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Aircraft trajectory optimization with dynamic input variables

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Abstract

The increasing demand for efficient and environmentally sustainable flight profiles requires innovative operational concepts. Short-term trajectory adaptations, considering dynamic input variables constitute a reliable solution. According to current air traffic regulations, flight trajectories are planned ground based and submitted to Air Navigation Service Providers for an overall validation according to airspace and sector capacity constraints. This initial flight plan often relies on static atmospheric forecasts for the entire flight. Sudden changes of atmospheric parameters such as wind speed and wind direction cannot be predicted precisely and are not considered in today's flight operations, except of severe weather phenomena. This paper investigates the benefit of en-route weather updates and subsequent short-term trajectory optimization. The resultant benefit of dynamic optimization during flight is assessed for varying shares of flights equipped with this novel capability within 1 hour of Europe's air traffic. Therefore, fuel, engine emissions and controller task load are used as assessment indicators. 75% of the frequently optimized trajectories gained in overall fuel savings with an increased task load of 5.4%.

Keywords Aircraft trajectory optimization · Dynamic input variables · In-flight information updates · Weather forecast

1 Introduction

In the aviation industry, aircraft operators are striving for a reduction of operational costs, specifically fuel-saving strategies in flight planning and flight operations. Current handling of flight plan data is used for an initial calculation of the operational flight plan (OFP) and its upload into the Flight Management System (FMS). However, according to current regulations (ICAO PANS-ATM [1]), the trajectory also has to comply with capacity constraints regulated by the air traffic flow management (ATFM) units, e.g., Europe's network manager. Thereafter, short-term changes can often no longer be considered and the trajectory is flown as filed. Flight path changes will be possible in case of available airspace capacities (as shortcut to the next FMS waypoint), or as operational diversions to avoid safety relevant events, such as severe weather (thunderstorms, turbulences, icing). However, it is well known that common short-term changes of atmospheric conditions (i.e., deviations from weather forecasts, as shown in Fig. 1) mainly result in differences of flight time, fuel burn, and the optimal paths [2, 3]. For example, a head wind component of 6 m per second over a distance of 100 nautical miles at FL 370 during approx. 13.5 min flight time results 15 kilograms (3%) extra fuel burn for an Airbus A320 with a gross mass of 67.7 tons) [4].

This paper investigates the benefit in fuel burn, time of flight, and air distance flown of periodically in-flight trajectory re-optimization and its application in flight operations. Therefore, new flight profiles are calculated hourly from the present aircraft position when new weather forecast data are available (e.g., Rapid Refresh, formerly Rapid Update Cycle [5]). An implementation of those procedures in today's air traffic operation would induce an unpredictable air traffic flow, which is why ground-based trajectory optimization is a critical issue for ATM. For this reason, three scenarios with varying shares of flights with in-flight optimization based on a historical real flight schedule are analyzed, regarding controller's task load.

An expected upcoming framework of digitization with improved data availability, and improved aircraft–ground

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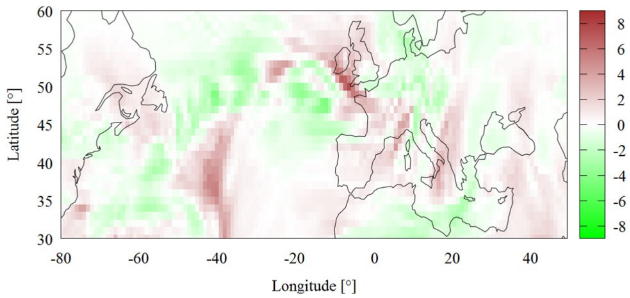

Fig. 1 Absolute change of wind speed [m/s] between 07:00 and 08:00 UTC on 2018-01-03. Red: Speed increase, Green: Speed reduction

and aircraft–aircraft communication will enable new opportunities for data updates, even during flight [6]. Based on this potential, the Single European Sky (SES) Initiative will drive a higher flexibility in flight profile implementation by 2038 in terms of referenced business trajectories (RBT) [7]. This is also recommended by the International Civil Aviation Organization (ICAO), forcing the reduction of restrictive flight operations between ATS routes if required navigation performance (RNP) is fulfilled [1].

Those in-flight trajectory optimization strategies are nontrivial because they require the consideration of dynamic input variables. Specifically, the significant effect of wind speed and wind direction on the optimum 4D trajectory is highly dynamic because the atmospheric conditions are underlying permanent fluctuations [2].

This paper is structured as follows: after a brief literature review of air traffic simulations with dynamic trajectory optimization in Sect. 2, the methodology of the applied simulation environment and the enhancement towards a trajectory optimization with dynamic input are described in Sects. 3, 4. Section 5 presents the benefits of those optimized single trajectories and also assesses the effects of those trajectories on airspace utilization and the controller's task load.

2 State of the art

The optimization of trajectories is already comprehensively embedded in research topics of trajectory-based operations (TBO) [8] considering a differentiation between dynamic input variables and dynamic optimization. Promising solution approaches of trajectory optimization are formulated as dynamic optimum control problems (OCP) or numerical approaches using simplified flight performance models and several objective functions [9–14]. The approaches are mostly based on steady input data assuming constant cruising altitudes, speeds and focusing on heading changes as function of time [11, 15, 16]. Hence, this analytical approach is limited to a small number of state variables, which, considering the unsteady flow characteristic, do not allow for a precise flight performance calculation. Numerical approaches (e.g., the A* lateral path finding algorithm) use discretized optimization methods and effective heuristics by considering a variability of flight performance parameters, such as wind speed and direction at different altitudes, airspace capacity constraints, and aircraft type-specific performance. Those approaches enable an overall assessment of the lateral and vertical profile [17–20] accompanied by a partial loss of the dependence on time due to missing actual aircraft speed information during the dynamic path search. Because the heuristic estimates a cost minimum between departure and destination, which is used as abort criterion for path finding, those algorithms need constant weightings of each node. With this method, a promising potential of free route trajectories regarding costs, emissions, and the environmental impact of condensation trails under single weather conditions has already been identified [17].

However, dynamic input variables such as wind fluctuations are significant for a realistic performance calculation, although the required input data are merely available during flight. González et al. [21] use wind as a dynamic input variable and investigate a corridor for probable flight path. Kamgarpour et al. [22] avoid severe weather conditions in the planning horizon based on time variations and the corresponding dynamic forecasts. In both calculations, the trajectory has not been improved while the aircraft is already in-flight.

