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Quantifying Resilience in ATM

Contrasting the Impacts of Four Mechanisms During Disturbance

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Abstract—Using traffic and passenger itinerary data for the European network, the cost resilience of four mechanisms, with phased stakeholder uptake, has been assessed under explicit, local and disperse disturbance: industrial action and weather. A novel cost resilience metric has demonstrated logical properties and captured cost impacts sensitively. Of these mechanisms, only A-CDM has been cost-benefit analysed in SESAR, yet the other three each demonstrate particular utility. Flight-, passenger- and cost-centric metrics are deployed to assess the mechanisms, with fully costed results presented, based on extensive industry consultation. Initial work on assessing mechanism payback periods has begun.

Keywords—cost-benefit; disturbance; resilience; resilience metrics; stakeholder uptake; strategic investment

I. INTRODUCTION

The main objective of the ComplexityCosts project [1] is to gain deeper insights into air traffic management (ATM) performance trade-offs for different stakeholders' investment mechanisms within the context of uncertainty. Despite uncertainty being one of the main factors generating reduced performance, behaviours are often driven by complex interactions and feedback loops that render it difficult to assess second-order impacts at a network level. The ComplexityCosts simulation model takes into account different stakeholders, according to corresponding tactical and strategic cost structures, and their interactions. This paper describes the implementation of the mechanisms and their cost assignments, at the tactical and strategic levels. Stakeholders' mechanism adoption is modelled according to three uptake levels: baseline (current situation), early adopters (mid-term) and followers (longer-term).

Uncertainty (and network performance detriment) is modelled by disturbances introduced into the simulation: the statistical models for the explicit disturbance types of industrial actions and weather are presented. Background (including air traffic flow management, ATFM) disturbance is also modelled as part of the baseline. The statistical parameters for these disturbances are derived from empirical data, including their spatial and temporal duration. The effect of the disturbances will be variously mitigated by the mechanisms. Different mechanisms might deliver different performance as a function of the spatial distribution of the disturbances. In some cases, a mechanism might be better suited for localised disturbances in the network, but provide a lower benefit when disturbances

affect the network in a wider manner. For this reason, each disturbance is modelled with two different spatial scopes: local and disperse.

TABLE I. FOUR MECHANISMS INVESTIGATED

Mechanism	Location focus	Primary investment	AO delay driver
1 Improving sector capacity with ATCO ^a hours	en-route	ANSP ^b	magnitude
2 Dynamic cost indexing (DCI)	en-route	airline	cost
3 A-CDM ^c	airport	airport	magnitude
4 Improved passenger reaccommodation	airport	airline	cost

a. Air traffic controller.

b. Air navigation service provider.

c. Airport collaborative decision making.

Table 1 shows the location focus (physical manifestation of the mechanism) and from where the primary strategic investment in the mechanism originates, noting that for (1) and (2) the main investor is not the airline, although it is the major beneficiary. Although airline delay magnitudes and delay costs are intimately related, the mechanisms focus more specifically on either the delay magnitude, or delay cost (final column). The latter applies when airline delay costs are (in theory at least) available at the decision-making point during tactical implementation of the mechanism (i.e. airlines applying DCI or controlling passenger reaccommodation tools). Most of the investment mechanism costs are expected to be paid for strategically (i.e. as sunk costs). However, we must also take account of any tactical ('running') costs associated with the mechanisms – such as variable fuel burn during aircraft delay recovery with DCI. Such costs are examined later. The most comprehensive, consolidated source of cost benefit analyses for SESAR is available through the proposal on the content of a pilot common project [4], which includes A-CDM as an enabler for deployment of the ATM functionality (AF) "airport integration and throughput functionalities". Further cost data on A-CDM *per se* are available in EUROCONTROL reporting [2, 3], and the availability of some cost data for this mechanism was a significant factor in its inclusion in the final list (Table 1). ComplexityCosts aims to extend, complement and compare such high-level analyses through the detailed simulations reported herewith. In previous work [16] we quantified the cost effectiveness of adding controller hours to area control centre regulations to avert the delay cost impact on airlines, whereby we also summarised the limited literature on this topic. This underpins some of the work developed here for mechanism (1).

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Mechanisms (2) and (4) have not been hitherto evaluated in the manner presented here, due in no small part to the difficulty of accessing the necessary confidential cost data from industry and of modelling them.

Before moving on to the detailed reporting of this paper, we close the introduction with some necessary definitions. The combination of a disturbance, mechanism and stakeholder uptake level, along with the corresponding input traffic and passenger itineraries, is referred to as a ‘scenario’, thus comprising 40 in total, plus the corresponding baselines. Having cause to frequently refer to ‘disturbance’, we define this at the outset as an event, either internal or external to a system, capable of causing the system to change its specified (stable or unstable) state, as determined by one or more metrics. A disturbance may thus potentially cause (or aggravate) a disruption. A disruption is an event where normal operations are significantly degraded. The term ‘resilience’ is central to the research, and is investigated in the following section. Section III then summarises key features of the model, with the first simulation results presented in Section IV. Conclusions and future research comprise Section V.

II. QUANTIFYING RESILIENCE

A. Qualitative foundations

Before being in a position to quantify resilience, it is first necessary to have a qualitative definition. This section summarises work presented in [1]. As pointed out in a recent review [8], too many different definitions, concepts and approaches are being used, such that: “[...] some definitions of resilience overlap significantly with a number of already existing concepts like robustness, fault-tolerance, flexibility, survivability and agility.” An overview of the evolution of the term in various fields of research is presented in [9], and a thorough review with numerous ATM examples has recently been published [5]. The first two milestones (see Table II) in the development of the term were its initial introduction in material testing [10] and the later adoption in ecology [19]. The latter led to widespread use of the term in the scientific literature. A third important milestone with relevance to air transport was the ‘resilience engineering’ paradigm introduced in 2006 [11], which led to (broader) qualitative modelling of resilience in ATM, from 2009 [12].

