# Air Traffic Flow Management Under Uncertainty: Interactions Between Network Manager and Airline Operations Centre

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***Foreword* - This paper describes a project that is part of SESAR Work Package E, which is addressing long-term and innovative research.**

***Abstract*—This paper is presenting the first results of the ONBOARD project, whose goal is to investigate the incorporation of information about the levels of uncertainty in Air Traffic Flow Management (ATFM). The efficiency of ATFM optimizations in preventing local demand-capacity imbalances is reliant on accurate predictions of future capacity states. However these predictions are inherently uncertain due to factors such as weather effects and unscheduled demand.**

**This paper describes the integration between two elements, the Airline Operations Centre (AOC) which calculates the necessary airspace user recovery plans to cope with adverse scenarios; and the Network Manager (NM) which solves the demand capacity balance problem incorporating uncertainty. The core research aspects are in the introduction of disturbance feedback within the Network Manager optimization, in order to produce tailored solutions for all scenarios.**

**The paper outlines the structure of the system and details of the AOC and NM algorithms. Results are presented demonstrating their interaction and the benefits of the disturbance feedback methodology.**

***Keywords* - *network management, uncertainty management***

## I. Introduction

Increasing levels of demand in global air traffic over the last few decades have begun to stretch the air traffic management (ATM) system [1]. This trend is set to continue with the Federal Aviation Authorities (FAA) predicting in 2009 that commercial passenger numbers within the US will reach one billion by 2021 [2]. In order to meet the predicted traffic levels, improvements are needed in all areas of ATM.

One of the difficulties in improving the performance of ATFM through optimization is the presence of uncertainty. Future capacity state predictions are inherently uncertain due to factors such as weather effects and unscheduled demand. In current practice and the SESAR concept of operations information that could be available on the uncertainty associated with the system is not used. The goal of the ONBOARD project is to see if improvements can be made in ATFM performance by explicitly incorporating information about uncertainty within the optimization in the Network Management planning and execution phases.

The project is focused on incorporating the two factors that jointly account nowadays for two thirds of the total ATFM delay in Europe; weather and knock-on effects. The approach taken in this paper is to develop two interacting algorithms, one acting as the AOC and the other as the NM. The concept of disturbance feedback from control research is applied within the NM to handle uncertainty information on unscheduled demand and weather forecast. The solutions produced via this methodology within the NM are then iterated, with the AOC providing alternative recovery plans for further iterations.

The paper begins with a platform overview including descriptions of the interactions between the different elements of the system. The Airline Operations Centre and Network Manager algorithms are then described in detail. Results demonstrating the integration of the algorithms and the effects of the disturbance feedback on the solutions are then presented. Finally the future directions of the research are discussed.

## II. Platform Overview

### A. Platform Description

The platform consists of two main components, the Network Manager (NM) and the Airline Operations Centre (AOC). Figure 1 depicts the high level system architecture. The Network Management algorithm is the core research goal of the project as this is where the uncertainty will be incorporated. The Airline Operation Centre algorithm is necessary in the project to interact with the Network Management algorithm and pursuits its own research challenges. More detailed information on this can be found in [3].

### B. Integration Description

As shown in Figure 1 the AOC and NM algorithms interact through a shared platform database structure. The rest of

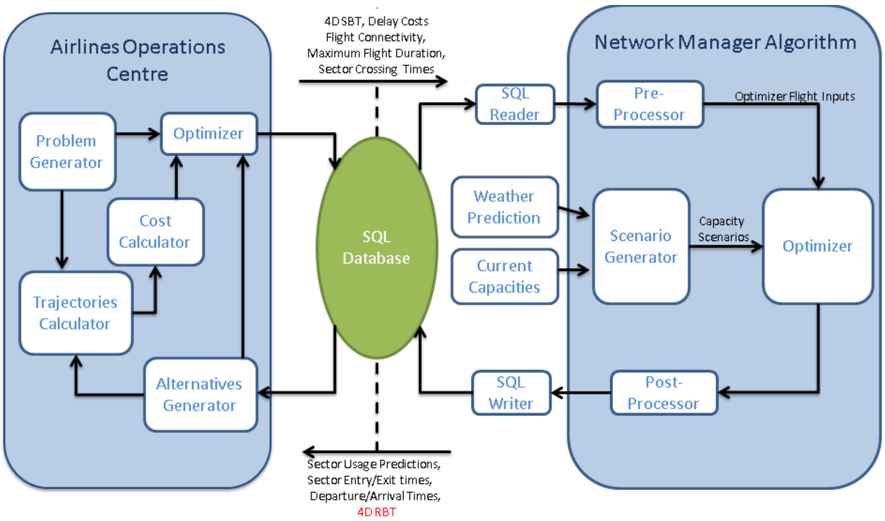


Figure 1. System Diagram

the processes are isolated within the separate algorithms. This allows the algorithms to communicate through a set of database tables, making the communication independent of programming languages or operative systems. This provides great flexibility to the development process meaning that the algorithms can be developed and operate independently.

