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Large-Scale Network Slot Allocation with Dynamic Time Horizons

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The purpose of this paper is to introduce an approach, which serves as initial step for the integration of adverse network impact information, like e.g. weather, to *tactical* European Air Traffic Flow Management (ATFM). A binary optimization methodology for large-scale linear problem decomposition with column-generation and structured variable pricing is combined with time-based problem segmentation to be able to dynamically integrate information on network impact states. The dynamic character of the approach is in line with SESAR 2020 objectives to improve the NM function in gathering benefits of short-term variations in network system states. A large-scale network scenario with a traffic sample of more than 25.000 flight plan data sets within European airspace is evaluated. Depending on the model time iteration, the Rolling Time Horizon concept adapts the ATFM optimization problem according to *actual* flight- and system-states. This segmentation approach shows improvements regarding the number of delayed flights, total delay sum and computation time and is suitable for future tactical ATFM optimization with dynamic network impact scenarios.

Keywords: air traffic flow management, slot allocation, column-generation, capacity, time horizon

I. INTRODUCTION

Air Traffic Flow Management (ATFM) in Europe is the function to balance air traffic demand with system capacities of airports and air traffic control (ATC) airspaces, called ATC *sectors*. Several ATFM sub-functions exist, which are assigned to four time-related execution phases [6]: (i) The Strategic phase starts at least 6 months before the day of operation and ends approximately 7 days before. This phase includes flight plan processing, coordination actions and pre-planning in terms of predicting highly congested network elements caused by respective traffic load of e.g. public mass events. Bottlenecks of traffic flows within the European Air Traffic Management Network (EATMN) are identified. (ii) The Pre-tactical phase applied during the six days before the day of operation allocates a range of Air Traffic Flow and Capacity Management (ATFCM) measures, like e.g. rerouting scenarios to individual groups of flights [7]. Furthermore, pre-tactical capacity regulations are planned according to the actual information state. (iii) The Tactical phase conducted on the day of operations regularly updates traffic rates and capacities. Especially in the case of adverse network impact, capacity profiles dynamically fluctuate according to traffic complexity patterns. A demand-capacity-balancing (DCB) process is applied, which integrates dynamic airspace management and pre-flight departure slot allocation. Finally, during the Ad-hoc phase (iv), activities conducted collaboratively by controllers and pilots, are applied to stabilize traffic flows within impacted airspaces and congested airports. Figure 1 depicts the time line and functions of the described ATFCM phases.

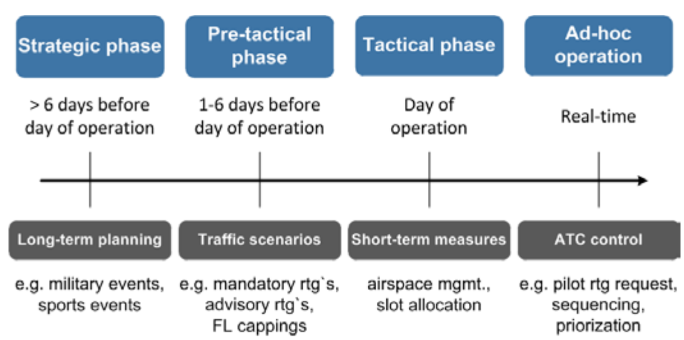

Figure 1. ATFM phases and functions.

The tactical phase is predominated by short-term slot allocation. In this context, ATFM slots shall not be mistaken with airport departure and arrival slots. Airport slots constitute *planned* time frames of 15 minutes length, negotiated within a slot conference on the basis of an airports capacity benchmark value. ATFM slots constitute tactically calculated take-off times (CTOTs) for which a flight departs on time within 5 minutes before and 10 minutes after CTOT.

During the tactical ATFM phase, Eurocontrol`s heuristic *Computer-Aided-Slot-Allocation* (CASA) algorithm performs assignments of ATFM slots to the set of flights being restricted according to demand-capacity-balancing (DCB) requirements. Thereby, the heuristic algorithm performs a *First-Planned-*

First-Served (FPFS) principle, and schedules flights according to their planned entry times into capacity-afflicted system elements, like e.g. ATC sector volumes. However, CASA might also restrict flights, which are originally not affected by capacity shortfalls, in order to comply with the First-Planned-First-Served (FPFS) principle. Moreover, every flight underlying more than one ATFM restriction is assigned to be delayed according to its *most penalizing* regulation along its planned 4D-trajectory.

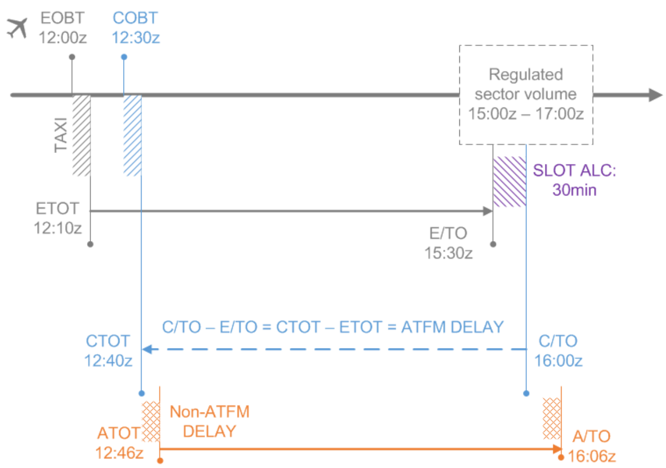

Figure 2. CASA-based ATFCM Slot Allocation Scheme. (adapted from Krebber (2001) [12]).