TABLE II. THREE MAJOR DEFINITIONS OF RESILIENCE

Terminology	Introduction	Field	State(s)	Key feature
Engineering resilience	Hoffman (1948) [10]	material testing	one stable state	inherent ability of the system to return to its original state
Ecological resilience	Holling (1973) [19]	ecology	multiple states	ability of the system to absorb disturbance
Resilience engineering	Hollnagel (2006) [11]	air transport	multiple states	safety-based design of socio-technical systems

The earlier ‘engineering resilience’ assumes one stable state only, with resilience being the ability to return to this original state, after disturbance. Ecological resilience, in contrast, refers to absorbing disturbance and access to multiple (stable or equivalent) states. An air transport system may also operate in

(essentially) equivalent states of safety or cost. The latter is the focus of ComplexityCosts, with safety being out of scope at this stage.

TABLE III. THREE CAPACITIES OF RESILIENCE

Capacity	Key feature	Key associations	ATM focus
Absorptive	network can withstand disruption	robustness; little or no change may be apparent	strategic
Adaptive	flows through the network can be reaccommodated	change is apparent; often incorporates learning	strategic and/or tactical
Restorative	recovery enabled within time and cost constraints	may focus on dynamics/targets; amenable to analytical treatment	tactical

A recent systematic review [13] across numerous domains, categorised three capacities of resilience, *viz.*: absorptive, adaptive, and restorative. These are summarised in Table III. The ‘key feature’ (second column) is taken from [14], to which we have appended some key associations and main ATM phases with which the capacity may be typically associated. From a performance-focused perspective, reliability may be considered as the presence of all three capacities; vulnerability may be considered as the absence of any one of them. For clarity of reference and to accommodate a definition of robustness within our framework, we align robustness with the *inherent* strength or resistance to withstand stresses beyond normal limits, i.e. the absorptive capacity of resilience. In [1], we also discussed (practically) instantaneous recovery, associated with (schedule) buffers and ‘buffer energy’. As will be expanded upon later in this paper, ComplexityCosts embraces all three capacities, taking into account both the strategic and tactical phases, with flow (aircraft and passenger) reaccommodation central to the model.

B. Quantitative developments

We have previously presented (*ibid.*) a quantitative discussion of resilience using state diagrams. Developing a metric for resilience, [8] commences with the formulation (1), where $\mathcal{R}(t)$ is the resilience of a system at time t . This describes the ratio of recovery at time t to loss suffered by the system due to a disruption event at time t_d . If the recovery is equal to the loss, the system is fully resilient; if there is no recovery, no resilience is exhibited. ([7] uses similar ratios in the urban context: a relatively rare example of work using real estimated costs.)

$$\mathcal{R}(t) = \frac{\text{Recovery}(t)}{\text{Loss}(t_d)} \quad (1)$$

The authors [8] go on to define a quantitative ‘figure-of-merit’ function, which specifies a system-level delivery metric. It is time-dependent and changes as the system state changes. Equation (1) is expanded (*ibid.*) to embrace a conditional figure-of-merit under a given disruptive event, and then further conceptually extended to include the time and costs required to restore the disrupted components. Such situations are illustrated with specific regard to investment mechanisms in [14]. These are implemented strategically and are designed to

result in a reduction of the tactical magnitude of the disruption from a given disturbance, in addition to speeding up the system recovery. Such expenditures are defined as “resilience-enhancing investments”. An extensive paper [15] reporting on an optimisation procedure for the restorative activities associated with the bridges of an urban network severely damaged by an earthquake, cites a normalised integral over time as a “broadly accepted” formulation of resilience. This is dimensionless and takes values in the range [0%, 100%]. For wider reviews of resilience metrics, see [5] and [13].

C. Novel cost resilience metric

In this section, we summarise the derivation of a novel cost resilience metric, R_C , which will be used to characterise the effectiveness of the ComplexityCosts mechanisms, in Section IV. Further details and early evaluations were presented in [1]. In order to take account of the time dependency when measuring resilience, causal summations, with specific regard to the mechanism and disturbance applied, are proposed. The precise time over which a given recovery occurs is difficult to assign, since propagation effects persist over many causally linked rotations during the (post disturbance) operational day. One operational day in the European airspace (see Section III(A)) is thus used as the boundary condition for the analyses.

The summation over events causally affected by the mechanism are denoted Σ^m , and as Σ^d for the disturbances. This allows specific assessment of the mechanism, *relative* to the effect of the disturbances. The cost resilience metric, by design, fully comprises *cost-based* components, as a result of the selection only of mechanisms that can be monetised. The tactical cost associated with a disrupted flight or passenger at time t in the absence of a mechanism is denoted $C_u(t)$, and in the presence of a mechanism as $C_u^m(t)$. It is also necessary to take account of any tactical costs associated with ‘running’ each mechanism, $C_m(t)$. (The example of variable fuel burn during aircraft delay recovery with DCI was cited in Section I, and such costs are detailed further in Section III(D)3). The final formulation for the cost resilience metric is presented as (2), with constraints (3)¹. Perfect resilience (complete cost recovery) gives $R_C = 1$; no recovery gives $R_C = 0$. If the mechanism were to induce greater costs than the disturbance alone, $R_C < 0$ obtains.

$$R_C = \frac{\Sigma_u^d C_u(t) - \Sigma_u^d \Sigma_m C_u^m(t) - \Sigma_m C_m(t)}{\Sigma_u^d C_u(t)} \quad (2)$$

Where:

$$\Sigma_u^d C_u(t) > 0; \quad \Sigma_u^d \Sigma_m C_u^m(t), \quad \Sigma_m C_m(t) \geq 0 \quad (3)$$

Such that:

$$R_C \leq 1 \quad (4)$$

¹ The first term in (3), i.e. the total cost of the disturbance, could in theory be zero. An example would be a relatively small disturbance fully absorbed by schedule buffer, due to robustness. However, only disturbances with some positive tactical cost will be modelled, such that we exclude zero values.

