4D Trajectory Prediction with stoachastic Input Parameters

2 authors:

Judith Rosenow
Technische Universität Dresden

Michael Schultz
German Aerospace Center (DLR)

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4D TRAJECTORY PREDICTION WITH STOCHASTIC INPUT PARAMETERS

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Judith Rosenow[(1)] and Michael Schultz[(2)]

[(1)] Technische Universität Dresden, Hettnerstraße 1-3, 01069 Dresden, Germany
Judith.Rosenow@tu-dresden.de
[(2)] German Aerospace Center (DLR), Lilienthalplatz 7, 38108 Braunschweig, Germany
Michael.Schultz@dlr.de

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ABSTRACT:

The 4D Trajectory Management, invented by the Single European Sky ATM Research program SESAR enables the possibility for airlines and air traffic control to increase the efficiency, although different air traffic stakeholders follow partly competitive target functions. Following time based operations airlines will be able to fly along optimized trajectories without waypoint constraints, as long as they reach certain predefined spatial coordinates at certain time stamps. This condition allows the air traffic control a precise air traffic flow management and therewith an increased air space and airport capacity. However, unknown weather conditions and uncertain weather predictions at flight level hinder airlines to precisely predict and calculate the optimized trajectory. In this study, the impact of uncertainties in wind direction and wind speed, as well as in air temperature on fuel burn, flight time, initial cruising altitude and on the lateral flight path of optimized trajectories is quantified with the help of the complex trajectory and air traffic flow management simulation environment TOMATO. Therefore, wind and temperature are varied within different ranges and the impact on the trajectory is analysed stochastically by analysing 1000 simulation runs per parameter setting. Significant differences from the optimized flight path under the original weather conditions are estimated for the optimized lateral flight path, which is very sensitive to changes in environmental conditions. However, by optimizing the trajectory under current weather conditions, airlines will still be able to come up with the constraints, given by air traffic control to increase the air space and airport capacity.

1. INTRODUCTION

Aviation is a strong and important global economic factor with promising potential regarding future developments, due to a growing global demand for air transport. In addition to the high expectation, this poses a challenge for all air traffic stakeholders to at least keep safety on the high level as it is, to increase the air transport efficiency and to deal with the growing public awareness of the aviation impact on climate change. Therefore, both, the US and Europe founded research initiatives and developed innovative applications for the air traffic future [1-3]. A promising solution strategy to adapt the air transport to future requirements has been identified and tested in the transformation of the today's clearance based Air Traffic Control (ATC) operation to Trajectory Based Operations (TBO) and by considering optimized flight trajectories [3]. For example, EUROCONTROL established the basic concept for the design of the future Air Traffic Management (ATM) by "Moving from Airspace to 4D Trajectory Management" [3]. The first step towards this action is called the "Time-based operations" and focuses on the deployment of airborne trajectories [4], which consider all constraints inflicted by the highly complex and dynamic environmental conditions [5]. This significant impact of atmospheric conditions on trajectory optimization and trajectory prediction will be analysed in this study.
Free routing (freely planed routes between a defined entry point and a defined exit point) is aspired, to enable optimized trajectories [4] under real weather conditions. This so called 4D Trajectory Management contains two important features: On the one hand, the optimized and freely planned Reference Business Trajectory (RBT), which is agreed by both cost efficiency driven airlines and capacity and safety driven ATC [2, 6] must be developed for each flight. Due to the time-based operation of the RBT, the trajectory is defined not only by spatial coordinates, but also by time stamps. This allows airlines to operate with