Beside the methodological side of dealing with dynamic input variables in trajectory optimization, solutions for numerous operational aspects are required. For handling dynamic input variables or changed weather forecasts, the computation instrument for trajectory and performance calculation on board is the aircraft FMS (especially past generations) and is not suitable for a dynamic trajectory prediction. Today's FMS databases are restricted to static wind predictions along those waypoints included in the filed flight plan. Both research associations, FAA's NextGen and the European SES program, aspire 4D trajectory-based operations and function for mission optimization on next-generation FMS [23]. However, these FMS will mainly be limited to their own specific navigation database. Commercial products such as the Flight Profile Optimizer or Godirect Flight Optimization have already enabled the re-calculation of the optimum vertical profile due to changed input data using the electronic flight bag (EFB) [24, 25]. Therefore, live data of weather and aircraft are considered but the lateral optimization is missing, mainly due to ATM restrictions. Forster et al. [26] use the EFB to visualize severe weather conditions and organize re-routings but do not provide a trajectory optimization. In the Traffic Aware Strategic Aircrew Requests (TASAR), NASA combined a lateral and vertical trajectory optimization in case of convective weather situations with onboard conflict avoidance algorithms, implemented on a

EFB [27, 28]. Hereby, the onboard algorithms suggest the aircrew with recommended trajectory improvements that are assumed as more likely to be approved by ATC.

By contrast, this paper focuses on the potential of a multi-objective optimization for the entire flight and investigates the consequence of re-planning trajectories to air traffic controller's task load from the traffic flow perspective. Finally, case studies of those products declare an annual cost-saving potential of 0.2–1%, which is low but within the typical range for airline fuel and cost-saving actions.

Our analysis differs from available research and commercial products by optimizing the entire profile using global weather updates, a 4D-trajectory calculation as well as the assessment of airspace utilization. Therewith, we do not only alter a trajectory in cases of bad weather conditions or shortcuts, but we additionally consider an in-flight potential of spontaneous wind changes provided by means of improved and frequent forecasts.

For this purpose, we enhanced our air traffic simulation environment called TOolchain for Multi-criteria Aircraft Trajectory Optimization (TOMATO) [18–20, 29] (compare Sect. 3), focusing on a precise trajectory prediction and an analytical tool for the demand in airspace capacity and controllers' task load. Thereby, we consider the methodological implementation of dynamic input variables without the renunciation of unsteady flow characteristics or heuristics in path finding. A comprehensive validation of TOMATO with the widely used AirTOp can be found in [30].

3 Pre-flight aircraft trajectory optimization

TOMATO has been used to optimize aircraft trajectories and quantify the operational costs and the environmental impact. Therein, the COmpromized Aircraft performance model with Limited Accuracy (COALA) is implemented for vertical trajectory optimization and an A* path finding algorithm is used for lateral trajectory optimization.

With the included assessment tool, trajectories are assessed and iteratively improved [19, 20]. The trajectory design criteria can be weighted with different optimization target functions such as minimum environmental, operational or time costs. Furthermore, a multi-criteria optimum can be chosen.

The separation of the lateral and the subsequent vertical profile may lead to solutions that are not globally optimal. However, the identification of the true optimum is unknown and it is not possible to prove whether the global optimum has been reached or not. The reasons for this are on the one hand the formulation of the correct target function at every point of the trajectory. On the other hand, the traceability of the correct execution of the target function for each point increases the complexity of trajectory optimization. The implementation of an iterative optimization strategy approaches the optimal solution within a non-measurable gap. Figure 2 illustrates TOMATO's iterative optimization process.

3.1 Lateral path optimization in TOMATO

In the first iteration, a lateral path with optimum direct operating costs is calculated for a given initial target altitude in a discretized space grid (variable resolution) or between waypoints of the latest Aeronautical Information Regulation And Control (AIRAC) cycle. This lateral path considers the present atmospheric conditions corresponding to the latest available weather cycle. If no AIRAC cycle is given, the resolution of the solution grid is user-defined and mainly based on the weather forecast information or finer, which can be significantly denser, compared to AIRAC. The used NOAA Global Forecast System GFS provides resolutions up to 0.25° [31]. The A* connects each node from the world grid (each with unique coordinates) towards the destination with minimum cost. The cost to use an edge between two nodes is determined by distance, a time-related cost factor and a mean cruising speed, which are initially assumed for each aircraft type. Each of the following iterations uses improvements of those values retrieved from the trajectory assessment module.

The most relevant input parameters for path finding are:

- Grid resolution or AIRAC cycle.
- Departure, destination and -time, aircraft type.
- Initial cruising altitude, initial mean cruising speed.
- Initial direct operating cost rates per time interval.
- Restricted airspace areas.

3.2 Vertical optimization in TOMATO

Within the iterative optimization procedure of TOMATO, the lateral path is used by the aircraft performance model

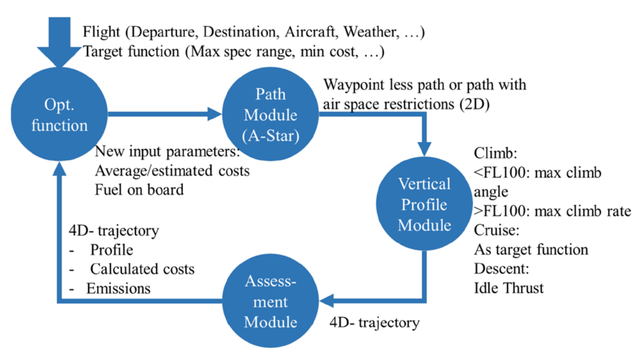

Fig. 2 Trajectory calculation and assessment process in TOMATO with improvement of calculation results in each step

COALA for the estimation of distances and weather information along the path [20, 32]. COALA analytically solves the equation of motion considering the required maneuver-specific forces of acceleration for each time step (1 s). Thereupon, the equation of motion is integrated gaining the corresponding true air speed and distance flown. The true air speed is used as a regulative variable in a proportional/integral/differential (PID) controller, wherein the lift coefficient is used as a controlled variable. The target true airspeed is calculated according to the target function given as trajectory design criteria mentioned above. This input target function additionally determines the algorithm to calculate the desired cruising speed. The vertical profile is calculated using continuous climb and descent operations. Except for thrust-specific fuel consumption and maximum available thrust during climb, the model is independent of the Base of Aircraft Data (BADA 4) performance model, where a validation for the trajectory optimization approach can be found in [33].