Whilst simple ratios furnish straightforward metrics, they may also be misleading². The number of assessment units (u , such as flights or passengers) should thus also be cited in their reporting, as with p values in statistical significance testing. The simple discipline of reporting “ $R_C = 0.50$ ($n = 10$)” c.f. “ $R_C = 0.50$ ($n = 1\,000$)” ($n = \Sigma u$) at least gives immediate insight that the latter had the wider reach.

III. THE COMPLEXITYCOSTS MODEL

A. Overview of the model

The ComplexityCosts model is a stochastic, layered network model that includes interacting elements and feedback loops. Stochastic elements include the baseline and explicit disturbance types, as previously introduced. (Note that, in contrast, the resilience models presented in the literature review were all deterministic.) 12SEP14, a busy traffic day, free of exceptional delays, strikes or adverse weather, forms the baseline simulation day, modelling major traffic and passenger flows to, from and within the European airspace. Flights were extracted from the Demand Data Repository (DDR2) dataset, with schedule data added from Innovata, and the database was then cleaned (e.g. to remove circular, positioning, light aircraft, all-cargo, and military flights). Each model scenario includes 26 860 flights.

Fuel consumption models are based on Base of Aircraft Data (BADA4) and Performance Engineering Program (Airbus) data, the latter being used to validate trajectory modifications due to tactical speed adjustments. The model also includes en-route wind modelling based on average cruise winds estimated from the trajectories.

Auxiliary power unit (APU) fuel burn allocations are as per [17]. CO₂ estimates are produced for at-gate (including engine fuel burn) and airborne flight phases (kg-fuel being multiplied by the standard factor of 3.16 to obtain kg-CO₂). The cost of fuel is assigned as 0.8 EUR/kg for the nominal cost scenarios (and 0.9 EUR/kg for the high cost scenario used within the DCI mechanism). Notwithstanding the multiple additional features implemented, as described below, much of the model’s underlying framework and operational rules are similar to the ‘POEM’ model [6], which also includes at-gate turnaround recoveries based on historical data. The fuller model features will be reported separately.

The model is written in MATLAB, using statistical, parallel and simulation packages, with extensive pre-processing. On a Quad 2.4 GHz, 64-bit core processor with 4GB of available RAM, a single scenario run takes between 5 and 20 minutes, depending on its complexity. An Amazon-cloud grid of five supercomputers (EC2 m4.xlarge) was deployed, the grid allowing data-sharing of simulation results in real-time. A full run, with all scenarios and baselines, takes 12 hours. The first results, presented in this paper, are typically based on 30 model runs per scenario.

² Take a simple example relating to equation (1): a €50 recovery of a €100 disruption. This would yield the same simple resilience ratio as a €50k recovery of a €100k disruption, i.e. both would give $\mathcal{R} = 0.5$.

B. Passenger itinerary assignments

The allocation of passengers to flights, with connecting itineraries and fares, is an important part of the model both with regard to the output metrics and mechanisms associated with passenger service delivery. In-house itineraries for 2010 were used as a starting point. The generation of the passenger itineraries deploys three datasets: individual itineraries for one day in September 2010 (used in the ‘POEM’ model [6]); aggregated September 2010 International Air Transport Association (IATA) itineraries (‘PaxIS’ data); and, a sample of anonymised, individual itineraries from September 2014 provided by a global distribution system (GDS) service provider. In order to calibrate the data to September 2014, aggregated passenger data from Airports Council International (ACI) EUROPE and Eurostat passenger flows were considered alongside published airline load factors. Overall, passenger growth, from 2010, was around 13% (according to Eurostat data).

For each individual passenger’s target itinerary, all possible options were computed considering the available flights on 12SEP14. This computation ensured that passenger itineraries with more than one leg were able to make their connection at the intermediate airport(s), whilst respecting the minimum connecting time (MCT). These options were then preference-scored based on a set of parameters that include the characteristics of the airlines used on multi-leg itineraries (e.g. airlines being members of the same alliance, or partners within an airline group), total itinerary duration and waiting times at connecting airports (where applicable).

Respecting the available seating capacity on each aircraft, itineraries were assigned iteratively, and probabilistically – to ensure that the final assignment reflected the variability observed in actual operations. After this assignment, there was a capacity evaluation to ensure that all flights were within their targeted load factor: if required, some itineraries were thus (stochastically) removed from flights. After this process, unallocated, target itineraries were assigned.

This iterative process ran sequentially for each of the three data sources. At the end of the process, flights still requiring passengers were allocated new itineraries generated based partly on the characteristics of existing passengers’ itineraries. Finally, a fare and passenger type (‘premium’ / ‘standard’) allocation was made (see Section III(D)2(d)). In total, there are over 3 million passengers in the modelled day, each with an assigned itinerary.

C. Differential stakeholder uptake

New technologies and tools are rarely adopted simultaneously by all users or stakeholders. Although high-level roadmaps have been developed within the ATM Master Plan [18] and the pilot common project [4], the ComplexityCosts model seeks to refine the relationship between selected mechanisms and stakeholder uptake, in the context of performance assessment.

Three uptake levels are considered for each of the mechanisms: baseline, early adopters and followers. In the baseline, the current concept of operation is captured, while the uptake of the early adopters and followers incorporates the further development of more advanced mechanisms. Each uptake level includes the preceding level(s). Baseline mechanisms are implemented in all the scenarios, e.g. the simplest delay recovery rules of dynamic cost indexing are always in place for a limited number of flights (see Section III(D)2(b)), reflecting current practice.