Each separate algorithm loads problem case information from the shared database. The problems are generated by an *Evaluation Scenarios Tool* which has been developed as part of the ONBOARD project in order to generate realistic problems based on a set of defined parameters, such as number of flights and airports considered.

## III. Airline Operations Centre

The main role of the Airline Operations Centre (AOC) algorithm is to calculate the necessary airspace user recovery plans to cope with adverse scenarios (e.g. significant traffic congestion at an airport or at an airspace volume), by updating the aircraft rotation plan (e.g. delaying, re-routing or cancelling flights; swapping slots) and retiming part of the flights schedule until the original flight schedule can be resumed.

The basic architecture of the AOC algorithm is shown on the left hand side of Figure 1. The AOC gives an initial desired plan to the Network Manager and then generates alternatives taking into account the Network Manager restrictions in an iterative process.

The Problem Generator module provides feasible problem cases for each set of flights. This module loads the problem information from the *Evaluations Scenario Tool*, as explained, and distributes aircraft through the network in order to assure that the problem is feasible, i.e. there are enough aircraft to fly the schedule.

The Trajectories Calculator module performs a two-step process. In the initial iteration, it calculates the optimal desired trajectory for each flight as a function of direct operating costs. Once the Network Manager has imposed constraints, this module calculates new trajectories for affected flights which take into account the restrictions.

The Cost Calculator module calculates the cost of flying all the trajectories generated before and after restrictions, considering direct costs (i.e. fuel cost, time related costs).

The Integer Program Optimizer module calculates optimal fleet assignment plans for several scenarios, taking into account the planned flight legs and associated costs by modelling the problem as an Integer Program (IP).

The Alternatives Generator module calculates alternative plans and their associated costs, taking into account the Network Manager restrictions. It generates sets of alternative flight plans to operate affected flights by re-routing, re-timing and updating trajectories.

### A. *Objective*

The objective of the AOC is to find the sequence of flights to be flown by each aircraft that minimizes the total cost and guarantees that all the planned flights have been flown once and only once. The optimization problem can be formulated as a linear integer programming optimization problem, which can be summarized as:

$$\min c^T x$$
$$\text{Subject to:} \quad Ax = b, \;\; x \leq C, \;\; C = 1, \;\; x \in 0,1^n \qquad (1)$$

Where $A$ is a matrix in which rows represent the nodes and columns the arcs; $b$ is a vector expressing net flow at node $i$; $c$ represents the cost of sending a unit of flow through an arc and $x$ is the vector of variables defined as:

$$x = \begin{cases} 1 & \text{if an aircraft operates arc } j, \\ 0 & \text{if no aircraft operates arc } j \end{cases} \qquad (2)$$

### B. *Time Line Network*

In order to represent the air traffic problem as an IP problem, a commodity flow model has been used. A generic commodity flow network consists of a set of nodes linked by arcs through

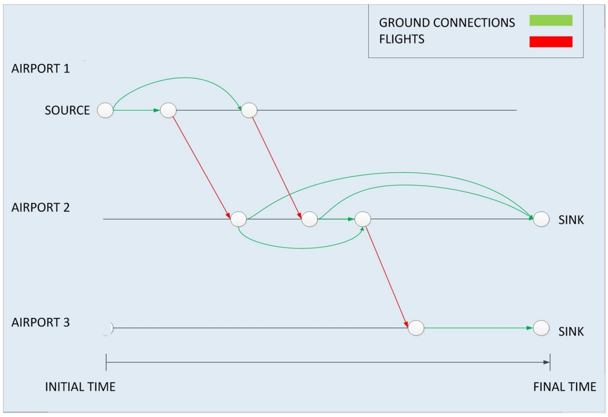


Figure 2. Time Line Connection Diagram

which commodities are sent. Each arc has a capacity, as well as a cost/profit associated with sending a unit of flow through it. Each node has a net flow associated with it. The problem variables are the levels of flow sent through each arc. It is important to note that source nodes (i.e. commodities initial position) and sink nodes (i.e. commodities final position) must be defined beforehand.

The commodity flow model used in the AOC has been termed the Time Line Network model. In this network each node represents an airport at an instant and each arc represents a movement between two nodes (two airports different times or one airport different times). Aircraft are the commodities which are routed through the network with every arc having a given capacity (the number of aircraft possible to send through) and cost/profit of sending an aircraft through it. A basic representation of this model is shown in Figure 2.