non-constant and optimized speeds. The ATC, on the other hand, can increase the airspace and airport efficiency due to a reliable time of arrival at defined spatial coordinates, at least at the Initial Approach Fix (IAF) [6, 7]. This time constraint is usually defined with a precision of minus two and plus three minutes around a target time and may be decreased to plus/minus thirty seconds in case of the implementation of a Controlled Time of Arrival (CTA) [7]. This target poses a challenge for pilots and controllers, due to the requirement of a precise trajectory prediction with partly unknown input parameters, because the atmospheric situation (specifically pressure, wind direction and wind speed) is subject to unpredictable dynamic fluctuations. Therewith, both operators (pilots and controller) are faced with an increased workload, which quantification is under investigation [7, 8].
For this purpose, the simulation environment TOMATO a TOolchain for Multicriteria Aircraft Trajectory Optimization has been developed [9, 10], which includes both an aircraft type specific performance model COALA (Compromised Aircraft performance model with Limited Accuracy) and an Air Traffic Flow Management ATFM Tool for the demonstration and analysis of a large number of simulated optimized trajectories regarding air space capacity [13], air space density [14] and controller's taskload [8].
With TOMATO, the important impact of atmospheric input parameters on trajectory optimization has been identified [8–11,13–15] and significant differences in flight time, optimized speeds, cruising altitudes and fuel burn have been calculated considering real weather conditions. From this follows a difficulty to predict the required target times and therewith to come up with the conditions of a successful 4D Trajectory Management.
Usually, air traffic simulations are developed to either focus on the trajectory level or for ATFM. Regarding ATFM, the commercial fast time air traffic simulator AirTOp [16] generates trajectories in a dynamic airspace structure and iteratively detects and solves conflicts [17–19]. Due to approximations in the aircraft performance modelling (BADA performance tables and the ISA Standard Atmosphere) and restrictions regarding the emission quantification, AirTOp is limited in trajectory optimization. Due to a large computational effort during conflict resolution, AirTOp is not able to implement optimized free routes with non-constant altitudes and speeds. The Test bench for Agent-based Air Traffic Simulation (TABATS) has been developed for the trajectory synchronization with uncertain arrivals under realistic weather conditions, but is specialized to airport slot allocation and to BADA performance tables [20–23]. The air Traffic Simulator BlueSky concentrates on ATFM without BADA for trajectory calculation [24] and the possibility of implementing externally generated trajectories is provided. However, stochastic input parameters are not useable.
When performing trajectory optimization, most approaches focus on the cruise phase only [28] [29] [30]. Albeit the authors use BADA [30] [31], a realistic flight performance is often neglected, and too many static parameters are assumed, e.g., constant speed and altitude. Even if a 3D or 4D optimization approach is proposed, most work consider the ability of instant step climbs during cruise only [29] [30], but there is no detailed investigation in climb and descent phases when optimizing a full trajectory. Either the path finding algorithm A* as well as the more general Dijkstra algorithm for searching shortest paths in a graph are employed [29] [31] or a limited number of variables is optimized in an optimal control problem [32] [28] and [33], considering conflictive target functions and real weather conditions. In this case, the discrete input parameters must be approximated by analytically solvable functions. From this follows a restricted number of parameters and a restricted flight performance model.

2. 4D TRAJECTORY PREDICTION WITH NON-CONSTANT AND STOCHASTIC WEATHER PARAMETERS

The impact of wind direction, wind speed and air temperature is accommodated optimizing an A320 trajectory from Vaclav Havel Airport Prague (LKPR) to Tunis-Carthage International Airport (DTTA) on 17th of May, 2017 at 12 a.m.. The wind components u and v are taken as stochastic variables to stress the model regarding the optimal lateral flight path. Due to large expected differences in the lateral flight path, the optimization is carried out twice. First, the lateral path is optimized in each simulation to show the solution of the optimization and second, the lateral flight path is fixed to the optimum path considering the real weather data to show the solution space for trajectory prediction. Furthermore, the temperature T [K] is varied, to investigate the optimum flight level prediction. The impact of the uncertainty in the atmospheric parameters on

- time of flight
- fuel burn
- cruising altitude at top of climb
- lateral deviation from the original trajectory

is investigated. In this case study the A320 aircraft is loaded with 10000 kg payload. The required fuel load of approximately 3400 kg is estimated iteratively for each flight. The parameters are varied one by one assuming a Gaussian distribution of the uncertainties.