In general, early adopters are a subset of stakeholders implementing the mechanism, often only in a subset of their operations. For follower uptake, other stakeholders incorporate the mechanism and early adopters widen their use and/or enhance its performance. This is discussed further in the next section.

D. Selecting the mechanisms and assigning the costs

1) Mechanism selection

The rationale for the selection of the mechanisms introduced in Table 1 was presented in [1]. A focus was maintained on fairly discrete and stakeholder-scalable mechanisms, rather than high-level instruments such as Functional Airspace Blocks. Mechanisms likely to be used as market-based responses to air transport evolution were also in scope, even if not explicitly part of the ATM Master Plan. Sources for costs were a primary consideration, as these are limited, and, without them, the metrics cannot be evaluated.

2) Mechanism implementation and uptake

a) Improving sector capacity with ATCO hours

As presented in [16], in some cases, ATFM delays may be reduced if ANSPs enhance their operations and manage to avert airspace regulations declared due to staff shortage. This mechanism is similarly implemented as a reduction of ATFM regulation in the airspaces that experience increase in demand due to aircraft re-routing to avoid a disturbance (e.g., traffic circumventing a region affected by industrial action).

Delay is typically generated for such flights since such regulations are not averted by the mechanism. The early adopter uptake considers two ANSPs implementing this mechanism (Maastricht Upper Area Control Centre and the UK) and in the follower uptake four more ANSPs are incorporated (those of Germany, Spain, France and Poland).

b) DCI

In the baseline implementation, a simple recovery rule applies of attempting to recover as much delay as possible when the delay exceeds 15 minutes at top of climb (TOC). This is applied to 10% of flights. It applies to flights of longer than 60 minutes and sets caps on extra fuel consumption. In the enhanced mechanism, the cost (fuel) and benefit (delay reduction) of recovering delay is estimated at TOC for all flights implementing the mechanism. This applies to carriers’ operations on flights to/from their main hubs, for the three largest European airports by passenger numbers in 2014: Heathrow, Frankfurt, Charles de Gaulle. In the follower

scenario, the number of airlines implementing the mechanism on operations to/from their hub increases (by a further eight airlines, including two low-cost carriers) and the airlines from the early adopters implement the mechanism in the rest of their network.

c) A-CDM

Based on [2] and [3], the benefit of implementing A-CDM is modelled as a reduction of the propagation of delay at the airport using distributions centred on 3% or 4% reductions. This reduction is expected as more predictability is achieved and resources are better managed. The benefits are staggered: baseline airports achieve 3% on average, these maturing to 4% in subsequent uptake levels; early adopters achieve 3%, these maturing to 4% at the follower uptake level, at which newly implementing airports achieve 3%. The uptake of airports follows the departure planning information (DPI) implementation at airports as reported by EUROCONTROL³.

d) Improved pax reaccommodation

The baseline models a local, airport-by-airport solution, where disrupted passengers missing connections are reallocated to subsequent flights, possibly with different routings, taking account of available space on such flights. This process simply minimises the cost of reaccommodating the passengers. Rebooking occurs firstly on the same airline, then within alliances, wherever possible. ‘Premium’ passengers (highest-yield passengers associated with high-end fares) are reaccommodated first. The enhanced mechanism includes proactive management of outbound flights by implementing wait-for-passengers rules, that minimises the cost in a network-wide (c.f. baseline, local) approach. The uptake mimics that of DCI: early adopters are major carriers for operations at their hub, whilst follower uptake includes the expansion of operations to their whole network and adds other airlines at their hubs.

3) Mechanism cost assignments

This section briefly summarises the detailed methodology developed for assigning the strategic (implementation) and tactical (‘running’) costs of the mechanisms. Several of these costs are presented in Section IV(A), where commercial sensitivities permit.

a) Improving sector capacity with ATCO hours

For this mechanism, the stakeholder making the investment is the ANSP (although this could be (partially) recovered later through airline user charges). The strategic cost is estimated from industry consultation as in the range EUR 1–3M per ANSP⁴, which we have scaled by ANSP size (number of ATCOs). The tactical costing follows the methodology of [16], assuming that full (i.e. not partial) shifts of controllers are required and by estimating ATCO ‘shortfalls’ with respect to the maximum possible number at each ANSP based on analysis of data from Aeronautical Information Regulation and Control

³ DPI Implementation Progress for CDM Airports, <http://www.eurocontrol.int/articles/cdm-airports> (Accessed July 2016).

⁴ This is a software implementation cost for improved ATCO shift management, *inter alia*.

(AIRAC) period 1313 to 1413. The tactical cost of controllers’ hours is based on [20].

b) DCI

Equipment and training costs are estimated for the strategic cost of implementing dynamic cost indexing. Class 2 (or higher) electronic flight bags (EFBs) are required to operate DCI. Based on expert industry consultation, an even distribution of Class 2 EFB uptake across 50% of European aircraft equipped with Class 1 EFBs is assumed. 40% of aircraft are assumed to be already equipped with Class 2 EFBs, and 10% with Class 3. Therefore, for 50% of aircraft that implement DCI, the cost of upgrading to Class 2 EFBs is considered. The training required is estimated at two hours per pilot affected by the implementation of the mechanism. Fleet pilot numbers are estimated from the airlines’ operations data, differentiating by the type of aircraft used. An estimation of the number of pilots operating routes affected by DCI is also used to compute the training costs. Following industry charging practice, the tactical cost of DCI is computed as a (fixed) percentage of the estimated benefit (net cost saving) to the airline.

c) A-CDM

The majority of the implementation costs for A-CDM are invested by the airport, handling agents and ANSP. These vary by airport size. Airline costs are mainly incurred by the major carrier at the airport, and are substantially less than for the airport (especially for smaller carriers). Explicit values collectively for all non-airline, and airline, stakeholders are estimated based on [2], [3] and industry consultation. Tactical costs are similarly derived.

d) Improved pax reaccommodation

The strategic cost of implementing the system is estimated based on industry consultation and proportional to the volume of passengers boarded yearly by the corresponding airlines. It is assumed that early adopter airlines already operate passenger reaccommodation software (irregular operations (IROPS) systems). For these early adopters, the software is assumed to be an upgrade of existing software, with the suppliers’ costs recuperated through the normal tactical charging regime. Implementation costs (again based on industry consultation) are applied to the follower airlines, however, these being based on airline size and within set cost constraints. The tactical costs of running the system are based on the number of passengers boarded by the implementing airlines (on the simulation day), as per industry practice. (Note that this charging philosophy is similar to that of DCI.)