Figure 2 depicts an exemplary slot allocation process of a flight planned to enter a regulated sector volume at an estimated time-over (E/TO) at 15:30z. The flight is now declared as ATFM-restricted with a calculated time-over at 16:00z, introducing an ATFM delay of 30 minutes. Estimated off-block (EOBT) and take-off (ETOT) times are going to be shifted accordingly. The actual delay also reflects a share of unpredictable delay originated by airline scheduling, airport operations, etc.

Inefficiencies of heuristic slot allocation are especially emerging during periods of stochastic network impacts, like e.g. weather. Especially convective cells with an average short lifetime of up to two hours are not easy to predict. Therefore, short-term forecasts, also called nowcasts, are not yet integral part of ATFCM information management in a collaborative manner. Stich et. al (2013) [14] and Zinner et. al (2008) [15] provide detailed information on nowcasting algorithms and utilization.

The motivation for this study to establish a dynamic slot allocation architecture with *rolling time horizons* is to integrate convective nowcasts within the process of tactical ATFCM. Network performance increase is expected to be justified by (i) reducing the share of weather-impacted airspace volume during convective impact, (ii) minimization of impact periods following (i), and (iii) a high nowcasting quality and update rate of high-fidelity nowcasts. Therefore, Rad-TRAM is DLR's same-titled radar-based tracking and monitoring algorithm [3]. It delivers reliable thunderstorm information by identifying and displaying hazardous cumulonimbus (Cb) objects (polygons) with a reflectivity of 37dBZ or above. Flying in these areas compromises flight safety, since they are characterized by strong hail and precipitation.

Applying nowcasting data for tactical network management in a structured manner assumes requirements concerning time-related decision deadlines and information management between Network Manager (NM) and the aircraft operator (AO). Clare and Richards (2012) [4] describe the integration of operational processes and requirements of both actors during times of uncertainty. In terms of slot allocation, an AO`s operational requirement is schedule stability. A means to do so is to swap slots within the airline fleet but also with other airlines at the same departure airport, if applicable. However, to guarantee an *optimal* tactical reaction on ATFM restrictions, CTOT assignment needs to be executed latest two hours prior to EOBT. To do so, flight plans need to be filed at least three hours prior to EOBT. However, a considerable share of CTOTs is assigned below two hours in advance and even short before off-block. These lately assigned CTOTs generally result from airline slot swopping, and shortly identified and coordinated regulations. In this context, the first step of convective nowcasting integration within tactical slot allocation is described in this article. It focusses on an operational design and functionality of a tactical ATFCM model, which will be able to regularly integrate weather updates into a dynamic slot allocation framework. However, the introduced model within this article considers system states in terms of historically assigned CTOTs rather than weather updates, which is part of future development stages.

This article is structured as follows: chapter 2 describes the applied network model with the mathematical computation structure. Chapter 3 describes the *'Rolling Time Horizon'* concept. Chapter 4 as a proof of concept provides respective results of an operational scenario. Chapter 5 gives a conclusion and outlook on future steps of effective ATFCM nowcasting information.

II. Model Implementation

A. *The Network Flow Environment*

The Network Flow Environment (NFE), which is developed at the DLR Institute of Air Transportation Systems, is a tactical ATFM model suite for pre-flight re-routing and slot allocation [13]. It consists of several functionalities to extract and process different data types for large-scale ATFCM slot allocation within the European ATM network. Flight plan- and infrastructural data from different data sources is matched according to the considered AIRAC cycle. Thus, the ATM network is represented by air route, airspace and airport data. Figure 3 provides an impression of network complexity of the European air route and airspace structure, like it is represented in NFE.

B. *Slot Allocation*

The slot allocation function is executed by two algorithmic approaches:

1.) NFE-CASA: The heuristic algorithm for slot allocation calculates CTOTs with the respective ATFM delay for given demand and capacity profiles. The FPFS principle generates balanced solutions, but does not follow an optimality criterion. It is designed to provide initial solutions transferred to the mathematical optimization module. The static character of the heuristic implies fixed demand and capacity profiles independent from predicted network states throughout the duration of the considered scenario. Allocated CTOTs of a preceding *iteration* do not impact demand states of following iterations, since the whole scenario is solved within a single calculation run. Static capacity regulations are being applied to reproduce a most realistic capacity behavior throughout the duration of a network scenario, typically representing one day. During the calculation, a Slot Allocation List (SAL) is computed. It contains planned flights of every capacity-afflicted entity in ascending order considering their estimated entry times (ETO). Slots are allocated accordingly. The earliest possible departure time $d > d_{0,f}$ of a restricted flight f is assigned to satisfy the capacity requirement. The most penalizing regulation, causing the highest individual flight delay, dominates its calculated departure time, since a single flight might enter more than one regulated entity.