2.1. Stochastic variation and characteristics of weather Data

The real weather conditions are provided as grib2 data, modelled by the Global Forecast System (GFS) using a Global Spectral Model (GSM) with spherical harmonic basis functions [34]. The optimized trajectory with the real weather data is stated as original trajectory (*Figure* **7**). Subsequent, after each (one second) wind and temperature data are multiplied with a newly generated random number (i.e., a normal variable, defined by different standard deviations). Wind data is given by two components u and v [ms^{-1}] of the horizontal wind vector $\vec{w}$. u represents wind directions parallel to the axis between East and West with positive values for wind coming from West (270°). v represents wind speeds parallel to the axis between North and South with positive values for wind coming from South (180°). The definition of the wind components is shown in *Figure 1*. The simulation is done for standard deviations of $\sigma_{u,v} = 1;\ 2;\ 3;\ 4;\ 5;\ 7$ and 10 ms^{-1}. Based on a mean horizontal wind speed of $\vec{w}$ = 50 ms^{-1} at cruising altitude a relative deviation of approximately $\hat{\sigma}_{u,v} = 2;\ 4;\ 6;\ 8;\ 10;\ 14$ and 20 % from the original value is represented.

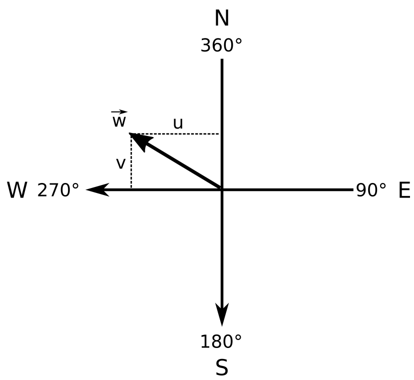

Figure 1. u and v components of the wind vector $\vec{w}$.

Figure 2 indicates mean values of u between -12 and 21 ms^{-1} at FL 360 of the Global Ensemble Forecast System (GEFS) between Prague and Tunis on 17th of May, 2017 at 12 a.m.. GEFS is a weather forecast model considering 21 separate forecasts, provided by the GFS. Furthermore, along the path maximum differences of $\Delta u = 14$ ms^{-1} have been forecasted for that day.

The weather data is provided at dedicated pressure levels p_i [Pa]. For each pressure level the geopotential height (i.e. the gravity adjusted height considering the variation of gravity with latitude and elevation) is given. The flight performance characteristics lift F_L [N] and drag F_D [N] depend on the atmospheric density ρ [kg m^{-3}] [35]

$$F_L = \frac{\rho}{2} {v_{TAS}}^2 A\, c_L \qquad \text{(Eq.1)}$$

$$F_D = \frac{\rho}{2} {v_{TAS}}^2 A\, c_D \qquad \text{(Eq.2)}$$

in Eq. (1) and (2) v_{TAS}, A, c_L and c_D denote true air speed [m s^{-1}], wing area [m^2], lift coefficient [a.u.] and drag coefficient [a.u.], respectively. Hence, optimum cruising altitude and speed depend on atmospheric density ρ. According to the ideal gas law

$$\rho = \frac{p}{RT} \qquad \text{(Eq.3)}$$

ρ depends on pressure p [Pa], temperature T [K] and the specific gas constant for dry air $R = 278.058$ J (kg K$)^{-1}$. To simulate the uncertainty in the prediction of the density ρ, the temperature T is varied with a proportional impact on the trajectory prediction. In this case study, the temperature is varied with standard deviations of $\sigma_{Temp} = 1; 2; 3; 4; 5; 7; 10$ and 12 K. According to the U.S. Standard Atmosphere, the temperature at cruising altitude (FL 360) at $h = 11000$ m is approximately $T = 216$ K [36]. Hence, the chosen standard deviations correspond to relative deviations of $\hat{\sigma}_{Temp} = 0.5; 1; 1.4; 1.8; 2.3; 3.2; 4.6$ and 5.5 %. Following Eq. 3 and assuming $p = 22700$ Pa and $T = 216$ K at cruising altitude, variations in temperature in the order of 10 K (approximately 5%) cause variations in density in the order of 10^{-2} kg m^{-3} (approximately 0.5%). Hence, differences in optimized cruising altitude are expected to be low. However, significantly larger variances in temperature are not realistic.