## IV. Network Manager

The focus of the Network Manager (NM) is on the subset of ATM which deals with allocating airspace resources such that the balance between capacity and demand is maintained in the presence of both enroute and airport capacity constraints. This is known as Air Traffic Flow Management (ATFM) and many studies, including Refs [4]–[9], have applied optimization to the problem to find the best solution (subject to some objective).

The scope of the system considered covers airport departure and arrival capacity limits at airports as well as enroute sector capacity limits. Control actions available are delays to the arrival, departure, and sector crossing times. Modelling of ATFM problems can broadly be divided into three categories: discrete decision models (sometimes referred to as Lagrangian models) which consider the individual plan of each aircraft in the problem (Flight-by-flight) [4], [5], [10], [11]; aggregate flow models (sometimes referred to as Eulerian models) which consider the flow rates and densities in control volumes but do not track individual aircraft plans [6], [12], [13]; and hybrids of the two (Eulerian-Lagrangian), which augment aggregate models to include some knowledge of individual flights [7], [9]. The NM adopts an Eulerian-Lagrangian or primarily flow-based ATFM viewpoint, meaning that a separate optimization stage is required to disaggregate the solution. Disaggregation is not discussed in this paper but has been extensively covered previously, for example in [14]. Flow re-routing decisions can also be handled under the formulation presented, but are not considered here.

The baseline flow based optimization model implemented is a slight reformulation of the model presented in Sun and Bayen [7] which was inspired by the Lighthill-Whitham-Richards theory [15], [16] and by the Daganzo cell transmission model [17], [18] commonly used in highway traffic. For ease of exposition of the disturbance feedback methodology the decision variables and objective are outlined below. For full details of the model the reader is directed to [7].

### A. Decision Variables

The decision variables introduced by the Sun and Bayen [7] model are integer variables which encode the control actions introduced.

$$\begin{aligned} u^i(k) &= \text{no. aircraft held back at cell } i \text{ in time period } k \\ u^{i,j}(k) &= \text{no. aircraft moving, cell } i \to j \text{ in time period } k \end{aligned} \tag{3}$$

Note the $u^{i,j}$ are only defined for indices where they are variable, i.e. for cell indices which represent a pair of connected cells. Sun and Bayen also use a cell state variable, $x^i(k)$, which represents the aircraft count in each cell, $i$, at each time period, $k$. We have reformulated to eliminate this variable to aid the inclusion of feedback.

### B. Objective

The objective to be minimized is a weighted combination of airborne delay and ground based delay, this allows the imbalance in the costs to be represented.

$$\min \sum_{k \in \mathcal{T}} \left( \sum_{s \in \mathcal{S}} \sum_{i \in \mathcal{B}(s)} c_a u^i(k) + \sum_{a \in \mathcal{A}} \sum_{i \in \mathcal{B}(a)} c_g u^i(k) \right) \tag{4}$$

Where $c_a$ and $c_g$ and the weightings on airborne delay and ground delay respectively. Note that this equation does not capture delays due to diversions on to longer routes. Re-routing is not explicitly considered in this paper however this matter is the subject of on-going research.

### C. Feedback

As already discussed due to the presence of uncertainty simply planning for the most likely, or ”nominal” capacity availability outcome will often result in demand capacity imbalances. Therefore uncertainty in the ATM planning phase is usually addressed by robust planning (to make an operation plan resilient to all possible capacity scenarios), contingency planning (e.g. predefined recovery plans for each scenario) and re-planning.

Robust planning involves designing a single plan which would satisfy the demand-capacity balance in all possible scenarios. Unfortunately such a solution is often infeasible and certainly would be very conservative. Instead it is desirable to create tailored solutions for each scenario, otherwise known as contingency planning. Agustin et al. [19] describe one approach to this type of planning rightly identifying that solutions cannot differ based on the scenario if it is unclear which scenario is coming to fruition. This kind of restriction has been termed as a set of non-anticipation constraints.

The approach taken in this paper is Model Predictive Control (MPC) with Disturbance Feedback [20]. Incorporating feedback into the solution is an efficient way to calculate contingency plans for a series of possible scenarios. As well as a single "nominal" plan, the decision variables of the optimization also include a set of feedback parameters. This enables future actions to depend on information that will become available between the time of planning and the time of execution: in this case, the feedback acts on the disturbances acting on the system, with the advantage of keeping the overall optimization linear. Including feedback in MPC reduces conservatism [21] by allowing the system to respond to disturbances.

The following equations describe how feedback can be incorporated such that the decisions $u^i(k)$ and $u^{i,j}(k)$ are allowed to vary with the disturbance signal $W$.