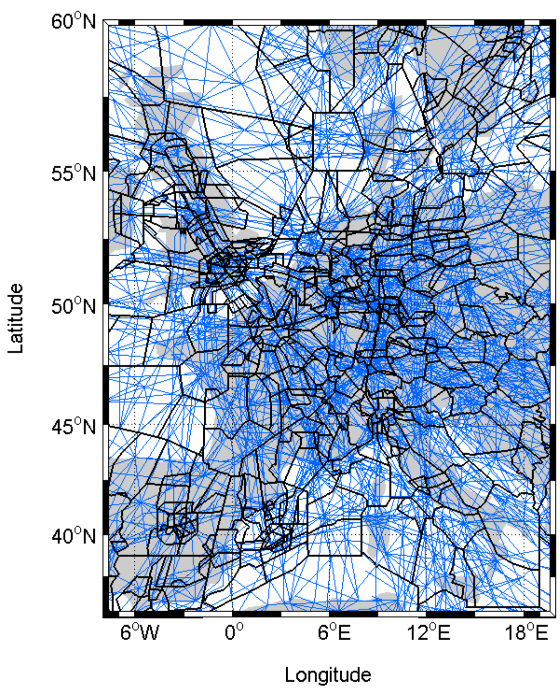

Figure 3. European air route and airspace network. Realistic airspace sectors and air routes are implemented within NFE, covering the whole European airspace. Thereby, every airspace sector volume is assigned to a maximum capacity value.

2.) Large-scale optimization: The allocation of departure slots according to an overall system delay minimization is performed by a binary-integer optimization module, which is able to handle large-scale ATFM problems in an acceptable amount of computation time. The slot allocation problem is implemented in MATLAB™ and applies pre-compiled libraries of the SCIP (*Solving Constraint Integer Programs*) 3.0.1 software framework [1] together with the SoPlex linear programming solver. SCIP is interfaced within NFE`s computational workflow via an adaption of the OPTimization Interface (OPTI) [5].

Capacity is defined as the maximum number of flight entries into an entity during one time slot. Thereby, the departure slot variable is the same as in Bertsimas and Stock Patterson (1998) [3]. It is

$$x_{f,d} = \begin{cases} 1\text{ , if flight } f \text{ obtains departure slot } d, \\ 0\text{ , } otherwise. \end{cases} \quad (1)$$

The objective $Z(x)$ is declared by equation 2. It is to minimize total delay cost with cost coefficients $\omega_{f,d}$ for every restricted flight $f \in F$ and slot $d \in D(f)$, whereas the set of possible departure slots $D(f)$ complies to time segmentation settings defined for the model. The set is limited according to a maximum departure delay.

$$Z(\boldsymbol{x}) = minimize \left(\sum_{f \in F} \sum_{d \in D(f)} \omega_{f,d} \cdot x_{f,d} \right). \quad (2)$$

Two types of constraints characterize the problem: The departure constraint ensures that every flight departs only once. This means, that every flight is assigned to exactly one departure slot d.

$$\sum_{d \in D(f)} x_{f,d} = 1 \quad \forall f. \quad (3)$$

The capacity constraint represents capacity restrictions of ATC sectors and airport departure and arrival counts. If the calculated entry time of flight f in sector (or airport) s with delay according to departure slot d is assigned to time slot t, the coefficient $a_{(s,t),(f,d)}$ is

$$a_{(s,t),(f,d)} = \begin{cases} 1\text{ , } if\ CTO_s(f,d) = t, \\ 0\text{ , } otherwise. \end{cases} \quad (4)$$

This coefficient serves as a transformation of departure times to sector entry times since the planned trajectories are fixed. The sum of all sector entries assigned to time slot t is restricted by the particular capacity $C_{s,t}$.

$$\sum_{f\,\epsilon\,F}\ \sum_{d\,\epsilon\,D(f)} a_{(s,t),(f,d)} \cdot x_{f,d} \ \leq \ C_{s,t} \quad \forall\, s,t. \tag{5}$$

The model does not assign premature departure times.

$$d \ \geq 0 \quad \forall\, d\,\epsilon\, D(f). \tag{6}$$

C. Large-Scale Problem Solving

The initial ATFM problem typically contains a huge number of decision variables as a product of

$$\textit{flight movements} \times \textit{departure slots}.$$

To improve computation times, NFE features a mathematical enumeration approach, called column generation [2]. This mathematical solution method for linear problems (LP) generates near-optimal results by dividing the original *Master Problem* (MP) to a subset of smaller *Restricted Master Problems* (RMP). Column Generation itself is well established in solving LPs with typically a huge number of decision variables, but a moderate number of constraints. This generally applies for an ATFM problem comprising the whole European ATM network, but also (pre-) tactical ATFM problems, like described in Kaufhold et al. (2007) [10].

