intersects the line defined by saturation limit K

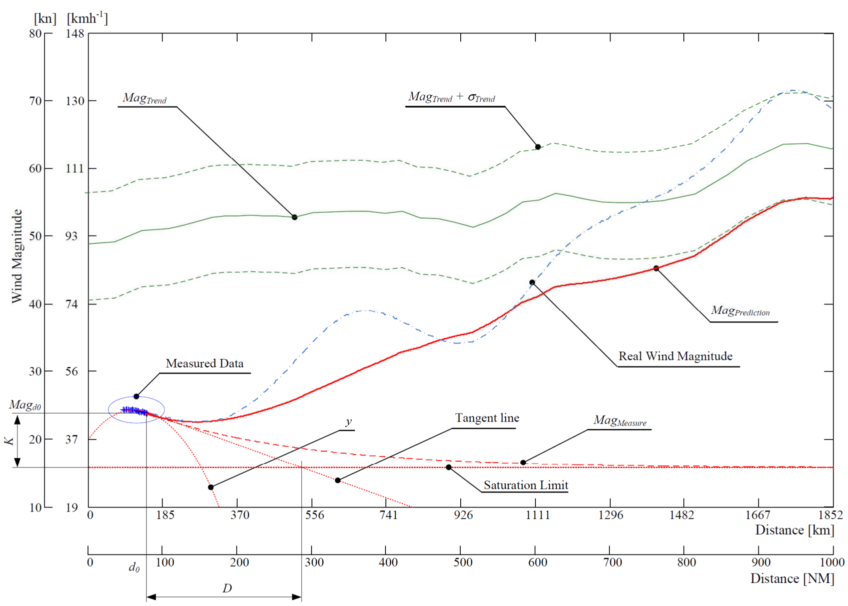

Fig.1. Wind Magnitude Prediction

B. *Standard Deviations*

The second part of the measurement model provides the estimation of the standard deviations associated with the predicted wind magnitudes at the trajectory points. The uncertainty of the measurement prediction increases with the increasing distance of the trajectory points from the current aircraft position d_0, (rpresented by an increase of the standard deviation). The standard deviation of prediction at the point d_0 is assumed to be zero[1].

The linear function for the measurement standard deviation is selected as the Standard Deviation Model (Fig.2). At the distance of the horizon H, the value of the measurement model

[1] The uncertainty associated to wind sensing is omitted for simplicity.

standard deviation $\sigma_{Measure}$ is equal to the value $\sigma_{Average}$. This value represents the average standard deviation value of the average wind trend σ_{Trend} (the historical data). The value of the prediction horizon is determined on the basis of the RUC database statistics [5].

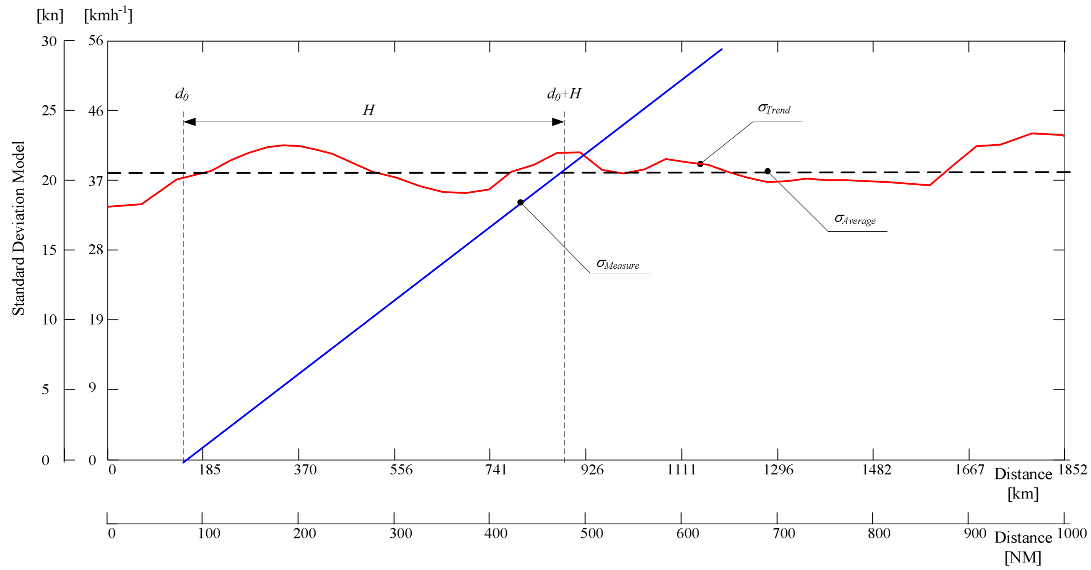

Fig.2. Standard Deviation Model

The measurement standard deviation model is:

$$\sigma_{Measure} = d\frac{\sigma_{Average}}{H} \tag{5}$$

where:

$\sigma_{Measure}$ … the standard deviation associated to the extrapolation of the measurement,

$\sigma_{Average}$ … the average standard deviation of the historical data.

C. *Blending Algorithm*

The prediction of the wind magnitude or bearing for the individual point of the flight plan is created by combination of the measurement prediction with the average trend value derived from weather database. Both of the values are weighted in accordance with their standard deviations [2]. The resulting value of the wind magnitude prediction is then:

$$Mag_{Prediction} = \frac{\sigma^2_{Measure}}{\sigma^2_{Measure} + \sigma^2_{Trend}} Mag_{Trend} + \\ + \frac{\sigma^2_{Trend}}{\sigma^2_{Measure} + \sigma^2_{Trend}} Mag_{Measure} \tag{6}$$

where the value $Mag_{Prediction}$ represents the resultant value of the wind magnitude measurement prediction. The value of the bearing is computed in the same manner.