Each hold-back decision variable is re-written as

$$u^i(k) = v^i(k) + \sum_{n:tw(n)<k}^{Nw} M_n^i(k) W_n(c) \quad (5)$$

where the new decision variables are $v^i(k)$, an affine or nominal decision, and $M_n^i(k)$, the feedback term relating uncertainty signal $W_n$ to decision $i$ at time $k$. The diversion decisions are similarly re-written:

$$u^{i,j}(k) = v^{i,j}(k) + \sum_{n:tw(n)<k}^{Nw} N_n^{i,j}(k) W_n(c) \quad (6)$$

Substituting (5) and (6) into the Sun and Bayen model [7] yields the final form of the model constraints with disturbance feedback. The objective is also augmented to take into account the delays introduced in the feedback solutions as well as the nominal case. The solutions are weighted by the probability of their respective scenarios occurring.

### D. Scenario Model

A scenario is a realization of the uncertain parameters in the given time horizon. In order to take into account the capacity uncertainty a set of capacity reduction scenarios are defined each having a given probability of occurrence and an associated set of capacity reductions with time period, $k$, $q(c, s, k)$, where $c$ indexes the scenario, and $s$ the sector.

Much previous work has been done on the definition of capacity reduction scenarios based on weather forecast data and airspace configuration data [22]–[24]. Recently this work has been brought together by Taylor et al. of the MITRE corporation [25] to allow a representative sample of weather impact scenarios to be developed with associated probabilities.

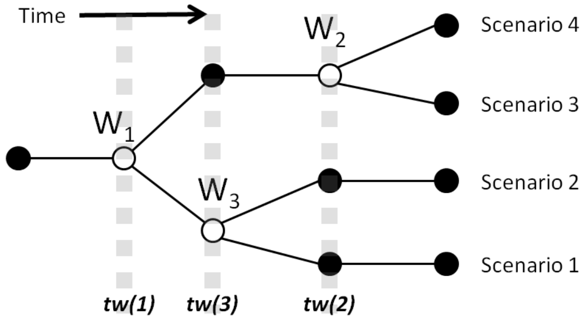


Figure 3. Scenario Tree

It is therefore assumed that such scenarios will be available to the NM.

Once defined, scenarios are grouped into a scenario tree structure, as shown in Figure 3. In this structure each root-to-leaf path represents an individual scenario. Each white branching node represents a point in time at which the scenarios divergence. Beyond the branching points there is a difference between the separate scenario branches. Differences can be modelling uncertainty in the speed, strength and path of disruptive storms.

These branching points are represented mathematically for each scenario, $c$, by the binary disturbance signals $W_n(c)$. These signals are those fed back in the feedback solutions at time periods beyond the times, $tw_n$ at which the result of each decision point $W_n$ becomes clear. The four scenarios in the example tree shown are represented by 3 binary decisions.

## V. Results

### A. Implementation

*1) Database Interaction:* The databases used to facilitate the interaction between the AOC and the NM are implemented in MySQL.

*2) AOC:* The prototype has been developed using C++ as a programming language and Eclipse SKD 3.5.2 as integrated development environment. The tool operates in Linux and for the optimization process is used the software package IBM ILOG CPLEX optimization studio.

*3) NM:* The NM optimization was translated into the AMPL modelling language [26]. An AMPL model file contains the constraint forms for all instances, while the data is written to an AMPL data file by a Matlab script. CPLEX 10.1 optimization software is used on a 3.4GHz PC with 2.98GB of RAM to solve all problems.

### B. Airline Problem Set-Up

The integration example problem presented in this work consists of a set of 30 flights between 5 airports with ICAO codes: EBCI, EDDB, EDDF, EDDN and EHAM. The flights are distributed through a day of operations between 6:00 to 16:00 hours. Each flight has an associated optimal nominal

TABLE I
COSTS SCENARIO PARAMETERS

| | | Strategic (€/hr) | Tactical (€/min) |
|---|---|---|---|
| Maintenance: | At Gate | 100 | 0.4 |
| | Airborne | 740 | 3.4 |
| Crew: | | 360 | 7.8 |
| Passengers Delay: | | | $c = 0.0172d^{0.774}$ |

trajectory and plan. All airspace sectors involved in the problem are considered to have a 5 aircraft capacity in any given 5-minute time window.

From the point of view of airline operational costs a reference cost set has been selected based on the study presented in Ref. [27]. The aircraft considered is the A320. Table I summarises the cost coefficients considered in the optimization processes.

### C. Capacity Reduction Scenarios

The storm case considered here is a combination of four separate storms, the first of which, "Storm 1" is subject to some uncertainty in its speed resulting in four different possible traversals. The combination of each of these traversal with the three certain storms form the four different weather impact scenarios. Each storm has capacity reduction strength 4, meaning affected sectors capacity is reduced to one aircraft per 5-minute time window. Table II outlines the paths and traversal times of Storm 1 for each individual scenario, $c_n$. Similarly, Table III outlines the paths and traversal times of the other three storms, which are the same across all scenarios. Note that, for example, S4 indicates Sector-4 and similarly A1 indicates Airport 1. The sector numbers relate to the map shown in Figure 4.