To achieve good results for this type of problem, it is generally not necessary to handle the complete number of variables. A restriction to a subset of variables within the RMP, which is later solved individually, delivers optimal results. Variables, which are not part of the RMP are treated implicitly within a high number of smaller so called *pricing problems*. To improve results, implicit variables are added to the RMP by generating new columns. In the context of this study, this means to consider for each flight f a new (delayed) departure slot $d\ \epsilon\ D(f)$, leading to new not yet considered variables $x^{P}_{f,d}$. This process, called *variable pricing* originated from decomposition algorithms with a polyhydral approach of cutting planes. Those *branch-cut-price* (BCP) algorithms dynamically add implicit variables that have *negative reduced cost*. Regarding the present delay *minimization* problem, negative reduced cost variables added to the RMP possess cost coefficients, which are sufficiently reduced for the variable to be cost-effective within the objective function. In other words, adding these variables to the RMP causes delay reductions to optimality.

Negative reduced cost are computed by considering the *dual prices*, which correspond to the dual equivalent of the LP, (called the *Dual Problem*, DP) and especially to the linear constraints. Thereby, each of the linear constraints of equations *(3)* and *(5)* relate to individual types of dual prices: (i) the departure constraints *(3)* relate to dual prices ξ_f as the share of cost, the solution might be improved by *cancelling* this flight, and (ii) capacity constraints *(5)* relate to dual prices μ_d, indicating the congestion state of capacity-afflicted network entities (e.g. an ATC sector). Values of μ_d represent the amount of cost added to the objective value, if additional flights penetrate the entity. The vectorial form of the departure constraint with $e_f = 1$ is

$$\boldsymbol{Gx} = \boldsymbol{e} \ \ (\boldsymbol{\xi})\ \epsilon\ \mathbb{N}^{F} \tag{7}$$

$$\boldsymbol{Ax} \ \leq \boldsymbol{c} \ \ (\mu)\ \epsilon\ \mathbb{N}^{S,D} \tag{8}$$

The minimization objective of the primal problem turns into the dual maximization objective. Primal vectors are converted to dual rows, meaning that dual cost coefficients are compiled by $\boldsymbol{e}$ and $\boldsymbol{c}$. Since $\boldsymbol{e}$ is a unit vector, cost coefficients of $\boldsymbol{\xi}$ are equal to one. Cost coefficients of $\boldsymbol{\mu}$ are compiled by the primal capacity vectors. The dual cost function is than

$$max\ \boldsymbol{\xi} + \boldsymbol{c}^{\mathrm{T}}\mu. \tag{9}$$

Every primal variable is associated to a dual restriction and vice versa. Since a variable may be restricted by two different restrictions, both dual variables appear in the dual restriction

$$\boldsymbol{G}^{T}\boldsymbol{\xi} + \boldsymbol{A}^{T}\mu \leq \boldsymbol{\omega} \tag{10}$$

for $\mu \leq 0$. $\boldsymbol{G}$ constitutes the coefficient matrix of $x_{f,d}$ in the primal constraint of equation *(3)* and $\boldsymbol{A}$ constitutes the coefficient matrix of a in the primal constraint of equation *(5)*. From an operational perspective, equation *(10)* expresses, that a flight should depart at a time, when the network congestion state decreased, even if this implies high departure delay, represented by cost coefficient $\boldsymbol{\omega}$. A dual restriction for a *specific* departure time slot d of a flight f and a column $\boldsymbol{A}_{f,d}$ is as follows:

$$\boldsymbol{\xi}_f + \boldsymbol{A}^{T}_{f,d}\mu \leq \omega_{f,d} \tag{11}$$

Reduced cost are computed by solving the sub-problem of finding variables with corresponding *violated* dual restrictions in the form

$$\boldsymbol{\xi}_f + \boldsymbol{A}^{T}_{f,d}\mu > \omega_{f,d} \tag{12}$$

The idea is to find primal variables, for which the dual restriction is not yet part of the dual RMP, and therefore are not part of the primal problem. An added dual restriction, which is violated by the actual solution of the dual problem, restricts the dual solution space. This may lead to a reduction of the dual cost function. Due to the dual correlation, reduced optimal dual cost lead to a reduction of the corresponding primal cost. This correlates to an improved primal cost function by adding the primal variable. Therefore, *reduced cost* $r_{f,d}$ constitute (i) the violation value of the dual restriction, and (ii) the value, by which the primal cost function is improved by adding the correlating primal variable:

$$\boldsymbol{r}_{f,d} = \omega_{f,d} - \boldsymbol{\xi}_f - \boldsymbol{A}_{f,d}^T \mu \tag{13}$$

If the reduced cost of the variable is negative, the variable may improve the cost function value and reduce the total system delay. For this reason, it is declared as *negative reduced cost* variable. Note that only flights with positive ξ may have departure slot variables associated with reduced cost, since sign restricted values of $\boldsymbol{\omega}\geq 0$ and $a\boldsymbol{\mu}\leq 0$ do not induce negative $\boldsymbol{r}$ of equation *(13)*. Due to the reduced number of variables, the search for optimal solutions of the RMP is shorter than in the MP, having a positive effect on computation time.