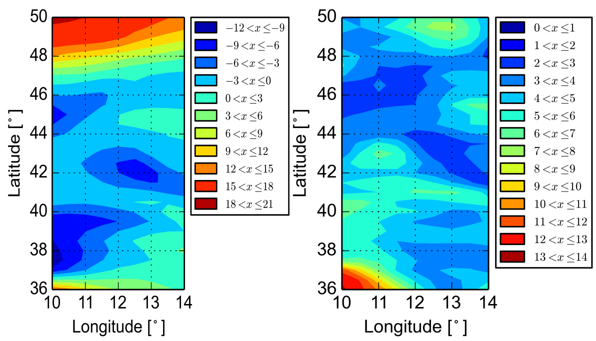

Figure 2. Mean values (left) and maximum differences (right) of wind component u between 21 weather forecasts (GEFS) along the path between Prague and Tunis on 17th of May, 2017 at 12 a.m..

The stochastic variation of the weather data per second imposes a significant and sudden change in weather data in space and time. This assumption is validated by ultra sonic anemometer measurements of temperature and wind components at the meteorological station Oberbärenburg in the Eastern Ore Mountains (Germany) in $h = 30$ m height above ground. Although the measurements have been taken above a forest within the atmospheric boundary layer and by far not at cruising altitude, the fluctuations in Fig.*Figure 3* and *Figure 4* give evidence for significant changes of wind speed and temperature over time. In *Figure 3*, half an hour (12 a.m.-12.30 a.m.) of high frequent 20 Hz data show fluctuations of $\Delta T = 4$ K and $\Delta v = 8$ m s^{-1}. The data in *Figure 4* have been taken over the whole day on 17th of May 2017 with a frequency of 20 Hz. Afterwards the data are averaged to minute values.

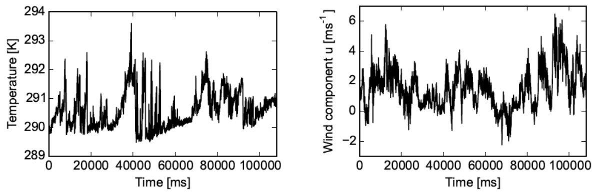

Figure 3. 20 Hz measurements of air temperature (left) and wind component u (right) during 30 minutes in 30 m altitude over Germany. Short-term fluctuations around $\Delta T = 4$ K and $\Delta u = 8$ m s^{-1} are realistic.

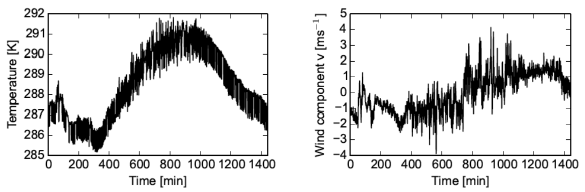

Figure 4. Minute averaged 20 Hz measurements of air temperature (left) and wind component u (right) during 24 hours in 30 m over Germany. Even after smoothing the data typical short-term fluctuations around Δu =3 m s^{-1} and ΔT= 2 K in 30 m altitude are shown.

2.2. Flight Performance Model COALA

The Compromised Aircraft performance model with Limited Accuracy has been developed for a precise and physically realistic trajectory optimization considering multi-criteria conflicting goals after carefully evaluating the required input parameters with main impact on trajectory optimization. COALA combines the impact of aircraft specific aerodynamics and the important influence of 3D weather information both affecting an optimized trajectory. COALA calculates v_{TAS}, thrust F_T, fuel flow $\dot{m}_f$, forces of acceleration a_x and a_y, flight path angle γ and total time of flight with a time resolution of $\Delta t = 1$ s. Aircraft type specific aerodynamically parameters, such as wing area A, maximum Mach number MMO, number of engines, aircraft dynamic mass and the drag polar depending on flap handle position and Mach number are also respected [11]. *Figure 5* shows the structure of COALA, specified for this case study.

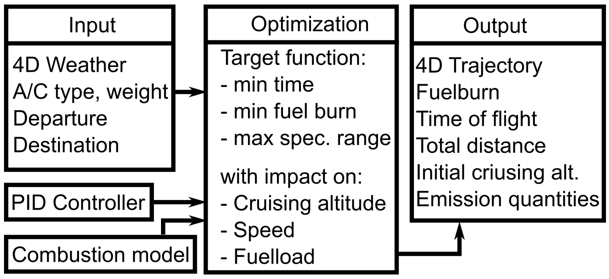

Figure 5. Sketch of workflow, input and output parameters of the flight performance model COALA. For more details of the model, compare [14].