The main input parameters of COALA are:

- Lateral path.
- Aircraft type, traffic load, initial fuel on board.
- Weather data.
- Objective function (min. fuel, time, operational costs, environmental costs, a specific cost index (CI) or weighting in each cost component).
- Target speed function.
- Target altitude functions.

The output of COALA is a 4D trajectory (latitude, longitude, altitude, time).

The GFS weather data are available for the calculation of the lateral and vertical profile in a gridded format and discretized for only four pressure heights relevant for typical cruising altitudes. For this reason, a linear interpolation of the weather information (wind, geo-barometric altitude, temperature, relative humidity) is performed. This is done first for the location and then for the altitude.

3.3 Trajectory assessment in TOMATO

In the third step of each iteration, an assessment of the trajectory regarding operating costs, fuel burn, and induced environmental impact including the radiative forcing of condensation trails is executed. Thereby, input parameters affecting the path finding algorithm (i.e., the assumed initial operational costs, a mean cruising altitude, a mean cruising speed and the tanked fuel mass) are adapted and taken over in the next iteration for the A* algorithm. For the assessment, the following input parameters are required:

- Direct operating cost rates for fuel, maintenance, insurance, depreciation, crew, and delay.
- En-route navigation charges.
- Environmental cost functions depending on emission species (CO_2, NO_x, H_2O, SO_4, HO, H_2SO_4, black carbon) and quantified environmental impact according to scientific state of the art knowledge.

With the help of this assessment, the objectives (e.g., CI, time costs, fuel costs, crew costs, etc.) can be calculated and compared either with the input target function or with the assessment of the last iteration. If a certain abort criterion or a maximum number of iterations is reached, the optimum 4D trajectory is stored together with the assessment results.

3.4 Airspace and task load assessment in TOMATO

The impact of the implementation of new air traffic controller systems, airspace configurations, or capacity planning methods are usually assessed with the task load of air traffic controllers. In a post-processing of TOMATO, the trajectories are assessed regarding changes in the required airspace capacity (i.e., number of aircraft per volume) and the resulting controller's task load. For both analyses, the airspace is split into artificial sectors defined by the geographical coordinates with an edge length of one degree. Therewith, an almost equal size of all sectors is realized for small observation areas. For each sector, the task load of the controller is then calculated for time intervals and compared for different scenarios.

There is a variety of subjective, physiological and activity monitoring methods along the genesis of new ATM systems [34]. The evaluation of the traffic flow shift due to the applied flight optimization is orientated on the controller's task load model CAPAN (Capacity Analyser) by Eurocontrol and Deutsche Flugsicherung (DFS. The TOMATO implementation is described in Rosenow et al. [35, 36]. This model provides predefined activities (traffic monitoring, radio telephony, coordination, clearances, conflict detection and conflict resolution) with an associated load per activity. Herewith, typical controller tasks (traffic monitoring and conflict resolution) can be expressed as a need of time in seconds to solve those tasks. The needed time for each task is declared not only according to the task type but also dependent on the flow of traffic (e.g., angle between crossing traffic). The associated times and the calibration of the model are based on the experience of the controllers with common used ATC systems.

Conflicts between aircraft are not counted explicitly. Due to constantly changing headings and altitudes, the highest task load category for conflict detection and resolution is applied based on the number of aircraft in each sector.

An acceptable limit of task load for capacity planning is usually set to 70%, i.e., a total of 2520 s of a full hour of working time. In practice, exceeding this capacity limit would result in a splitting of the sector with involving additional controller teams. Here, due to the artificially selected sector dimension of 1° lateral resolution and no vertically partitioning, the size of the investigated ATC sectors is in the same dimension as real ATC sectors. However, to ensure comparability of the scenarios, the apportionment is avoided and the sector dimension remains constant. For this reason, it is expected that the sum of the task load in many sectors will be greater than the specified capacity level. The calculated task load is, therefore, only a theoretical comparison value, which, however, indicates a direct traffic shift. As a reference for the comparison, historical traffic scenarios can be used, which will also have a task load greater than 2520 s per sector. Since safe flight operations have already taken place here, a fundamental transferability of the results can be assumed.

4 In-flight aircraft trajectory optimization

4.1 Concept of in-flight trajectory optimization

The following section introduces a basic process of optimizing flight trajectories during flight and describes a necessary approach for data exchange. As soon as weather updates are available, the trajectory is periodically re-optimized. Hereby, we consider differences in fuel, emissions quantities, and operational costs between the old trajectory and the dynamic trajectory adjustment. Figure 3 illustrates the concept of the operational process behind the dynamic trajectory re-calculation.

In current procedures (Fig. 3, solid lines), the airline's dispatch department calculates an initial trajectory and OFP according to airspace constraints. This trajectory is provided to the crew for cross-checking the integrity of the flight plan data and transferring it to the FMS. Optionally, the EFB uses the data showing enhanced information (present aircraft position, planned route, performance calculation).

During flight, a supporting decision for a trajectory re-optimization request is carried out, defined as triggers (Fig. 3, dotted lines). During the climb and descent phase, triggering is avoided due to the dense airspace and the already intensive workload of pilots and controllers. Here, the filed OFP or latest validated trajectory by ATC is used. During cruise, one of the following situations and events might be used as triggers, implying a re-optimization process:

- New weather forecast data (usually each hour).
- Identification of severe icing/turbulence (extending the onboard weather radar range which is limited to < 200 NM, compared to Forster et al. [26]).
- Right before the Top of Climb (ToC) or a (unexpected) deviation from the filed flight plan.
- Diversions, e.g., as a result of ATC advisories.
- Change of the objective function (e.g., increasing time costs or increasing interest in contrail avoidance).