III. 'Rolling Time Horizon' Concept

An ATM network underlies many different restrictions throughout the period of one day. The flexibility to be able to react on new situations constitutes one of the most important algorithmic features of a tactical ATFM model. The *Rolling Time Horizon* concept, implemented within NFE`s computational workflow considers changing system states, and moreover, implicates solutions of past optimization cycles. Every computation cycle includes a reformulation of system capacity and demand. Thereby, the set of flights, for which the departure time is not yet fixed, depending on the *actual* model time stamp, constitutes the input vector for the slot allocation. All other flights not yet landed represent *fixed* network demand. The combination of a macroscopic problem definition in terms of reducing the set of flights and the set of relevant network system elements for every horizon cycle, together with problem decomposition leads to a very efficient workflow and decreasing computation times.

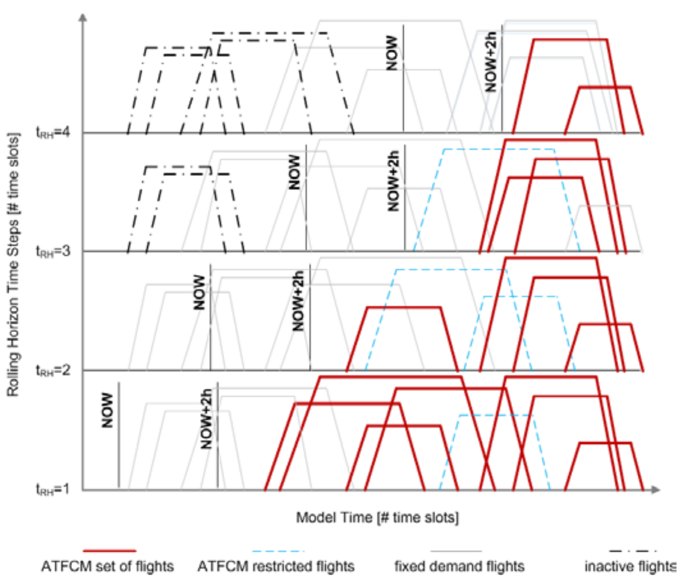

Figure 4. 'Rolling Time Horizon' concept functionality with 4 iteration steps. In contrast to NFE`s iteration time granularity, which correlates to time slot length (default: 15 minutes), the example depicts iteration time steps of two hours.

Figure 4 provides a functional example of the *'Rolling Time Horizon'* concept. The horizontal axis represents the scenario time and runs over all time slots being part of the chosen model time frame. The vertical axis represents 4 exemplary iteration steps of the *rolling time horizon*. Ordinary flight profiles, basically indicating EOBT and ETA, are assigned to the *rolling time horizon* iteration steps. Since flight plan uncertainty is not represented, the total set of flights stays the same.

Thereby, the classification of 4 different sets of flights is determined according to the *actual* horizon time (*'NOW'*): (i) the ATFCM set of flights contains all flights, for which *EOBT>NOW+2h*, which satisfies the AOs operational requirement in terms of schedule stability and recovery, (ii) ATFCM restricted flights represent those flights being assigned to ATFCM delay *at the respective iteration*. It is possible, that a flight is restricted within successive iterations as an optimization result in terms of overall delay minimization. The third set of flights (iii) is not considered for tactical ATFCM, since those flights already departed. However, they still *use* network capacity and need to be counted for demand quantification. Flights, already landed (iv), and being inactive regarding ATFM activities according to their callsign and conducted flight leg, are not considered for the actual and future iterations. The process chain, which is executed within each iteration, is provided in figure 5.

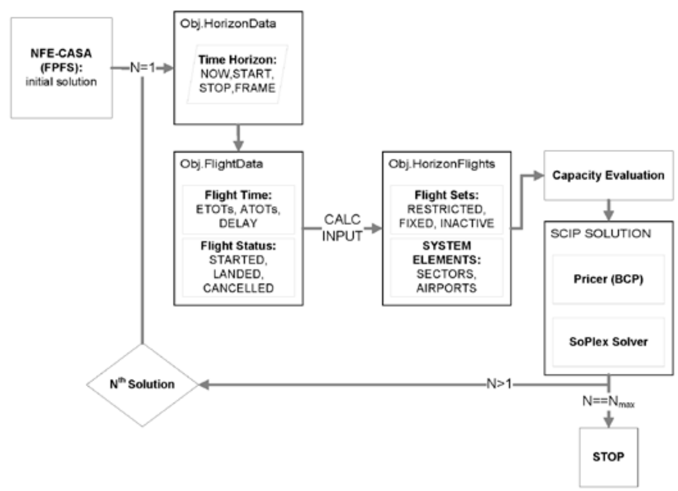

Figure 5. 'Rolling Time Horizon' process chain constituting NFEs slot allocation optimization module. *N* depicts the number of 'rolling' iterations providing the N^{th} RMP for problem solution.

The initial solution is provided by NFE-CASA, representing a possible but non-optimal solution following the FPFS principle. It is used to initialize the RMP. Consequently, preceding solutions *N>1* are used to initialize subsequent RMPs.