For multi-objective optimization, COALA uses target functions for v_{TAS}, flight path angle γ and cruising altitude. The target values are continuously calculated for each time step and used as controlled variable. The values are controlled using c_L as regulating variable in a proportional-integral-derivate controller. Due to missing calibration data, Base of Aircraft DAta (BADA), provided by EUROCONTROL [37] [38] are used for the approximation of the drag polar, i.e. the functional relationship between c_D and c_L, maximum climb thrust MCL and $\dot{m}_f$.

Therefore, a limited accuracy is accepted. Regarding $\dot{m}_f$, errors of "less than 5%" for BADA 3 and "well below 5%" for BADA 4 are considered [39]. If the aircraft type is available, BADA 4.1 will be used for the benefit of a higher accuracy.

In this case study, v_{TAS} for a maximum climb angle γ [rad] up to the safety level of 10000 ft, where a maximum climb rate w [ms^{-1}] is aspired. In general, the climb profile is adapted to the aspired cost index with a speed adjustment factor α of the true air speed [12]. A deceleration of v_{TAS} (i.e. $\alpha < 1$) causes a steeper climb profile with a lower v_{TAS} at the top of climb (TOC). A higher v_{TAS} (α > 1) causes a shallower climb profile with a higher true air speed at TOC. During cruise, α directly manipulates the cost index CI, which is iteratively achieved, after the assessment of the trajectory. During cruise, in the present case study, $R_{\max}$

$$R_{max} = \frac{v_{TAS}}{\dot{m}_f} \qquad \text{Eq.(4)}$$

is chosen as target function for v_{TAS} and cruising altitude. Therewith, the ratio between true air speed and fuel flow is maximized. During continuous descent, a maximum lift/drag ratio E [a.u.]

$$E = \frac{F_L}{F_D} \qquad \text{Eq.(5)}$$

is aspired.

2.3. Simulation Environment TOMATO

The architecture of the TOMATO simulation environment is very modular and described by Förster et al. [9]. TOMATO iteratively connects three optimization tools (sub modules) and

assesses the trajectory. For complexity reasons, the overall optimization has been split into two modules. The first module is a lateral path optimization by employing the A* algorithm in the presence of winds and ice-supersaturated regions (this is important for contrail formation). The A* module uses ATC en-route charges, as well as prohibited or restricted areas to find the cheapest lateral path at a initially predefined altitude. Those path-influencing factors, which are not already available in form of fees or costs (e.g., the effect of winds), are transformed into cost values. The formation of condensation trails is also transformed into costs per time step depending on daytime and flight path [9, 14, 40].
In the second step, COALA calculates and optimizes the vertical flight profile along the optimized lateral path. With the implemented engine model, detailed performance and emission data for each time step during the flight are determined and used for the assessment. Therewith, the optimization is done in a real 3D workspace. *Figure* **6** shows the optimization cycle and workflow of TOMATO. After the assessment (third module), the determined performance and cost data are available for the next iteration step with benefits especially for the lateral path calculation (e.g., by using a different cruising altitude or flying beyond ice-supersaturated regions to avoid contrail formation or looking for different flight levels with more suitable wind direction). TOMATO iteratively estimates the required fuel mass by considering the fuel burn of the last iteration step.
TOMATO has been used for several post analyses to estimate the influence of the simulated trajectories on the ATFM (impact on air space capacity, number of separation infringements [14], characteristics and distribution of separation infringements [13] and controllers taskload [8]). Therewith, the criterion validity of TOMATO could be shown in various applications [8–14].

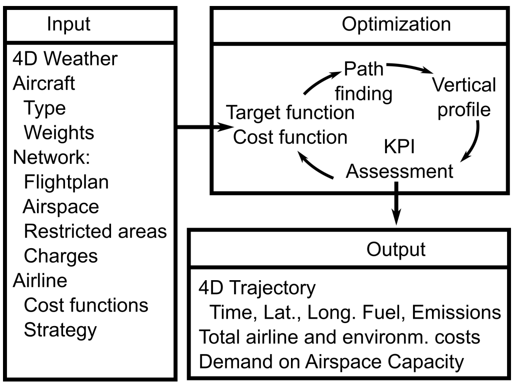

Figure 6. Workflow in TOMATO, simplified to the most important parameters and modules.