These storm transitions are converted into a scenario tree by identifying the points at which the scenarios diverge and modelling these as branching points with associated binary values $W_n$. The appropriate capacity reductions are then stored in the previously discussed parameter $q(c, s, k)$ for use within the optimization.

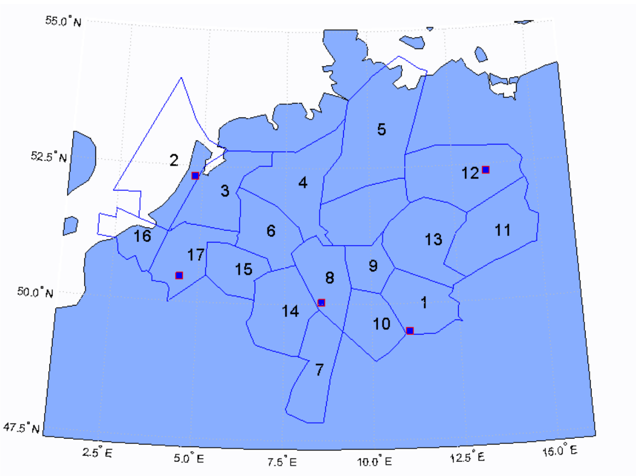


Figure 4. Problem Scope

### D. NM Solutions

In this section the output of the NM's first iteration with the AOC, in a case conducted with NM objective weightings $c_a = 2$ and $c_g = 1$, will be discussed in detail in order to demonstrate the benefits of incorporating feedback. Four solutions will be compared. Firstly the AOC's ideal plan as submitted to the NM will be analysed, then the solution considering only the "nominal" weather impact scenario, $c_1$. A single-plan robust solution and finally the disturbance feedback solution will also be compared. Table IV summarises the statistics being discussed.

*1) AOC Ideal:* If the AOC ideal flight plans are accepted demand-capacity-imbalances were found to occur in between 13 and 15 sector-times depending of the scenario enacted. As would be expected in this case there is no ground or airborne delay.

*2) Nominal:* If only the "nominal" scenario, $c_1$, is considered in the optimization, as would be expected delays have been introduced in order that no demand-capacity-imbalances occur when this scenario is enacted. As the problem case explored here has a relatively sparse population of flights, this solution is also adequate for two further scenarios, $c_2$

TABLE II
STORM 1: TRANSITION PATHS FOR EACH SCENARIO, $c$

| | Time Periods | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 380 | 450 | 520 | 590 | 610 | 660 | 680 | 700 | 730 | 745 | 750 | 770 |
| $c_1$ | A4 | S1 | S9 | S4 | S4 | S3 | S3 | S3 | A2 | A2 | A2 | A2 |
| $c_2$ | A4 | S1 | S9 | S9 | S4 | S4 | S3 | S3 | S3 | A2 | A2 | A2 |
| $c_3$ | A4 | S1 | S9 | S4 | S4 | S3 | S3 | S3 | S3 | S3 | A2 | A2 |
| $c_4$ | A4 | S1 | S9 | S9 | S4 | S4 | S4 | S3 | S3 | S3 | S3 | A2 |

TABLE III
STORMS 2,3 AND 4: TRANSITION PATH FOR ALL SCENARIOS, $c_n$

| | Time Periods | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 480 | 540 | 600 | 660 | 680 | 720 | 740 | 780 | 800 | 830 | 860 | 890 | 920 | 950 | 980 |
| Storm 2 | | | | | A4 | A4 | S1 | S1 | S9 | S9 | S4 | S4 | S3 | S3 | A2 |
| Storm 3 | A2 | S3 | S6 | S14 | S14 | S8 | S8 | A1 | | | | | | | |
| Storm 4 | | | | | | | | | | A1 | S8 | S4 | S3 | S2 | A2 |

TABLE IV
COMPARISON STATISTICS BETWEEN AOC IDEAL, NOMINAL, ROBUST AND DISTURBANCE FEEDBACK SOLUTIONS

| | Scenario | No. Sector Capacity Breaches | Ground Delay |
|---|---|---|---|
| **AOC Ideal Plan** | $c_1$ | 13 | 0 |
| | $c_2$ | 13 | 0 |
| | $c_3$ | 13 | 0 |
| Solve Time: 4.6 s | $c_4$ | 15 | 0 |
| **Nominal** | $c_1$ | 0 | 18 |
| | $c_2$ | 0 | 18 |
| | $c_3$ | 0 | 18 |
| Solve Time: 4.9 s | $c_4$ | 2 | 18 |
| **Robust** | $c_1$ | 0 | 20 |
| | $c_2$ | 0 | 20 |
| | $c_3$ | 0 | 20 |
| Solve Time: 14.5 s | $c_4$ | 0 | 20 |
| **Disturbance Feedback** | $c_1$ | 0 | 18 |
| | $c_2$ | 0 | 18 |
| | $c_3$ | 0 | 18 |
| Solve Time: 130.3 s | $c_4$ | 0 | 20 |