E. Types of disturbance

1) Overview, and re-routing

As introduced earlier, explicit disturbance types of industrial actions and weather are part of the model scenarios, both at local and disperse levels. Background (including ATFM) disturbance is also modelled as part of the baseline. For the explicit disturbances, except the local weather disturbances impacting specific airports, flights affected by the regulations generated may (statistically) decide to re-route to

avoid the ATFM delay. Re-routing uses historical data of actual flight plans and waypoints, and an A* search algorithm (widely used in pathfinding between multiple nodes) to find the shortest, viable new route. Points within the boundaries of the ATFM regulations are withdrawn from the graph before computing the new route. Fig. 1 presents two examples of possible re-routings around French industrial action. ANSPs implementing additional ATFM regulations to manage the extra flow resulting from re-routings are also accounted for, consistent with *a posteriori* analysis of industrial action days.

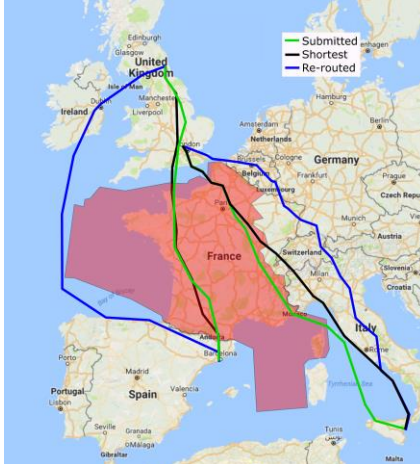


Figure 1. Example of re-routing around industrial action.

For the explicitly considered disturbances, the delay generated is approximated by Burr distributions based on analysis of all the regulations of the corresponding four disturbance categories for AIRAC 1313–1413. The geographical location of these ATFM regulations and their temporal durations are based on regulations implemented on specific days. In this analysis, the number of ANSPs affected and the intensity of the delay generated have been considered. Outline details of each delay model are presented as follows.

2) Background (baseline) disturbance

Background ATFM delay is based on the delay observed for 12SEP14 (the baseline simulation day), as reported in the corresponding DDR2 data, considering flights entering each regulation. The delay that a regulation generates is randomly shuffled between flights affected by the regulation, both to preserve the original distribution and also introduce a degree of stochasticity. Non-ATFM background delay is also modelled, taking account of aggregated (September 2014 [21] and full-year 2014 [22]) primary and reactionary delay categorisations.

3) Industrial actions

The analysis of delay generated by industrial actions during the period AIRAC 1313–1413, and of various data sources (post-operational reports and Central Office for Delays Analysis (CODA, EUROCONTROL)), allows us to model the corresponding Burr delay distributions and to assign increased probabilities of flight cancellations and re-routing.

a) Local

These regulations' locations and temporal durations are based on ATFM regulations implemented on 24JUN14, when major industrial action was implemented in French airspace. The effect is large but limited to the region of the French ANSP.

b) Disperse

For the disperse case, regulations due to industrial actions on 30JAN14 are considered. On that day, there was industrial action declared in the airspaces of Austria, France, Hungary Portugal and Slovakia.

4) Weather

Two distributions of delay are used: one for ATFM regulations at airports and another for ATFM regulations in the airspace. The values of the Burr distributions and the probabilities of having delay assigned are different in each case. For the airspace case re-routing is also possible.

a) Local

ATFM regulations due to weather on 18OCT14 are used. The selection of this day gives us a local geographical scope focused at airports. The regulations were localised at airports in Germany, Switzerland and the UK.

b) Disperse

25JUL14 was selected as a day when ATFM regulations were implemented in the airspace at a disperse geographical scale: six airports were affected in three ANSPs (Poland, Portugal and Switzerland) and 36 regulations were applied in the French, German, MUAC, Portuguese, Spanish and UK airspace.

F. Airline cost impacts

The tactical cost of delay to the airlines is the fundamental cost impact assessed in this research. (In future, it may be extended to other stakeholders.) Summing across the contributing tactical component cost types for assessment units (u) as a function of delay duration (t), furnishes $C_u(t)$, thus enabling an evaluation of (2) for each model scenario, as reported in the results of Section IV. The main costs of airline delay are comprised of fuel, passenger, maintenance, crew and (strategically) fleet costs. Produced partly within the remit of ComplexityCosts, new delay cost values have been calculated [17] as an update to those published by the University of Westminster for the reference year 2010, extended to fifteen aircraft types, and based on an airline consultation specifically regarding the cost of passenger delay to the airline, since this comprises such a significant proportion of delay costs and is the most difficult to estimate (we thus elaborate on this next). Passenger, crew and maintenance costs draw directly on [17]. Fuel models were discussed in Section III(A). The passenger cost assessment draws on various sources of evidence, with a particular focus on the impact of Regulation (EC) No 261/2004 [23] and proposed amendments thereto. This regulation establishes the rules for compensation and assistance to airline passengers in the event of denied boarding, cancellation or delay.

In addition to these hard costs of delay, the soft costs of passenger delay (associated primarily with market share loss driven through unpunctuality) are also applied. The rules governing Regulation 261 compensation payment entitlements and airline practice, particularly when taking into account associated reactionary delay effects, are highly complex, and legal advice was thus taken. In summary, the two types of disturbance applied, and their associated reactionary delays, do not entitle passengers to compensation.