3. IMPACT ON TRAJECTORY OPTIMIZATION

As expected, large deviations of the input parameters cause the large deviations between the resultant trajectories. If the lateral path is optimized in each wind parameter variation, the impact on the lateral deviation will be large, compared to fuel burn $\sigma_{Fuelburn}$, time of flight $\sigma_{Flighttime}$ and initial cruising altitude $\sigma_{Altitude}$. Temperature uncertainties are expected to influence the flight performance, i.e., $\sigma_{Fuelburn}$ and $\sigma_{Altitude}$. Furthermore, differences in flight time and fuel burn are relatively small, compared to differences in the input parameters. From this follows, pilots will be able to reach the time stamps at given spatial coordinates, as long as they can fly along optimized flight paths with optimized speeds.
According to the ICAO Performance Based Navigation (PBN) concept [41], Along Track Tolerances (ATT) (i.e., the deviation from the planned trajectory along the flight path) are burdened with higher uncertainties than Cross Track Tolerances (CTT) (i.e., the lateral deviation from the planned trajectory). Hence, the on board flight management system (FMS) follows the planned track very precisely and adjusts the true air speed within the aircraft specific boundary conditions given by the MMO. Assuming an inflight trajectory optimization, the FMS must identify the wind and density optimized flight path, which will differ significantly from the planned one, depending on the precision of the weather forecast or the uncertainty of the pressure and temperature measurement. *Figure* **7** shows the optimized lateral path with wind speeds of the resultant wind vector $\vec{w}$ between 5 and 20 ms^{-1} along the path at FL 360.

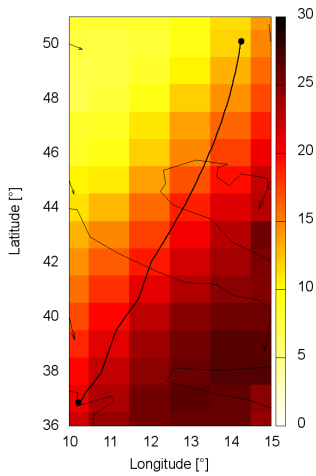

Figure 7. Optimized lateral flight path (black) between Prague and Tunis in the real weather scenario. Contours denote wind speeds [ms^{-1}] at FL 360 of wind vector $\vec{w}$.

3.1. Uncertainty of wind direction and wind speed

The impact of the uncertainty of wind direction and wind speed on trajectory optimization is significant in the lateral path (Fig. 8 and 9).ss

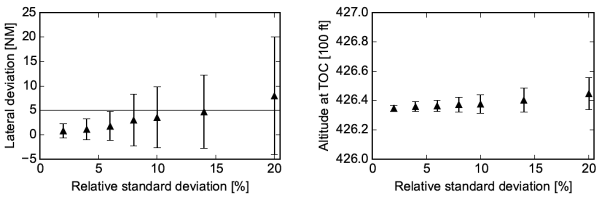

Figure 8. Mean values and standard deviations of lateral deviations from the original flight path (left) and of initial cruising altitudes at TOC (right), as a result of fluctuations in wind speed in the lateral and vertical optimization with different relative standard deviations.

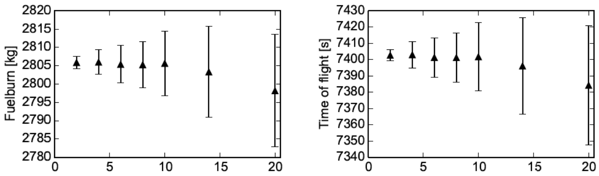

Figure 9. Mean values and standard deviations of changes in Fuel burn and time of flight as result to fluctuating wind speed with different relative standard deviations.