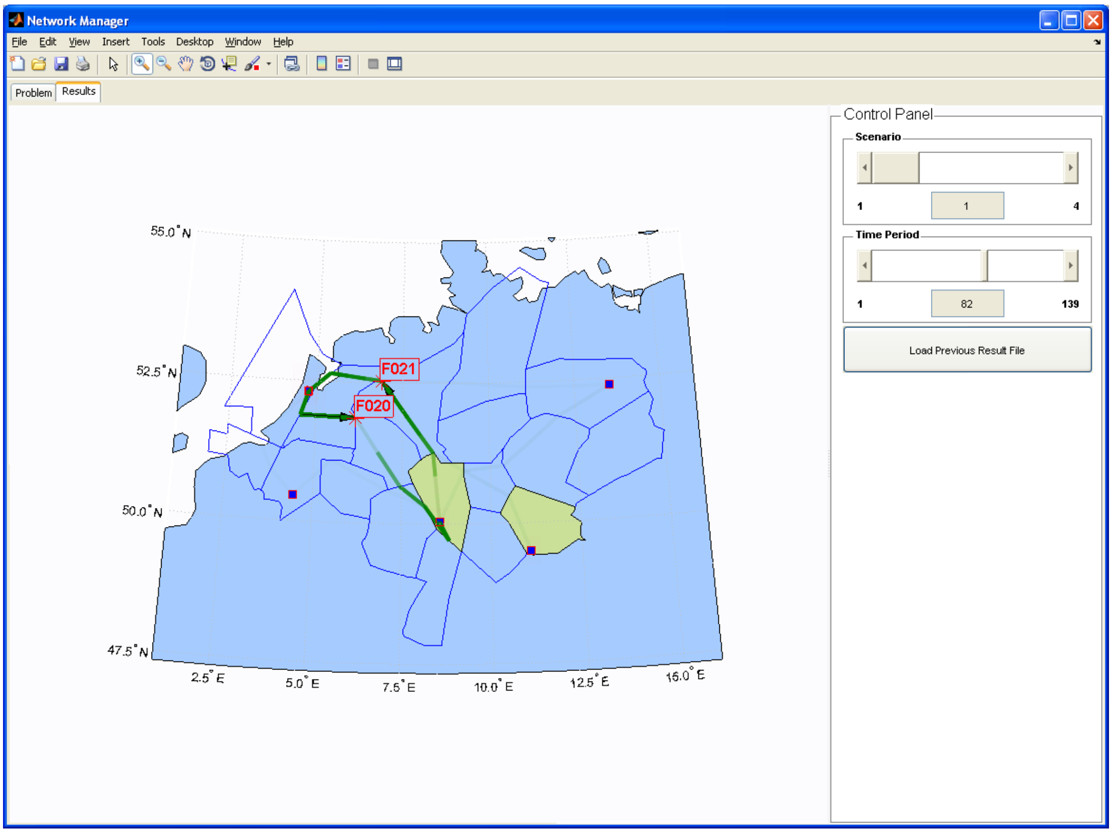


Figure 5. Problem Scenario 1

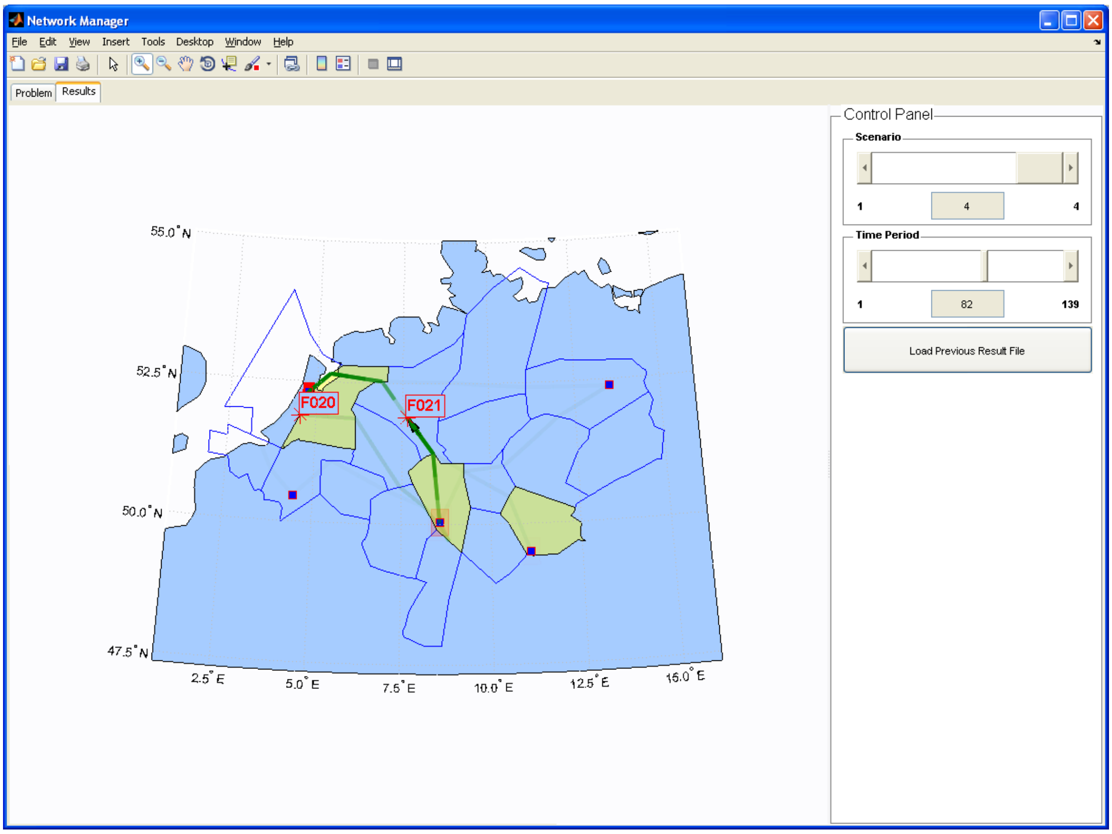


Figure 6. Problem Scenario 4

and $c_3$. However, in the final scenario, $c_4$, demand-capacity-imbalances were found to occur in 2 sector-times.

*3) Robust:* In the robust case one plan is made to satisfy all scenarios. As a result no demand-capacity-imbalances occur. However the price paid for this is that in all scenarios are subject to the most conservative level of delay required in any one scenario. As previously mentioned in more dense problem cases it is also highly likely that a robust solution is infeasible.

*4) Disturbance Feedback:* The disturbance feedback case also incurs no demand-capacity-imbalances. However, as tailored feedback solutions are developed, the minimum amount of delay needed for each scenario can be applied.

Figures 5 and 6 demonstrate the effects of feedback on the interactions between three aircraft, F017, F020 and F021 which all require the use of one sector, S3. Figure 5 shows the state of the aircraft at time period 82 (time = 765 mins) in scenario $c_1$. In this scenario there is no restriction on sector S3 and the three flights overlap their use of the sector (F017 has just finished using the sector and landed prior to this still). However, in scenario, $c_4$, depicted in Figure 6 sector S3 is subject to weather impacted capacity and therefore can only allow one aircraft to