Such triggers can be consolidated by the EFB which is monitoring the aircraft position and updates of flight relevant information. However, each triggered re-optimization requires a data uplink and downlink providing an optimization request and input data, which is usually not required on board (compare Sect. 3). Otherwise, a fully ground-based optimization with a subsequent sharing of the 4D trajectory between airline and ATC is required. The latter would reduce the required bandwidth and data volume, which in the first case would contain several bytes for the optimization request sent by the EFB and less than 1 Mb for trajectory uplink,

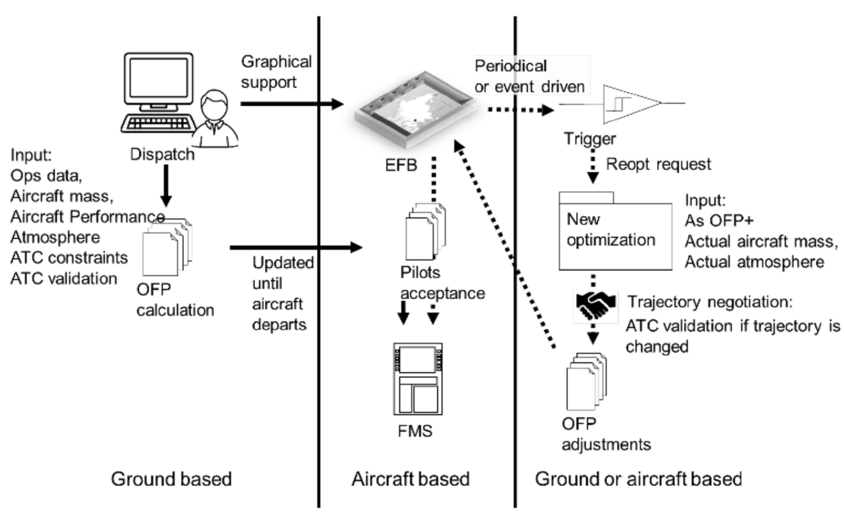

Fig. 3 Operational updating process of the trajectory with solid arrows representing the current and dotted arrows enhancing the process

depending on resolution of time and space. The on-board optimization (using the EFB) and weather data uplink will be possible by future communication technologies which will be able to provide up to 10 Gbit per second based on 5G mobile communication technology [37] (VHF Datalink Mode 3: 31.5 kbps). Significant differences of the trajectory after re-optimization, e.g., different waypoints or altitude changes, require a second ANSP validation. This could be only done with Eurocontrol's Integrated Initial Flight Plan Processing System (IFPS), if this system is able to validate RBTs from TBO concepts in real time. After validation, the filed flight plan in the FMS will be updated.

4.2 Dynamic input variables in in-flight trajectory optimization

Each triggered trajectory re-optimization may require different input data according to the objective function. Those input variables for TOMATO, which may be changed during the flight, are listed in Table 1. The aircraft dry operating mass as well as the traffic load are kept constant.

Dynamic weather input affects the complete set of weather data. In particular, this includes wind direction, wind speed, temperature, geometric altitude, and relative humidity. To compare trajectories before and after in-flight optimization, the configuration of the airspace does not change.

If the next weather dataset is published, this information will be used for the calculation of the trajectory. At each triggered point, TOMATO's iterative process (Fig. 2) is applied. Therefore, the current aircraft position defines the starting point and the temporally closest weather data set. Each lateral position and altitude, where a re-optimization has been triggered, is treated as a fixed waypoint which must be overflown in all subsequent re-optimizations. After reaching the last triggered position and pressure altitude, the flight proceeds to the destination based on the new cost calculation (and weather data set). Thereby, the old path is fixed and not influenced by the new weather. During the assessment (Fig. 2), only the costs of the future flight path are used for iterative optimization.

No further significant changes to the implemented optimization processes of the lateral and vertical profiles are required. In addition, TOMATO was adapted in such a way that an automated calculation and assessment of the entire in-flight optimized flight takes place. For this purpose, in the first step, all weather data and their updates were loaded into the system and are then activated according to the flight progress and optimization point of time. Since TOMATO and the numerical methods do not use random variables for the optimization, it is assumed that every change or improvement of the new calculated trajectory is a consequence of the change of the input values.

As the A* heuristic cannot handle dynamic input variables, the costs for connecting nodes along the grid can only be modeled with a single weather data set per flight segment (1 h, in most cases). Hence, in each optimization step (i.e., each flight segment), the actual weather data set is assumed as steady and does not change over time, because a time-linear interpolation of the weather behavior does not correspond to reality. However, this approach underestimates the accuracy of today's weather forecasts, as no time-related change in the weather is considered. This can result in a reduction of the calculated fuel-saving potential in reality. However, this approach represents the current practice of long-haul flights, which are planned and filed at least 1 h before departure. These flights then spend several hours in this presumed weather behavior without updating the input values and the trajectory.

Using the re-optimization procedure described above, different scenarios are simulated with an increasing amount of re-optimized trajectories in a real historical air traffic scenario above Central Europe.

5 Applications of in-flight optimization

5.1 Single trajectory in-flight optimization

The following section investigates the potential of the in-flight optimization problem using TOMATO. As a first step, we formulate a scenario with a single flight departing 05:06 UTC in Nairobi, Kenia (NBO) and arriving at approximately 14:41 UTC in Paris, France (CDG) on January 3rd, 2018. The reference weather scenario is chosen on a typical day with no significant dynamics in weather change. The aircraft

Table 1 Adapted input variables for triggered trajectory re-optimization

Trip fuel	Fuel on board
Fixed waypoints	Actual aircraft position, AIRAC if necessary
Cruising flight level	Fixed by initial value, as triggered or as a result of optimization
Weather	Nearest to trigger and changing with forecasts, if available
Time costs, fuel price	As initial or updated, if available
Cruising speed	Fixed by initial value, as triggered or as a result of target optimization
Cost calculation	Rest of the flight after trigger

is a Boeing 787 with a traffic load of 60 tons. We distinguish between three different operational cases:

- The tracked/reference flight path, retrieved from the Eurocontrol Network Manager Operations Centre (NMOC) [38] in the SO6 traffic file format with varying resolution in time and space.
- The initially optimized and flown trajectory following single aircraft trajectory optimization (Sect. 3) with constant input parameters.
- The final optimized flight with triggered re-optimizations each hour following in-flight aircraft trajectory optimization (Sect. 4) during cruise.