However, regarding baseline delay, approximately 40% of primary delay, and its associated reactionary delay, does fall within the eligibility of compensation payments. During disruption, within airline alliances, flight rebookings for missed connections are calculated using IATA pro-rotation rules. Outside such agreements, following a separate airline consultation and internal calculations, passengers are rebooked at the pro-rated fare, plus 75%.

G. Model calibration

To assess the basic validity of the model's key output metrics, the baseline values (i.e. with baseline mechanisms but without the explicit disturbances) are compared with published values. These are shown to be in good agreement, in Table IV.

TABLE IV. DELAY CALIBRATION METRICS

Metric	Calibration target	Model baseline
Flight departure delay (mins/flight)	10.7 ^a	10.2
Flight arrival delay (mins/flight)	10.0 ^a	10.2
Reactionary delay (reactionary/total %)	46.6 ^a	42.1
Cost of delay (Euros/flight)	103 ^b	104

a. All European Civil Aviation Conference traffic, September 2014 [21].

b. All European Civil Aviation Conference traffic, full year 2014 [17].

(Values to 3 s.f.)

Regarding the passenger allocations described in Section III(B), the overall passenger load factor for the baseline traffic day was 83.5%. This compares well with the Association of European Airlines' 'total scheduled' load factor for the month, 83.6% [24].

Other calibration checks using ACI EUROPE statistics⁵ showed total, model-allocated passengers at the busiest ten airports to be slightly higher, but within 6% of ACI figures. The top 100 airports were all within 11%.

IV. SIMULATION RESULTS

A. Comparative cost resilience results

TABLE V. STRATEGIC COSTS OF MECHANISMS

Mechanism, by stakeholder uptake	Improved sector capacities	DCI, fuel nominal	DCI, fuel high	A-CDM	Improved passenger reaccomm.
With early adopters	5 000	—	—	11 300	0
With followers	16 400	—	—	53 100	—

(Costs in k Euros; 3 s.f.)

⁵ Personal communication; adjusted to one day of traffic.

TABLE VI. TACTICAL COSTS OF MECHANISMS

Mechanism, by stakeholder uptake	Improved sector capacities*	DCI, fuel nominal	DCI, fuel high	A-CDM	Improved passenger reaccomm.
With early adopters	2 500	—	—	3 800	—
With followers	20 000	—	—	17 900	—

* Costs are assigned per disturbance type; values shown in table are averages over disturbance types.

(Costs in Euros; 3 s.f.)

Table V shows selected strategic costs of the investment mechanisms, as described in Section III(D)3. These are the implementation costs of the mechanisms. Note that the 'with followers' costs include the 'early adopters' costs, as these are assessed in the model against the total benefit of the early adopters and followers. Costs indicated '—' cannot be shown due to commercial sensitivity⁶. Those for DCI are comparable with the improved sector capacities and A-CDM values. The improved passenger reaccommodation value for the followers is lower than other values in the same row; the corresponding early adopter value is zero, as discussed earlier.

Those tactical costs shown in Table VI are the 'running' costs of the mechanisms for the (single) simulation day. Apart from DCI, the tactical costs for these mechanisms are calculated in advance. In practice, (relatively small) adjustments could be made tactically based on more flexible ATCO payments, to A-CDM costs and passengers' boarded (for the reaccommodation tool costs), but the pre-simulation estimates are believed to be robust.

In contrast, the DCI tactical costs are derived directly from the savings made by the airlines, and are thus calculated dynamically. Although, again, costs indicated '—' cannot be shown due to commercial sensitivity⁶, the DCI values (in each row) are similar to the improved sector capacity and A-CDM costs, being somewhat lower for the followers (but of the same order of magnitude). The passenger reaccommodation tool running costs are the highest in each row, but remain comparable with the others.

Of note, is that the DCI costs *fall* (averaged over all scenarios) by around 10% between the nominal and high cost fuel cases. This is because fuel burn falls by the same amount, as the number of occasions when it becomes cost effective to speed up to recover delay decreases with the higher fuel cost. The implications for the R_C values will be discussed later.

Table VII and Table VIII show the results of the R_C values calculated for the 40 scenarios introduced in Section I. The values are shown in pairs, i.e. for local and disperse disturbances, for each combination of stakeholder uptake and mechanism.

Firstly, we note that the local and disperse values are comparable in each case, demonstrating that the formulation of R_C (2) is effectively capturing the comparative effects of the mechanisms relative to the respective baselines.

⁶ These results have been disclosed to the ComplexityCosts Project Officer.

TABLE VII. COST RESILIENCE UNDER INDUSTRIAL ACTION DISTURBANCE

Mechanism, by stakeholder uptake & disturbance level	Improved sector capacities	DCI, fuel nominal	DCI, fuel high	A-CDM	Improved passenger reaccomm.
With early adopters					
local	0.038	0.020	0.019	0.008	0.024
disperse	0.049	0.017	0.016	0.004	0.021
With followers					
local	0.237	0.056	0.064	0.007	0.008
disperse	0.271	0.058	0.067	0.004	0.009

(All values relate to n = 26 860 flights.)

TABLE VIII. COST RESILIENCE UNDER WEATHER DISTURBANCE

Mechanism, by stakeholder uptake & disturbance level	Improved sector capacities	DCI, fuel nominal	DCI, fuel high	A-CDM	Improved passenger reaccomm.
With early adopters					
local	0.027	0.008	0.016	0.002	0.000
disperse	0.020	0.002	0.010	0.012	0.004
With followers					
local	0.210	0.053	0.064	0.002	-0.000 ^a
disperse	0.211	0.044	0.057	-0.000 ^a	0.005

a. Adjusted from small negative values statistically equivalent to zero.

(All values relate to n = 26 860 flights.)