occupy it in any given time window. As a result of this restriction the three flights, F017, F020 and F021 must make cross the sector in turn, meaning that both F020, and F021 are delayed on the ground, and therefore appear further back in their trajectories in Figure 6.

TABLE V
NM MEASURES, ITERATION 1

| Flight Id | Resource Id | OTA (mins) | TTA (mins) |
|---|---|---|---|
| 16852 | EDUUFULL | 503.6 | 513.6 |
| | EDUUFFMML | 512.0 | 522.0 |
| | EDYYMNHI | 514.7 | 524.7 |
| | EDYYFLELO | 534.4 | 544.4 |
| | EDYYZEELO | 548.6 | 558.6 |
| | **EHAM** | 550.7 | 560.7 |
| 1227 | EDYYMNHI | 564.9 | 574.9 |
| | EDYYFLELO | 582.1 | 592.2 |
| | EDYYZEELO | 596.2 | 606.2 |
| | **EHAM** | 598.3 | 608.3 |
| 2223 | EDYYFLELO | 635.9 | 645.9 |
| | EDYYRHHI | 643.6 | 653.7 |
| | EDUUNTMML | 656.2 | 666.2 |
| | EDUUFFMML | 660.8 | 670.7 |
| | EDUUSLNH | 663.3 | 673.3 |
| | **EDDF** | 666.6 | 676.6 |
| 2224 | EDUUFFMML | 718.7 | 743.7 |
| | EDUUSLNH | 721.3 | 746.3 |
| | **EDDF** | 724.6 | 749.6 |
| 1229 | EDYYMNHI | 680.9 | 690.9 |
| | EDYYFLELO | 698.1 | 708.2 |
| | EDYYZEELO | 712.2 | 722.2 |
| | **EHAM** | 714.3 | 724.3 |
| 16854 | EDUUFULL | 911.6 | 916.6 |
| | EDUUFFMML | 920.1 | 925.1 |
| | EDYYMNHI | 922.7 | 927.7 |
| | EDYYFLELO | 942.4 | 962.4 |
| | EDYYZEELO | 956.6 | 976.6 |
| | **EHAM** | 958.7 | 978.7 |
| 1233 | EDYYMNHI | 912.9 | 917.9 |
| | EDYYFLELO | 930.1 | 945.2 |
| | EDYYZEELO | 944.2 | 959.2 |
| | **EHAM** | 946.3 | 961.3 |