The object-based *'Rolling Time Horizon'* process chain contains three main object class functions: (i) a time object (*Obj.HorizonData*), (ii) a flight data object (*Obj.FlightData*), and (iii) a horizon (flight) data object (*Obj.HorizonData*). The capacity evaluation and the SCIP solution including the BCP framework and the solver complete the horizon chain. Every iteration $N=1...N_{max}$ includes different sets of relevant flights and system inputs and consequently a new solution, which updates the RMP. It than serves as initial solution for the $N+1^{th}$ iteration. Thereby, during the execution of the horizon *loop*, one flight may be assigned to different *CTOTs*, depending on system states in terms of network impact characteristics, but also to time settings and individual flight states. A *final CTOT* (which correlates the actual take-off time, *ATOT*) may be assigned latest two hours prior to *EOBT*. However, the flight's ATOT (representing its *ETOT* or an assigned *CTOT*) is fixed two hours prior to its *planned* off-blocks. If no slot within the *set* of departure slots is identified by the solver, the flight will be cancelled, since the maximum ATFM delay is exceeded. Therefore, the flight data object class evaluates (actual) take-off times, evaluating the solution of the previous iteration. The horizon (flight) data object initiates flight sets and respectively *used* system elements for the *actual* SCIP solution process.

IV. Methodological Application

A. Scenario Specification

An extensive scenario of a whole day is investigated, which has been gathered during the summer campaign of DLR`s project "Weather and Flying" in 2012 [9]. Table I. provides relevant traffic data parameters. It contains estimated flight plans provided by the Eurocontrol Human Machine Interface (CHMI) [8].

TABLE I. TRAFFIC DATA

Day	Traffic Data			
	IOBT from	*IOBT* to	*# flights (total)*	*# flights (model)*
05/07/2012	00:00z	23:59z	29.732	25.988

In total, the traffic sample contains 29.732 flights, of which a share 87% is considered within the model. These flights are part of the MP and constitute the initial demand structure for the presented large-scale solution framework. Flights not considered within the model, include an incomplete data set in terms of departure and/or arrival airport, or did not depart within the Initial Flight Plan Processing Zone (IFPZ).

Table II. provides quantities of network elements. The total available number of airports and ATC sectors represents NFEs infrastructural framework, constructed according to the affective AIRAC. The share of network elements being part of the specific scenario model is lower, since they represent those network parts experiencing traffic demand throughout the scenario.

TABLE II. NETWORK DATA

Day	Network Data			
	# ATC sectors	*# airports*	*# ATC sectors (model)*	*# airports (model)*
05/07/2012	638	3.750	620	1009

Table III. provides information on ATFM regulations initiated by the NM throughout the day. A high number of weather related en-route capacity regulations is observed, since it is characterized by scattered thunderstorm activity with convective cells mainly concerning EDMM, EDUU and EDWW (see figure 6). On this day the highest number of capacity regulations was initiated throughout the summer of 2012. Thereby capacity regulation due to ATC capacity (CAP) and weather (WX) dominated. The relatively high number of cancelled (CNL) regulations indicates weak predictions of these cells. This might be attributed to the embedded character, which complicates correct prediction of convective cells. In total, 25 en-route regulations could not be assigned to the static ATC sector model, since changing airspace configurations are not reproduced within NFE yet. However, the sector model is designed to cover as much regulations as possible.

TABLE III. REGULATION DATA

Day	Regulation Data					
	concerned traffic volumes				*regulation causes*	
	# total	*# airspace*	*#airport*	*#CNL*	*# CAP*	*#WX*
05/07/2012	197	89	42	41	29	73

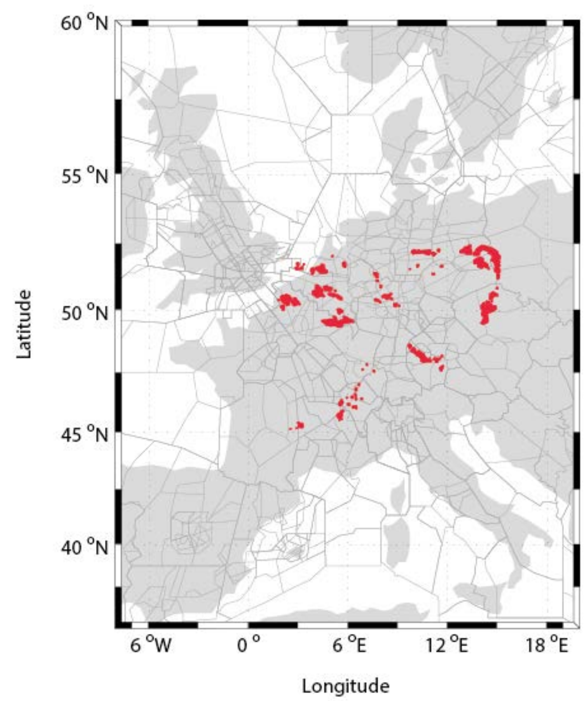

Figure 6. Thunderstorm activity (Rad-TRAM objects) at 19:00z inducing a major share of weather related capacity regulations mainly assigned to en-route airspace.