Comparing the early adopter values (upper two rows in each table) with the corresponding followers (lower two rows in the same tables), it is apparent that the improved sector capacity and DCI mechanisms offer notably increased cost resilience as the scope of the mechanism (stakeholder uptake) is increased. This is not apparent for the A-CDM or improved passenger reaccommodation mechanisms. The rationale for this is likely to be attributable to the relative colocation of the disturbances and mechanisms. The improved sector capacity provisions are typically close to the disturbances, and the DCI mechanism is fairly widespread through the network. Initial analyses suggest that the positive effects of A-CDM are less well colocated with the disturbances in terms of having a notable amelioratory impact. This is less likely to be the reason for the lower values for the passenger reaccommodation tool, since its spatial implementation mimics that of DCI, as explained earlier: we will thus return to these lower values.

By the time the follower stakeholder uptake is incorporated into the model, it is notable that the R_C values for each mechanism are very similar when comparing the industrial action and weather disturbances. This levelling effect is as expected, as the location of the early adopters becomes less of a factor relative to the disturbances (and the delay subsequently propagated more widely through the network as reactionary delay) as the mechanism uptake becomes more widespread.

Also of note is that the R_C values appear overall to be relatively low in magnitude. Further research would be required to investigate these values under different conditions and modelling assumptions, although none of the values is close to the upper limit of unity (perfect cost resilience). It should be borne in mind, however, that the values are summated over a wide network area and many flights, yet they

still seem to behave logically and sensitively. Of particular interest in further work, would be to examine more *localised* cost resilience values, for example with widespread disruption in one airspace region (or state), and applying specifically to more highly impacted flights, or flights passing through that region. It would then be expected that the cost resilience values would all increase markedly.

Before concluding this summary of the R_C results, it is worth being reminded of the fact that the DCI and passenger reaccommodation mechanisms are, to a certain extent, self-determining with respect to their cost resilience, since both mechanisms are charged to the airspace user relative to their efficacy and usage, respectively, as described in Section III(D)3. The low passenger reaccommodation R_C values are discussed in the next section. Addressing the DCI values, as observed in the previous section, these costs *fall* by around 10% between the nominal and high cost fuel cases. However, the R_C values are fairly stable across these cases, i.e. within given rows. This is because the mechanism is here actively trading off the cost-benefit of speeding up to recover delay, and there is a consistent fall (of around 5%) in the cost of delay between the nominal and high cost fuel cases.

B. Resilience in the context of disaggregated metrics

In this section we explore further the high-level cost resilience (R_C) results, through the use of a small *selection* of the dedicated metrics evaluated for each of the scenario and baseline runs. These include flight-centric and passenger-centric metrics, as it is necessary to differentiate between the two, as established in the literature (see [6] for European examples, and a literature review). The cost-centric metrics also draw on [17].

The selection of results presented in Table IX will be referred to by the corresponding row numbers, and standard z tests are applied to assess the statistical significance of differences (in each case, the minimum number of flights included is 26 860). These values are also aggregated over all scenarios for each mechanism, to furnish a convenient overview of performance. In further reporting, such analyses will be disaggregated by disturbance type and stakeholder uptake, building on the corresponding observations of Section IV(A).

Of initial note is that the key metrics of Table IV are significantly deteriorated, as expected, in Table IX, i.e. under the influence of the explicit disturbances applied. Considering the average flight arrival delays (a), the improved sector capacities mechanism performs better than the other four ($p = 0.00$, x4). The two DCI fuel cases are statistically the same ($p = 0.89$), but perform somewhat better than A-CDM⁷. A-CDM, in turn, produces a flight arrival delay significantly lower than the passenger reaccommodation mechanism ($p = 0.03$). The clear performer here, however, is once again the improved sector capacity mechanism, with the other four producing essentially similar results.

⁷ $p = 0.02$ (nominal fuel price), $p = 0.01$ (high fuel price).

TABLE IX. SUMMARY DISAGGREGATED METRIC RESULTS

Metric	Improved sector capacities	DCI, fuel nominal	DCI, fuel high	A-CDM	Improved passenger reaccomm.
(a) Flight arrival delay (mins/flight)	14.9	17.3	17.2	17.8	18.4
(b) Pax arrival delay (mins/pax)	25.1	27.9	27.8	28.3	28.4
(c) Pax / flight delay (ratio: a / b)	1.69	1.61	1.61	1.59	1.55
(d) Cost of delay (Euros/flight)	287	318	316	328	328
(e) Reactionary delay (reactionary/total %)	44.2	44.9	44.8	45.7	47.4
(f) Airborne fuel burn (tonnes/flight)	8.94	8.45	8.45	8.93	8.93
(g) Airborne CO ₂ (tonnes/flight)	28.3	26.7	26.7	28.2	28.2

(Values to 3 s.f.)

The average passenger arrival delays (b) are in the same order, across the mechanisms, as the flight arrival delays, although the distribution is a little flatter. However, the standard deviation of these means (not shown) are considerably higher than those of the flight delays, consistent with observations that passenger delay distributions are typically much wider than those of flights [6]. As a consequence of this, there is no significant difference ($p > 0.55$, x6) in performance between any pairs of mechanisms for the four mechanisms in the right-hand side of the table. In other words, only improved sector capacities out-performs other mechanisms in this respect ($p < 0.01$, x4). These statistical significance patterns are exactly reflected for the costs of delay (d), such that the improved sector capacities mechanism offers, on average, across all the scenarios and compared with the other mechanisms, an extra total cost saving to the airlines of approximately EUR 930k during this busy traffic day.

In row (c), the ratio of the passenger to flight arrival delay is shown. Lower values indicate relative better performance in managing passenger delay. As might be expected, the passenger reaccommodation mechanism shows the best ratio (1.55). These values are in agreement with similar ratios previously reported [6] in the European context for the ratio of arrival-delayed passenger over arrival-delayed flight minutes (1.3 – 1.9), these tending to be higher, as might be expected, under greater disturbance.