Icing and other severe weather conditions are not considered to achieve a focused assessment of the in-flight optimization approach. Echoing these assumptions, only the ToC and periodic weather updates each hour have a triggering effect. NOAA and GFS provide the weather data in GRIB2 data format [39] with a spatial resolution of 0.25 degrees. The weather data are updated in 4-h cycles with hourly forecasts included in each cycle. Figure 4 exhibits the tracked path and profile in black, modeled with TOMATO, and the initially optimized trajectory in green. Figure 5 indicates the finally flown profile, where triggers are highlighted as black squares.

The final cost and fuel burn assessment of this flight (NBO-CDG) considering dynamic weather conditions depending on actual position, altitude and time is summarized in Table 2. Obviously, differences between the reference/tracked, the initial and the final trajectory are marginal because only minor lateral improvements were found by TOMATO (compare Fig. 4) and the reference trajectory almost follows the great circle, which equals the minimum time track in this special case. Nevertheless, there is a tendency for further fuel savings in the case of the application of an in-flight optimization (680 kg of fuel saved compared to the reference and 175 kg compared to the initial optimization). However, it should be noted that the resulting delta fuel is within the fuel flow error of the BADA model used, which amounts to 2.77% for a Boeing 787-800 Rolls-Royce (B788RR) during cruise [40]. Hence, fuel savings cannot be

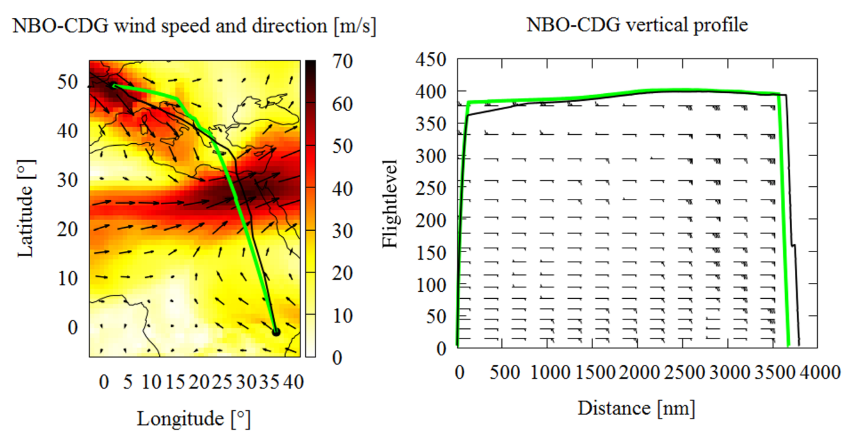

Fig. 4 Historical (black) and initially optimized flight path (green). Wind data from 06:00 UTC is shown at a pressure altitude of 227 hPa (FL 360)

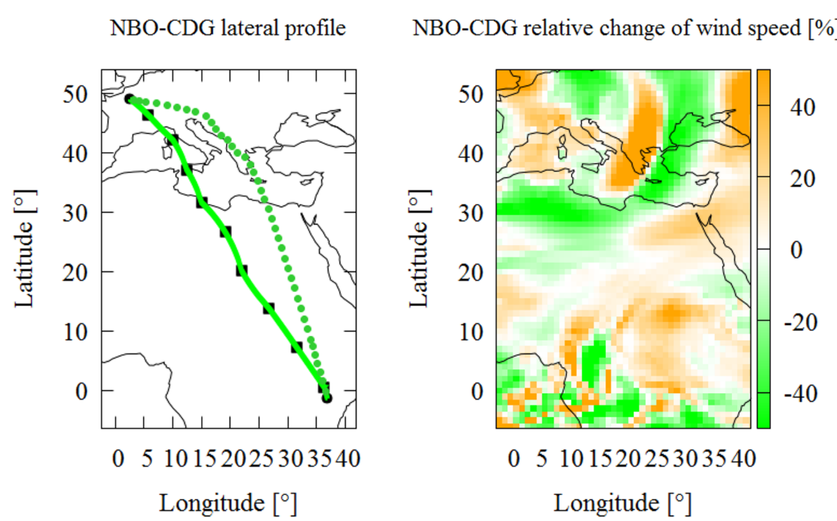

Fig. 5 Final lateral profile (green) of the in-flight optimized trajectory (dotted: initial optimized profile). Black squares represent *optimization triggers*. Right: Areas of increased (orange) and decreased (green) wind speed in percent between 06:00 UTC and 15:00 UTC

Table 2 Assessment of the single flight NBO-CDG for different optimization steps with a single pre-flight optimization (initial) and with a dynamic optimization (final)

	Tracked (reference)	Initial	Final
Operating Costs (€)	127,159	127,363	125,527
Emission Costs (€)	3956	4070	5490
Fuel Burn (kg)	42,665 (100%)	42,160 (− 1%)	41,985 (− 1%)
Flight Duration (min)	575	555	559
Air Distance (km)	7330	7350	7312
Ground Distance (km)	7038	7240	6937

determined exactly. Furthermore, the assessment uses linear interpolation between the weather updates, resulting in smoothing out of atmospheric turbulences.

Figure 5 indicates significant differences in the filed flight path after each optimization step, especially at the ToC. Depending on the extent of change in trajectory and atmospheric conditions, a new flight path would require another ANSP validation check. Furthermore, the controller's task load would increase by operating along the new profiles, which should be considered in the task load assessment.

5.2 Multiple in-flight optimization and airspace assessment

After exemplifying the impact of dynamic optimization on a single trajectory, the potential analysis at a large scale has been examined using the corresponding traffic scenario (tracked/reference, retrieved from the Eurocontrol NMOC). Again, changes in sector utilization and controller's workload compared to the tracked/reference scenario have been determined following the methodology described in Sect. 4.1. Thereby, the share of re-optimized trajectories is gradually increased (0%, 10% and 27%). Table 3 summarizes the scenario parameters.

Assuming that the most demanded sectors would be the most restrictive sectors [41], we define an area of interest (AOI) including these sectors and enabling the focus on workload estimation with reduced computational effort. Figure 6 shows the AOI as bounding box as well as the direction of motion of high-level wind in a time horizon of 10 h. The illustrated North Atlantic jet stream and the jet stream in the African/Arabian airspace will probably infer the most flight plan updates.