### *E. AOC Response / Iterations*

Several iterations between the AOC and the NM have been carried out on the example problem described above. Each iteration consists of three steps: AOC shares an ideal plan, NM applies restrictions and AOC re-adapts the plan taking into account these restrictions. This iterative process repeats until the problem has converged, when the AOC plan meets all capacity restrictions. Several runs were conducted each using different weightings within the NM optimizations objective. The outputs from two iterations conducted with weightings $c_a = 1$ and $c_g = 100$ are shown in Tables V-VII. These results demonstrate the algorithms iteration leading to coherent results.

Table V contains delays introduced by the NM for the nominal weather case in the first iteration plan. As expected based on the NM weightings heavily penalizing ground delay, all the suggested delays are mid-air. As seen, the delays are applied to specific trajectory sectors and are presented referenced to the original trajectory, i.e. Target Time of Arrival (TTA) and Original Time of Arrival (OTA). TTA and OTA are measured in minutes from 12 midnight. It can be seen that in this case, 7 of the 30 flights were delayed airborne or on ground, by between 10 and 25 minutes.

TABLE VI
AOC RESTRICTED FLIGHTS ALTERNATIVES

| Flight Id | Alternative |
|---|---|
| 16852 | On Ground Delay (600) |
| 1227 | On Ground Delay (600) |
| 2223 | Modified Trajectory (0.95) |
| 2224 | On Ground Delay (1500) |
| 1229 | Modified Trajectory (0.95) |
| 16854 | On Ground Delay (300) |
| 1233 | Modified Trajectory (0.95) |

Table VI presents the alternatives generated by the AOC taking into account the NM delays. In this problem the AOC generated both types of alternative, delaying departures and replanning slower trajectories, in response to the NM interaction. On ground delays are presented with the total minutes delay and modified trajectories with the associated speed factor applied. It is necessary to remark that from the airline point of view this set of alternatives is the cost optimal solution taking into account the NM delays. Since each change in the planned schedule flights affects the rest of the network, the NM response includes a new set of measures to introduce delays into this new ideal plan, see Table VII.

As seen, the second iteration measures set affects to 3 flights. In this particular case, these 3 flights were included in the initial plan but with different delays. The iterative process continues until converges and no more measures are applied.

## VI. CONCLUSION

The structure of a combined AOC/NM ATFM system has been outlined in this paper. The integration of the two parts of the systems has been discussed and results have shown that the database interface defined is working well and initial iteration results are coherent.

TABLE VII
NM MEASURES, ITERATION 2

| Flight Id | Resource Id | OTA (mins) | TTA (mins) |
|---|---|---|---|
| 2223 | EDYYFLELO | 635.9 | 640.9 |
| | EDYYRHHI | 643.8 | 648.8 |
| | EDUUNTMML | 656.9 | 666.9 |
| | EDUUFFMML | 661.5 | 671.5 |
| | EDUUSLNH | 664.3 | 674.3 |
| | **EDDF** | 667.6 | 677.6 |
| 16854 | EDUUFULL | 916.6 | 921.6 |
| | EDUUFFMML | 925.0 | 945.0 |
| | EDYYMNHI | 927.7 | 947.7 |
| | EDYYFLELO | 947.4 | 967.4 |
| | EDYYZEELO | 961.6 | 981.6 |
| | **EHAM** | 963.7 | 983.7 |
| 1233 | EDYYMNHI | 913.4 | 923.4 |
| | EDYYFLELO | 931.7 | 946.7 |
| | EDYYZEELO | 946.1 | 961.1 |
| | **EHAM** | 948.2 | 963.2 |

More detailed analysis of the NM output during a single iteration has demonstrated the benefits, in terms of reduced delays, of a disturbance feedback approach to capacity uncertainty over a single robust plan. During the remainder of the project the disturbance feedback model will be further developed to reduce computation by intelligently fixing potentially redundant feedback values in the pre-solve of the optimization scheme.

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