The reactionary delay values (e) offer some insight into other performance characteristics of the passenger reaccommodation mechanism. Here, it is likely that the cost-based local rebooking (early adopters), then extended wait rules for passengers (followers), suffer from negative impacts further ‘downstream’ (on subsequent rotations) during the operational day. Decisions, as modelled, such as to wait for passengers, are locally good, but globally do not offer the expected benefits, for example due to delays being subsequently compounded by further ATFM regulations being applied. This is partly manifested by the highest reactionary delay ratio (47.4%) occurring for this mechanism. This presents particular further opportunities for exploring these impacts in the network. Higher reactionary ratios for passenger-oriented solutions were also reported in [6], as an

expected consequence of waiting aircraft. It is also to be noted that this is the major reason for the low R_C values reported earlier for this mechanism: these R_C values are robust with respect to the assumed tactical costs and change relatively little if these are revised significantly downwards.

Regarding the average airborne fuel burn (f), it is interesting to note that the cross-scenario average of 8.45 tonnes/flight increases to 8.82 tonnes/flight (not shown) for both DCI fuel cost cases when only the early adopters are included. In other words, it is the extension to the follower cases that brings the average fuel burn down to below those of the other mechanisms, as we might expect from the mechanism with greatest specific focus on ‘smart’ fuel consumption. The airborne CO₂ (g) is a linear function of the fuel burn (f), as described earlier, and is included in the table to directly show the comparative outputs. For example, based on the 26 860 flights, DCI (under either cost assumption) produces approximately 40 kilotonnes less airborne CO₂ in the network during the busy simulation day relative to improved sector capacities⁸ ($p = 0.00$, x2), yet still performs comparably well in (a) and (b), as discussed.

C. Taking account of the strategic investments

TABLE X. STRATEGIC COST RECOVERY PERIODS

Mechanism, by stakeholder uptake	Improved sector capacities	DCI, fuel nominal	DCI, fuel high	A-CDM	Improved passenger reaccomm.
With early adopters	1	6	5	10 (1 ^a)	≈ 0
With followers	< 1	4	3	(5 ^a)	2

a. Based on airline implementation costs – see main text.

(Cost recovery periods to nearest traffic-adjusted, high-disturbance month.)

Table X shows indicative cost recovery periods for the mechanisms investigated. These basic values are subject to refinement during further model scenarios, in particular investigating biases introduced due to the colocation, or separation, of the disturbances and mechanisms. These highly simplified payback periods, illustrating the future potential of the model, are calculated by simply dividing the implementation costs of Table V, by the net cost savings of each mechanism, averaged over all the disturbances. These are not calculated in time-discounted Euros and assume that all the days in which the mechanism applies experience the same high levels of explicit disturbance. The values are proportionally corrected, however, for the fact that the sample day had relatively higher traffic than a typical day, such that we might expect recovery over lower-volume traffic days to take longer.

With these several caveats in mind, it is apparent that the improved sector capacities mechanism offers rapid payback, as does the passenger reaccommodation mechanism. For the latter, the cost recovery for the early adopters is of course effectively instantaneous, since the software upgrade was assumed in the model to be made on the basis of tactical recovery costs only. With full implementation costs involved for the followers, and running costs based on passengers

⁸ Or any other mechanism, since the non-DCI values in row (f) are practically the same.

boarded, the recovery period (in terms of high-disturbance months, it is again stressed) is still quite low.

DCI recovery periods are comparable in order of magnitude, with the slightly lower values for the *higher* fuel cost case reflecting its corresponding somewhat superior cost efficiency, as reflected in the majority of the R_c values. The A-CDM value of 10 months is artificially high for two reasons. Firstly, it is biased by the colocation issue. Secondly, the implementation costs are borne largely by non-airline stakeholders, whereas the benefit is calculated only as a delay saving to the airlines (note that this is also the case with the improved sector capacities). The A-CDM values shown in parenthesis are for *airline* strategic (implementation) costs (not shown). These produce payback results comparable with the other mechanisms. (The value for the followers based on Table V was excessively large and is not shown.)

V. CONCLUSIONS AND FUTURE RESEARCH

Using traffic and passenger itinerary data for the whole European network, the cost resilience of four mechanisms, with phased stakeholder uptake, has been assessed under local and disperse disturbance. In the only model of its kind, as far as the authors are aware, a novel cost resilience metric has demonstrated logical properties and captured cost impacts sensitively. We have compared and contrasted the cost benefits of the four diverse mechanisms. Of these, only A-CDM has been assessed within the SESAR context, yet each of the other three demonstrates particular strengths. It would be instructive to explore these further.

Several features of the model may be improved upon, particularly the downstream behaviour of the passenger reaccommodation mechanism, and colocation effects. In addition, higher specification of the disturbances and the construction of a wider sample of traffic and passenger itinerary inputs would be useful. Enhanced airline behaviours (e.g. tactical responses to industrial action and strategic responses to changes in Regulation 261) could also be included. As mentioned, of particular value would be to explore more localised cost resilience values, and to examine the results to date in more detail using further flight-, passenger- and cost-centric metrics: of those deployed in the model, only a small selection has been used here. There is also an opportunity, probably a necessity, to use advanced data visualisation tools to more comprehensively map the large data outputs from each scenario. Initially promising work on payback periods has begun, with opportunities to broaden the included stakeholder costs and to assess cost recovery periods over more typical operational days. Despite uncertainty being one of the main factors generating reduced performance, behaviours are often driven by complex interactions and feedback loops that render it difficult to assess second-order impacts at a network level. Feedback loops in the model could thus potentially generate new emergent macroscopic behaviour, and analysis thereof is a key next step towards the goal of improved cost-benefit analysis in ATM.

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