Here, differences between the original path, obtained by an optimization following the original Grib2 weather data exceed the Cross Track Tolerances of $CTT = 5$ NM, when wind speed and direction are varied by at least 4 %. The impact of uncertainties in wind speed and direction on fuel burn, initial cruising altitude and time of flight are relatively small, because the trajectory has been successfully optimized for each run. Relative differences in the standard deviations (usually between 0.05% and 0.5%) of each resultant trajectory parameter (e.g., $\sigma_{Fuelburn}$, $\sigma_{Altitude}$, $\sigma_{Flighttime}$) are far below the relative standard deviation of the varied wind speed (i.e., $\hat{\sigma}_{u,v}$ on the x-axis in Fig. 7 and 8). However, the large lateral deviations in $\sigma_{Fuelburn}$, $\sigma_{Altitude}$ and $\sigma_{Flighttime}$ give evidence, that deviations in flight time, altitude and fuel burn will be significant, if the aircraft is forced to fly along the planned trajectory. Hence, inflight optimization is an important procedure for trajectory prediction to reach the planned time stamps and to assure a benefit for both, pilots and controllers. This effect is analysed in Section 4 (*Figure **10***, *Figure **11*** and *Figure **12***), where the lateral path is fixed to the optimized one considering the original weather data.

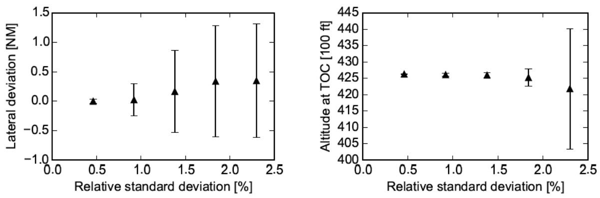

Figure 8. Impact of fluctuations in temperature on lateral deviations and optimum initial cruising altitudes.

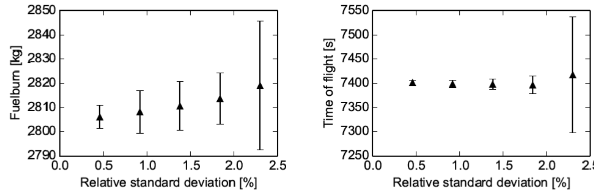

Figure 9. Mean values and standard deviations of changes in fuel burn and time of flight, caused by uncertainties in temperature measurements, expressed in relative standard deviations around a modelled temperature value.

3.2. Impact of the accuracy in air temperature on the trajectory optimization

An uncertainty in temperature measurement or forecast at flight level is expected to have a significant influence on the vertical path and therewith on fuel burn and initial cruising altitude. In fact, the relative standard deviations $\sigma_{Fuelburn}$, $\sigma_{Altitude}$ and $\sigma_{Flighttime}$ reach higher values, but are still below the expected model accuracy of the trajectory prediction (compare *Figure **10*** and *Figure **11***). Differences in fuel burn of approximately $\sigma_{Fuelburn} = 1$ % are simulated for a temperature fluctuation around $\sigma_{Temp} = 2.5$ %, compared to $\sigma_{Fuelburn} = 0.05$ % when wind speed is varied around $\sigma_{u,v} = 2.5$ %. Very small mean values of the lateral deviation of the trajectory from the original one (here, $CTT = 0.3$ NM) cause relatively large relative standard deviations of $\sigma_{CCT} = 200$ %. However, absolute values of $\sigma_{CCT} = 1$ NM are negligible. As expected, significant fluctuations in the initial cruising altitude at FL 400 are simulated, which is above the vertical separation minimum and hence would influence the ATFM, when inflight optimization would be applied.

4. IMPACT ON TRAJECTORY PREDICTION

In the following, the impact of uncertain weather conditions will be analysed, if the lateral path is fixed. This assumption corresponds to the idea, that pilots are restricted to the filed trajectory in the lateral path and adaptions are only possible to speed and altitude.

4.1. Uncertainty of wind components u and v assuming a fixed lateral path

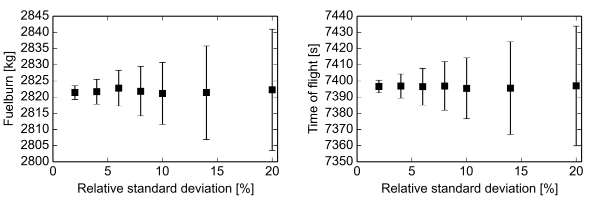

Figure 10. Impact of uncertainties in wind component u and v on fuel burn and flight time with assuming a fixed lateral path.