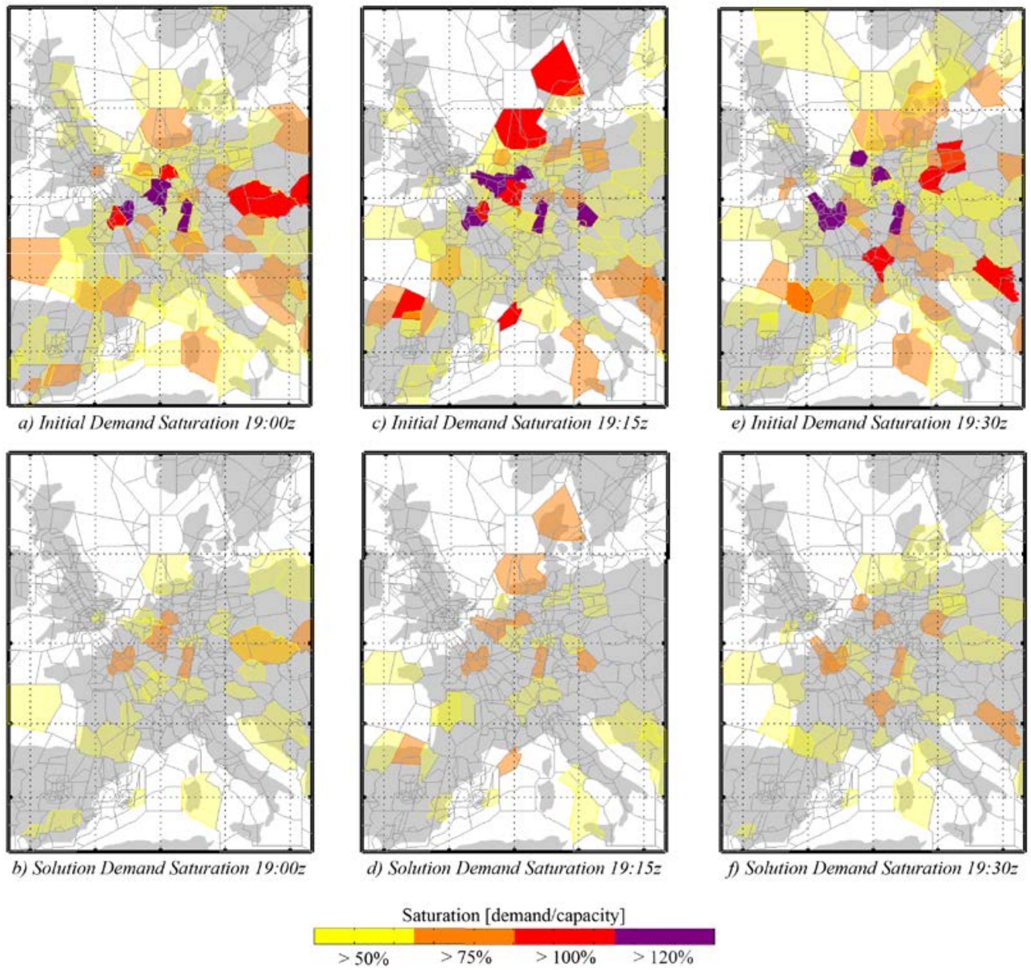

Figure 7. Comparison of network saturation before and after solution. 11 weather related en-route regulations have been initiated between 18:00z and 21:00z, constituting a major share of weather regulations

Table IV. provides information of the *Time Horizon* structure. Scenario start- and end-time references refer to EOBT of the *earliest flight* planned to depart, and ETA of the latest planned arrival time. Thereby, scenario start time is

$$Time_{start} = EOBT_{first} - 2h,$$

and scenario end time is

$$Time_{end} = ETA_{last} + D(f)_{max},$$

with $D(f)_{max}$ as the maximum delay representing the set of possible departure slots. Since in this case, 1590 minutes correspond to *02:30z* next day, the latest ETA is *00:30z* next day, since maximum ATFM delay being assigned by the model is set to 120 minutes. ATFM delays exceeding the maximum value cause flight cancellations and cost penalties in $Z(\boldsymbol{x})$.

TABLE IV. TIME HORIZON DATA

Day	Time Horizon Data			
	time values			***iterations***
	start time [min]	***end time [min]***	***slot length [min] (time frame)***	***# time-frames***
05/07/2012	0	1590	15	105

B. Evaluation

Figure 7 provides qualitative impressions of network saturation states before and after computational processing for three points in time at which a major share of en-route weather regulations is active. Plots a), c) and e) state the initial saturations of traffic demand (flight entries) compared to maximum nominal capacity for each ATC sector in the network. The most congested sector is EDUUSLN1S, experiencing demand rates of more than 120% between 19:00z and 19:30z and is regulated at a maximum capacity of 8 entries per timeframe. Nominal base capacity is 17. The majority of overloads, especially over Poland, can be traced back to convective activity. Plots b), d), and f) present *solution* saturations. A tendency to maximum possible saturations of formerly overloaded sectors is visible and goes in line with the minimum- emerging ATFM delay target.