Furthermore, the number of flights has been limited to a set of candidates for trajectory re-calculation during cruise. Long-haul flights with several hours of flight time as well as flights with a departure time later than the latest available weather update are expected to have the highest fuel-saving potential. However, flights with a minimum of 60 min are mainly restricted by ATC constraints as SIDs, STARs, or altitudes (cruising in lower airspace). Subsequently, we prioritize medium- and long-haul aircraft as candidates for optimization and consider small jet and turbo props only

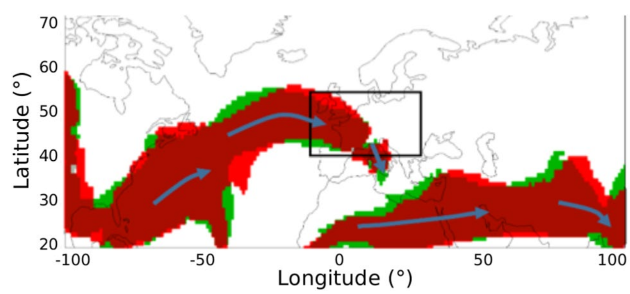

Fig. 6 Motion of medium and high-speed wind fields (> 35 m/s) from 06:00 UTC (green) to 16:00 UTC (red) with trend arrows and the AOI as black box

Table 3 Scenario definition for dynamic optimization and airspace utilization assessment

Date	Jan. 3rd, 2018
Time of interest	06:00–16:00 UTC
Number of flights	14,955
Weather data	NOAA GFS, Grib 2, 1.0°
Weather update rate	Hourly
Spatial resolution	0.3°
Area of interest AOI	Western and Central Europe Latitude [°] = [41.0…54.0] Longitude [°] = [− 8.0…25.0] (cf. Figure 6)
Share of inflight optimization	0% (reference), 10%, 27%
Minimum flight level in cruise	FL 250
Re-optimization trigger	ToC, 60-min weather update
Minimum criteria for re-optimization candidates	60 min flight time, maximum altitude above FL250, assigned aircraft type from below
Used aircraft performance types	A310, A319, A320, A321, A330, A380, B737-800, B747-800, B777, MD11, B787, B767-300

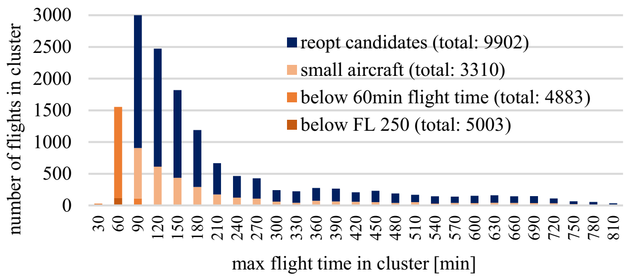

Fig. 7 Number of Candidates for in-flight optimization

for airspace assessment. Figure 7 indicates the number of candidate flights for in-flight optimization (blue) compared to non-suitable flights, which are characterized by cruising altitudes below FL250 and with a flight time of less than 60 min, and not implemented small aircraft type.

However, these assumptions restrict the assessment of those flights to airspace utilization with input from SO6 flight plan data only. It should be noted that a second trajectory validation using Eurocontrol IFPS is not possible with historical flights. Furthermore, the intended waypoint-less optimization represents a future concept of operation.

Figure 8 shows the tracked/reference (left) and the scenario with a 27% share of dynamically optimized trajectories and the resulting task load in each sector as heat map. It should be noted that the used sector dimensions (1° lateral, complete upper air space) do not represent the real ATC sector shapes and are used only to compare the traffic complexity. The evaluations are made for the most demanding time interval 10:00–11:00 UTC representing the basic trends similar for all other time intervals. The maximum measured values of the task load increased slightly from 11,931 s in the tracked/reference scenario to 11,975 s in the 27% scenario. However, the average task load increased by 214.6 s (growth by 5.4%). Figure 9 indicates the change in task load distribution for both scenarios with a trend towards higher air space complexity due to trajectory optimization. Note, also in the initial optimization case, the average task load increased by 2.7% due to traffic complexity.

In summary, dynamic optimization increases the controller's task load, considering the most demanding scenario for conflict detection due to non-constant headings and altitudes of all aircraft [35]. The results of the task load assessment and the potential of the optimization is shown in Table 4 for a share of 10% and 27% aircraft using this capability.

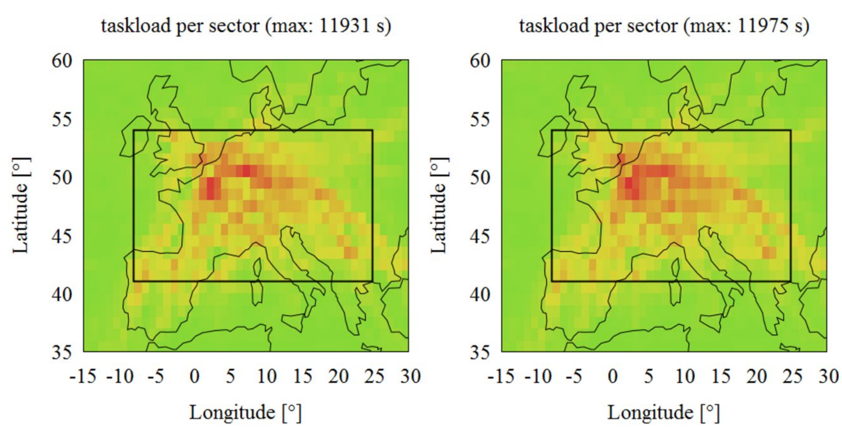

Fig. 8 Task load assessment (10:00–11:00 UTC) for the reference (left) and the 27% scenario (right). Green: minor task load, Red: maximum task load

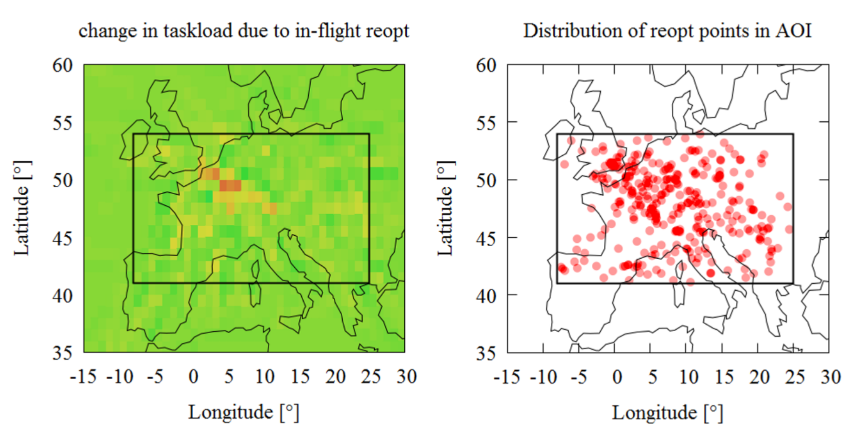

Fig. 9 Left: Change of task load (Red: increase up to 3042 s, Green: reduced (− 1622 s) or neutral). Right: Density plot of re-optimized points (AOI only)