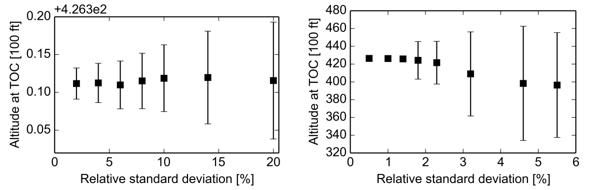

Figure 11. Deviations of the altitude at TOC, for different relative variations in wind component u and v (left) and temperature (right). The lateral path is constant.

If the lateral flight path does not consequently follow the wind optimum solution and is fixed to a defined distance, fuel burn and time of flight will be higher (*Figure **10***) in a fluctuating wind field, compared to the optimum solution (*Figure*) with a lower standard deviation due to the constant distance of the lateral path. This phenomenon shows the necessity of an in-flight trajectory optimization, as soon as weather updates are available. On average, 20 kg (0.7 %) fuel could be solved between Prague and Tunis. Despite a constantly changing wind situation, the altitude at the TOC will be very stable at FL 426 (*Figure **11***), if the lateral path is fixed, because this metric is mainly driven by flight performance.

4.2. Uncertainty of temperature assuming a fixed lateral path

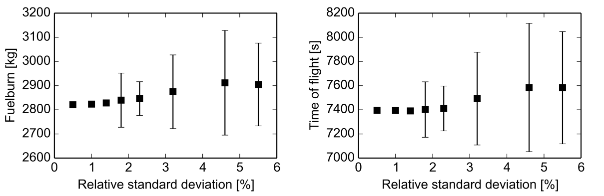

Figure 12. Impact of uncertainties in temperature on fuel burn (left) and time of flight (right) along a fixed lateral path.

Large standard deviations in the altitude at TOC under uncertain temperature conditions of 8000 ft (18 %) (*Figure **11***) are combined with large differences in the climb profiles (i.e., rate of climb) and pose great challenges for ATFM.

Due to not optimum lateral flight paths (as long as the lateral flight path is fixed during the trajectory optimization), fuel burn and time of flight increase with increasing uncertainty in the temperature (*Figure **12***) and are significantly higher than under optimum conditions (*Figure **11***). Differences of 400 kg cause (14 %) an instable trajectory prediction, optimum speeds and altitudes strongly depend on the aircraft mass, which is, as a consequence difficult to predict.

5. CONCLUSIONS

In this paper, the impact of uncertainties in the prediction of wind speed, wind direction and air temperature on the trajectory prediction, i.e., the ability to reach certain spatial coordinates at certain time stamps is quantified and discussed. Thereby, the lateral path has been optimized in each simulation run (assuming an inflight trajectory optimization). This means, the aircraft is able to optimize its flight path, depending on current weather conditions. Thereby, an important impact of wind speed and temperature on the lateral flight path, as well as on the initial cruising altitude has been identified. Additionally, the lateral path has been fixed to the optimum solution for the real weather data (assuming a trajectory prediction). In this case, the trajectory is mainly impacted by large uncertainties in the climb profile (in case of temperature fluctuations). Surprisingly, fuel burn and time of flight are more stable (with higher mean values), when the flight path is fixed to a constant distance, although it does not follow optimum wind conditions any more.

Considering the features of the 4D Trajectory Management, where aircraft should be allowed to follow their optimized trajectory, as long as they reach certain spatial coordinates at certain time stamps, the results of this study identify a conflict between both features, because aircraft will only be able to come up with the time constraints, when lateral deviations from the planned trajectory are allowed. This in turn causes a great challenge for the ATC, as far as weather prediction is burdened with uncertainties. On the other hand, this study could show that the optimization algorithm, implemented in TOMATO is able to come up with sudden fluctuations in the input parameters and finds optimum solutions, so that the aircraft will be able to reach at least the FAF at the given time, because the time of flight did not change significantly over all simulations.

More work has to be done to identify other significant uncertainties in trajectory calculation. The stochastic variation of the wind components is not as realistic as possible. The u component (between East and West with positive values for west winds) has to be varied stronger (up to values of $u = 200$ ms^{-1}) for simulating air currents like jet streams. Furthermore, the impact of the variation in the input parameters on flight time, fuel burn and cruising altitude will be estimated without a lateral trajectory optimization. After that, further aircraft specific input parameters like the aircraft mass and fuel flow will be burdened with uncertainties and their impact on the trajectory prediction will be estimated.

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