TABLE V. TIME HORIZON (OPTIMIZATION) OUTPUT

Day	Time Horizon Output			
	flight data			***iterations***
	# delayed flights	***# cancellations***	***total delay [min]***	***computation time [ø min]***
05/07/2012	683	1513	16.443	4.9

Table V. provides optimization results. Compared to yearly averages, those results indicate the high number of regulations, since the number of cancelled flights is comparatively high. Note, that a flight is cancelled, when no (delayed) departure slot is found 150 minutes before $EOBT$. The computation time per time horizon, which includes the whole computation chain (see figure 5) decreases with each iteration and the number of flights being part of the actual problem.

The number of flights and corresponding decision variables with reduced negative cost within the RMP is provided in figure 8. The average number of possible departure times per flight with reduced negative cost is four. Note, that only flights are counted, that need to be considered during optimization, i.e. flights not cancelled, fixed or already landed. However, we actually face infrequent instabilities considering $N+1^{\text{th}}$ solution initializations. Therefore, the allocation of delay shares to explicit flights occasionally underlies slight deviations which result in minor capacity-demand inaccuracy. However, we validated the priced problems with static SoPlex optimization runs, resulting in correct total system cost. Close examination of individual demand and capacity profiles displayed no critical imbalances.

It is likely, that within the next step of considering stochastic network impact events, the number of variables within the time horizon cycles fluctuates accordingly. The goal is to reduce the number of variables within the RMP in using good forecasts of system states. Therefore, the consistently decreasing number of variables represents perfect forecasts, especially in terms forecast availability and prediction time.

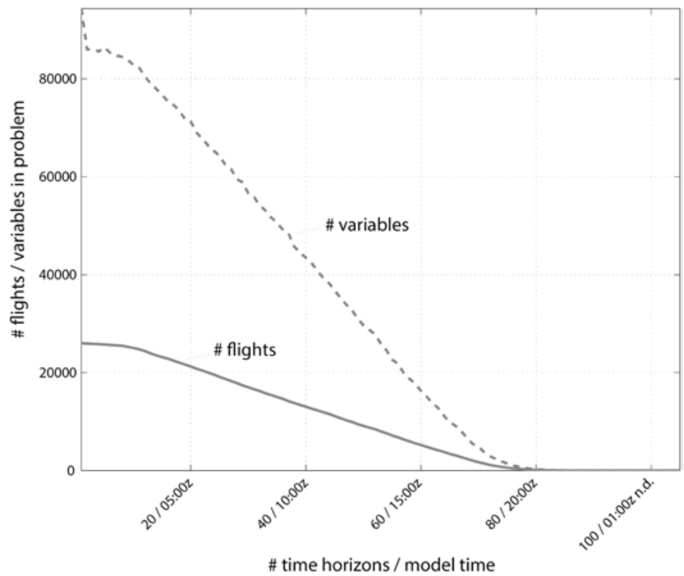

Figure 8. Flights and decision variables in time horizons.

The share of assigned delay per time horizon is provided by figure 9. Moreover, the time period, within which major en-route weather regulations have been active, is highlighted. Those en-route regulations generate delay shares over 4% per time horizon around three hours in advance, indicating the scenario specific average flight time to regulated ATC sectors.

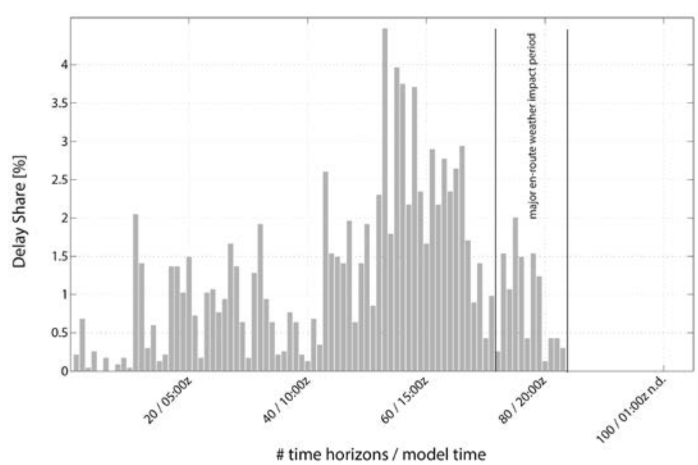

Figure 9. Assigned delay shares per horizon.

V. CONCLUSION AND OUTLOOK

This study presents an optimization framework to improve departure slot allocation by integrating (short-term) network impact information and network system states into a dynamic ATFM optimization framework. It is based on a '*Rolling Time Horizon'* concept, which iteratively divides the static ATFM problem into sub-problems, which – in a second stage – are solved by structured variable pricing. Problem segmentation mainly depends on model time and respective flight- and network states.

A large-scale ATFM scenario of one of the most impacted days during summer 2012 is evaluated, showing the functionality of the concept in terms of solving such a highly restricted scenario within operational computation times. Compared to realistic CASA slot allocation, optimization results improve the number of delayed flights as well as the total delay sum. Another advantage of the approach is the reproducibility of the behavior of the applied mathematical framework. Therefore, delay sensitive flights and network elements can be identified.

Future activities will focus on an integration of probabilistic network impact information to validate the approach in terms of robustness and efficiency with changing forecasts of network impacts. Therefore, a concept will be developed, that especially focusses on short-term weather forecast utilization. Moreover, additional ATFM measures like re-routing options and dynamic airspace configurations will be considered.

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