III. Algorithm Implementation and Setting

The proposed algorithm was implemented and tested in the Matlab and FMS. During the implementation and testing phase some simplifications have been done. The simplification consists in the fixed setting of the saturation limits[2].

For the testing purposes and the evaluation the K and H coefficients of the measurement model have been preset to the given value (the coefficients have not been changed automatically). These values of the coefficients were:

- The saturation limit K corresponds to the 20% of the

$$Mag_{d_0} : K = \begin{cases} 1.2, k > 0 \\ 0.8, k < 0 \end{cases},$$

- The prediction horizon H = 741km (400NM).

A. *Selection of the Scenarios*

The selection of the test scenario is based on the analysis of the RUC weather grid database which includes the tracks of hourly generated weather reports and weather forecasts over US. Analysis of the weather grid defined suitable realistic wind scenarios to test the enhanced prediction algorithm.

The study [1] describes the scenario which represents average weather (i.e. the wind pattern with the highest probability of occurrence) and the extreme weather scenario (i.e. the wind pattern with the highest differences between wind values on grid).

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[2] The value of the saturation limit is correlated with the wind dynamic behavior and it can be set automatically based on the analysis of results.

For the demonstrative purpose of the presented paper "One month scenario" is presented. The scenario was created for the comparison of the prediction algorithm behavior while the input conditions were selected from the period of several days during the year. Compact, one month period (28 days) year with the wind pattern about a noon was used for the testing.

B. Analysis Methodology

The performance of the presented algorithm (EWPA) was assessed by the comparison with the standard prediction algorithm (SPA) in absence of the wind forecast. The simulated flights have been conducted along the selected trajectory (i.e. CRUISE phase of flight between Los Angeles and Minneapolis).

The analysis of the results through 'one month scenario' was processed by the stochastic analysis of the complete set of the TP errors from the single days (one month scenario). For the assessment of the prediction quality of the SPA and EWPA algorithms, the following metrics were used:

- *Mean* - Mean value of the absolute difference between the measured (real) and the predicted wind magnitude (bearing) values.
- *MSE* - Mean Squared Error of the difference between the measured (real) and the predicted wind magnitude (bearing) values.
- *Delay* - Delay on a selected time horizon caused by the worst orientation of the wind prediction error. Impact of the error in the wind magnitude is calculated for the pure head-wind direction. Impact of the error in the wind bearing is calculated from the bearing error of pure 100 knots strong cross-wind towards head-wind[3].

C. Analysis results

The results of the algorithms comparison for wind magnitude are presented in the Table 1.

TABLE I. ALGORITHMS COMPARISON RESULTS

	EWPA			SPA		
Prediction Time [min]	***MSE [km^{2}h^{-2}]***	***Mean [kmh^{-1}]***	***Delay [s]***	***MSE [km^{2}h^{-2}]***	***Mean [kmh^{-1}]***	***Delay [s]***
8	4.1	1.5	0.9	32.6	4.3	2.4
15	27.8	3.9	4.3	106	7.6	8.3
20	68.6	6.1	9	182	9.8	14.4
30	223	11.3	24.7	353	13.5	29.9
60	962	22.2	99.5	806	20.4	91.1

Improvement on the shorter time horizons (i.e. 8min, 15min, and 20min) in the case of the Enhanced algorithm follows from figures 3 and 4. The reduced variability of the errors in the short time horizons indicates better adaptation to the natural dynamics of the wind (table I, MSE).

The box plot format of the figures allows an illustration of the evolution of the extreme and percentile values according to the prediction time. The EWPA algorithm performance is better than the SPA performance in the short time horizon (8-20 minutes). The results for both algorithms are comparable also for the longer time horizon (30-60 minutes).

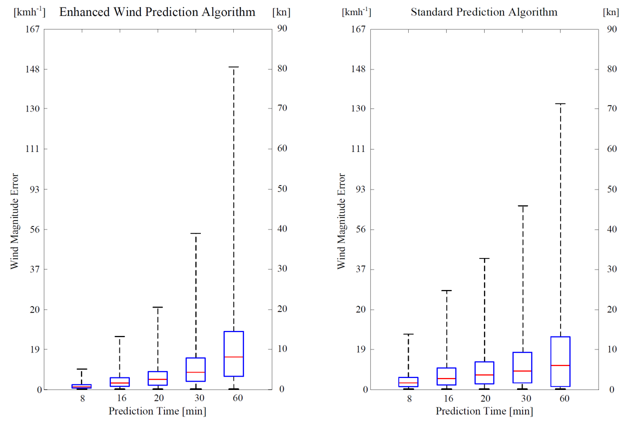

Fig.3 (left - EWPA) and Fig.4 (right - SPA) Algorithm Comparison

IV. CONCLUSION

The presented example indicates the EWPA ability to significantly improve trajectory prediction for the cruise level flight by the enhanced processing of the measured data used in a combination with the known historical wind trends along a selected trajectory. For longer prediction time horizons (above 1 hour) the algorithm EWPA cannot match the methods based on the presence of the actual up-to-date wind forecast, nevertheless numerous ATM applications using the short time are in use.

The proposed EWPA algorithm shows better prediction accuracy and precision, mainly for the short prediction horizons (up to 20 minutes), than the SPA.

The performance comparison of the EWPA algorithm with the methods using the actual up-to-date wind forecast is planned for the future work.

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[3] The selected speed is M0.78.