Table 4 Results of ATC task load assessment (10:00 UTC to 11:00 UTC) and total fuel-saving potential

	Reference	10% In-flight opt. (990 flights)		27% In-flight opt. (2673 flights)	
		Initial opt	Final opt	Initial opt	Final opt
Fuel burn savings, per flight (kg)	– (Total: $1.2875*10^{8}$)	404	473	435	506
Air distance reduction, per flight (kg)	– (Total: $6.0378*10^{10}$)	172	205	177	212
Sector in assessment (when task load > 1 s)	341	341	341	341	341
Avg. sector task load (s)	3935.8	3998.4	4003.9	4097.3	4150.4
Sectors with increased task load, avg. value (s)	–	17%, +198	17%, +201	26%, +277	26%, +291 s
Sectors with decreased task load, avg. value (s)	–	3%, −170	3%, −172	6%, −237	6%, −230
Number of sectors with task load > 2520 s	246 (72%)	250 (73%)	250 (73%)	258 (75%)	257 (75%)
Maximum task load (s)	11,931	11,914	11,608	11,869	11,975
Number of re-optimizations	–	–	Total 125 0.26/h (max: 5/h)	–	Total 309 0.64/h (max: 10/h)

Reference: tracked flights from Eurocontrol SO6 traffic file; 10% and 27% scenarios represent a share of 10% and 27% of all Flights with a In-flight optimization capability

6 Summary and conclusion

Today, aircraft trajectories are constrained by airspace structure (e.g., ATS routes), sector capacity and a less flexible planning and negotiating process. Hence, trajectories are filed by operators and are accepted by ATC only with special consideration of ATFM. The flight efficiency depends on atmospheric conditions such as wind speed and direction, which are hardly to predict due to their dynamic fluctuations, especially several hours in advance. Hence, the flight path is calculated in a single and steady atmosphere, which could potentially be outdated at actual departure time. This paper investigated the potential of re-calculated trajectories when the aircraft is already in cruise, whenever a weather update is. Therefore, the aircraft trajectory optimization simulation environment TOMATO has been applied for a set of flights with a flight time longer than 60 min, cruising altitudes higher than FL 250, and aircraft types larger than mid-haul category for a European air traffic scenario from January 3rd, 2018. After an initially waypoint-less optimization using time-independent weather conditions from the recent forecast, the trajectory has been re-calculated the first time at ToC and afterwards each hour corresponding to the weather update cycle from GFS and NOAA.

Dynamic changing wind conditions and jet streams result in significant modifications of the trajectory with changes in the lateral and vertical profile. Considering an example of a single flight (NBO-CDG), a fuel-saving potential of approximately 1%, compared to a historically tracked reference flight was shown. The expected fuel saving due to re-calculations in the dynamic weather conditions is marginal compared to the initially optimized trajectory based on the boundary conditions of the reference flight (approx. 17% fuel saving). Safety is considered in the pre-tactical phase by assessing the airspace usage and the controller's task load within several sectors. Integrating both the initially optimized trajectories as well as the dynamically optimized trajectories into an air traffic simulation with real historical flights results in a change in lateral distribution of aircraft and in an increase of the controller's task load. Due to dynamic changes of flight plans, the controller's task load for conflict detection and resolution increases significantly. The additional workload due to optimization with dynamic input seems manageable but depends on how frequently it is employed and on the share of aircraft using the capability for re-optimization. To conclude, the dynamically optimized trajectories are possibility for a fuel burn benefit. However, the benefit significantly relies on precise weather information. However, considering the future implementation of TBO (e.g., SESAR RBT), a dynamic trajectory optimization would result in short-term fuel savings.

Future research should certainly further investigate the effect of additional task load by re-planning of airborne flights by considering human factors and real ATC sector shapes. This raises research questions regarding the parameterization of the workload by dividing the ATC controller and pilot tasks into individual activities with a better estimation of their duration. The methods shown can then be used to conduct a deeper analysis of the complexity of the airspace. This also allows to draw conclusions when the capacity is saturated due to re-optimization: how many re-optimizations are possible, e.g., in a period or a sector and how does this limit relate to our assumptions about the share of in-flight optimization capability?

References

1. International Civil Aviation Organization (ICAO).: 999 Robert-Bourassa Boulevard, Montréal, Quebec, Canada H3C 5H7. PANS-ATM, Procedures for Navigation Services—Air Traffic Management, Doc 4444, 16th Edition, Order Number: 4444, ISBN 978-92-9258-081-0 (2016)
2. Rosenow, J., Schultz, M.: 4D Trajectory prediction with stochastic input parameters," in Advanced Aircraft Efficiency in a Global Air Transport System, Toulouse (2018)
3. Lindner, M., Zeh, T., Fricke, H.: Reoptimization of 4D-flight trajectories during flight considering forecast uncertainties, in 67th DGLR Kongress, Friedrichshafen (2018)
4. Eurocontrol Experimental Center.: EEC Technical/Scientific Report No. 2009-009, Eurocontrol, Brussels (2009)
5. National Oceanic and Atmospheric Administration (NOAA).: Rapid Refresh (RAP), [Online]. Available: https://rapidrefresh.noaa.gov/ (2018). Accessed 15 may 2018
6. Büchter K.D., Sizmann, A.: High-Bandwith Aeronautical Telecommunication Options, in 63th DGLR Kongress, Augsburg (2014)
7. SESAR Joint Undertaking.: European ATM Master Plan, Belgium (2015)
8. International Civil Aviation Organization.: The Aviation System Block Upgrades—ASBU (2013)
9. Hargraves, C.R., Paris, S.: Direct trajectory optimization using nonlinear programming and collocation. J. Guid. Control. Dyn. **10**(4), 338–342 (1987)
10. Ringerz, U.: Aircraft Trajectory Optimization as a Wireless Internet Application. J. Aerosp. Comput. Inf. Commun. **1**, 85–99 (2004)
11. Sridhar, B., Ng, H., Chen, N.: Aircraft trajectory optimization and contrails avoidance in the presence of winds. J. Guid. Control Dyn. **34**(5), 1577–1584 (2011)
12. Soler, M., Zou, B., Hansen, M.: Flight trajectory design in the presence of contrails: application of a multiphase mixed-integer optimal control approach. Trans. Res. C **48**, 172–194 (2014)
13. Murietta, M., Botez, R.M.: Vertical Navigation Trajectory Optimization Algorithm for a Commercial Aircraft. American Institute of Aeronautics, USA (2014)
14. Patrón, R.S., Botez, R.M.,Labour, D.: Flight trajectory optimization through genetic algorithms coupling vertical and lateral profiles, in ASME 2014 International Mechanical Engineering Congress and Exhibition, Montreal (2014)
15. Wickramasinghe, N.K., Harada, A., Totoki, H., Miyamoto, Y., Miyazawa, Y.: Flight Trajectory Optimization for Modern Jet Passenger Aircraft with Dynamic Programming. Air Traffic Management and Systems, pp. 87–104. Springer, Tokyo (2014)
16. Jardin, M.R., Bryson, A.E.: Methods for computing minimum-time paths in strong winds. J. Guid. Control Dyn. **35**(1), 165–171 (2012)
17. Rosenow,J., Förster,S., Lindner,M., Fricke,H.: Impact of multi-critica optimized trajectories on european air traffic density, efficiency and the environment, ATM Seminar, Seattle (2017)
18. Rosenow, J., Lindner, M., Fricke, H.: Impact of climate costs on airline network and trajectory optimization: a parametric study. CEAS Aeronaut. J. **8**(2), 371–384 (2017)
19. Förster, S., Rosenow, J., Lindner, M., Fricke, H.: Toolchain for Optimizing Trajectories under real Weather Conditions and Realistic Flight Performance. Greener Aviation, Brussels (2016)
20. Rosenow,J., Fricke,H.: Flight performance modeling to optimize trajectories," in 65. DGLR Kongress, Braunschweig (2016)
21. González-Arribas,D., Soler,M., Sanjurjo,M.: Wind-based robust trajectory optimization using meteorological ensemble probabilistic forecasts, in Sixth SESAR Innvation Days, Delft (2016)
22. Kamgarpour,M., Dadok,V., Tomlin,C.: Trajectory generation for aircraft subject to dynamic weather uncertainty, in 49th IEEE Conference on Decision and Control, Atlanta USA (2010)
23. SESAR Joint Undertaking, Clean Sky 2 Joint Undertaking Work Plan 2014-2015, SJU (2014)
24. Pacelab.: Case study: fuel efficiency takes flight, PACE, Berlin (2016)
25. Honeywell.: Godirect flight optimization, product sheet, Phoenix, (2017)
26. Forster, C., Ritter, A., Gemsa, S., Tafferner, A., Stich, D.: Satellite-based real-time thunderstorm nowcasting for strategic flight planning en route. J. Air Trans. **24**(4), 113–124 (2016)
27. Woods,SE., Vivona,RA., Roscoe,DA., LeFebvre,BC., Wing,DJ., Ballin,MG.: A cockpit-based application for traffic aware trajectory optimization, in AIAA Guidance, Navigation, and Control (GNC) Conference, Boston (2013)
28. Wing,DJ. Burke,KA., Henderson,J., Vivona,R., A.,Woodward. J., "Initial implementation and operational use of tasar in alaska airlines flight operations," in Aviation Technology, Integration, and Operations Conference, Atlanta (2018)
29. Lindner,M., Förster,S., Rosenow, J., Fricke,H.: Ecological impact of air traffic control en-route charging zones in multi criteria optimized flight paths, Greener Aviation, Brussels (2016)
30. Rosenow, J., Fricke, H., Luchkova, T., Schultz, M.: Impact of optimised trajectories on air traffic flow management. Aeronaut. J. **123**(1260), 157–173 (2019)
31. National Centers for Environmental Prediction/National Weather Service/NOAA/U.S. Department of Commerce.: NCEP GFS 0.25 Degree Global Forecast Grids Historical Archive. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory, https://doi.org/10.5065/D65D8PWK (2015)
32. Rosenow,J., Förster.S., Fricke,H.: Continuous climb operations with minimum fuel burn, in Sixth SESAR Innovation Days, Delft (2016)
33. Mouillet,V., Nuić,A., Casado,E., López Leonés,J., Evaluation of the Applicability of a Modern Aircraft Performance Model to Trajectory Optimization, in IEEE/AIAA 37th Digital Avionics Systems Conference (DASC) https://doi.org/10.1109/dasc.2018.8569732 (2018)
34. Đokić,J., Investigation into Air Traffic Complexity as a Driver of a Controller's Workload, Dresden: PhD thesis (2014)
35. Rosenow,J., Fricke,H., Schultz,M.: Air Traffic Simulation with Multi-Criteria optimized Trajectories, in Proceedings of the 2017 Winter Simulation Conference, Las Vegas (2017)
36. Rosenow, J., Fricke, H.: Impact of multi-criteria optimized trajectories on European airline efficiency, safety and airspace demand. J. Air Trans. Manag. (2019). https://doi.org/10.1016/j.jairtraman.2019.01.001
37. International Civil Aviation Organization, "4G/5G Mobile Technology Application in Civil Aviation," in 13th Air Navigation Conference, Montreal (2018)
38. Eurocontrol, "Demand Data Repository Web Portal," [Online]. Available: http://www.eurocontrol.int/articles/ddr2-web-portal. Accessed 14 Jan 2018
39. National Centers for Environmental Prediction NCEP/NOAA, NCEP Products Inventory, [Online]. Available: http://www.nco.ncep.noaa.gov/pmb/products/gfs/. Accessed 2018
40. Poles,D., Nuic,A., Mouillet,V.: Advanced aircraft performance modelling for ATM: analysis of BADA model capabilities, Eurocontrol, Brétigny-sur-Orge (2010)
41. Eurocontrol, Performance review report 2016, Belgium, 06/2017

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