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Delay propagation – new metrics, new insights

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Abstract—**Network delay propagation is intimately linked with the challenges of managing passenger itineraries and corresponding connections. Airline decision-making governing these processes is driven by operational and regulatory factors. Using the first European network simulation model with explicit passenger itineraries and full delay cost estimations, we explore these factors through various flight and passenger prioritisation rules, assessing the performance impacts. Delay propagation is further characterised under the different prioritisation rules using complexity science techniques such as percolation theory and network attack. The relative effects of randomised and targeted disruption are compared.**

Keywords–delay propagation; percolation; network attack; passenger-centric; flight prioritisation; Granger causality

I. INTRODUCTION

Delay is a common feature of transport networks and has been much studied in the specific context of air traffic management and more widely in aviation. Of particular interest is the phenomenon of delay propagation, whereby the primary (causal) delay of one flight results in secondary (reactionary) delay incurred by other flights. In air transport, the susceptibility of the system to such effects is driven by various dependencies between flights, most notably those of aircraft rotations (a delayed aircraft is late for a subsequent operation), crew dependencies (e.g. late crew on one flight are not available for their next duty) and passenger connectivities (e.g. an outbound aircraft is held awaiting delayed inbound passengers). Direct, aircraft-aircraft reactionary delay is known as 'rotational', whereas indirect effects between different aircraft (such as those due to connecting passengers) are known as 'non-rotational'.

Airlines typically have one or more contingencies in place to manage such eventualities, including options such as aircraft swaps or spare crews, or buffer times in flight schedules and passenger connection times. Nevertheless, these contingencies come at a cost, often referred to as the 'strategic' (opportunity) cost of delay and reflected through reduced utilisation, thus comprising a complex trade-off against the risk of incurring tactical delay costs on the day of operations.

Despite the high costs associated with delays, it is perhaps somewhat surprising that the ratio of propagated (reactionary) to primary delays in Europe has remained fairly flat since 2010. As we shall quantify later, just under half of all delay minutes are still attributable to reactionary delay in Europe. A significant challenge remains in terms of trying to improve this performance without compromising other aspects of service delivery, such as user flexibility.

Placing such analyses in a passenger-centric context further compounds the difficulty of modelling delay propagation and of gaining insights into potential improvements. As we shall demonstrate, the average delays of (delayed) flights and passengers are not the same. The air transport industry is lacking passenger-centric metrics; its reporting is flight-centric. Trade-offs between these metrics need to be better understood, as they are observed to move in opposite directions under certain types of flight prioritisation. With growing political emphasis on service delivery to the passenger, and passenger mobility, how are we to measure the effectiveness of passenger-driven performance initiatives in air transport if we do not have the corresponding set of passenger-oriented metrics or understand the associated trade-offs in the context of delay propagation? The generation and propagation of delay in the network is intimately linked with the challenges of managing passenger itineraries and corresponding connections. Airline decision-making governing these processes is, in turn, driven by operational and regulatory factors. In this paper, we explore these effects through various flight and passenger prioritisation rules, assessing the corresponding performance impacts.

Reporting results from the 'POEM' (Passenger-Oriented Enhanced Metrics) simulation model (please see 'Acknowledgement'), these performance impacts are measured through new and existing metrics, including passenger-centric and flight-centric metrics based on airline delay costs. Recent new work on these data, drawing on complexity science techniques such as percolation theory and network attack, are used to compare the relative effects of randomised and targeted disruption on delay propagation.

Whilst we focus on the European perspective regarding the operationalisation of our model and the specific regulatory drivers, we refer often to the US context – particularly in terms of existing research and performance data. Indeed, as will be demonstrated, much of the earlier research in passenger metrics was developed in the US, spurring the need for corresponding work in Europe. It is hoped that the modelling presented and analytical techniques will be of common value. The paper begins with a review of current performance, target setting and regulation.

II. PERFORMANCE AND POLICY CONTEXTS

A. Performance context

TABLE I.   US AND EUROPEAN PERFORMANCE IN 2013 (TO 1 D.P.)

Region	Total flights [a]	Arrival		Cancelled	Rotational reactionary delay [c]
		On-time [b]	Delayed [b]		
US	15.1m	78.3% [d]	19.9% [d]	1.5% [d]	42.1%
Europe	9.6m	82.7% [e, f]	15.8% [e, f]	1.5% [g]	41.9%

a. Source: [1].

b. Delay c.f. schedule – US: ≥ 15 minutes; Europe: > 15 minutes. Both include early arrivals.

c. Sources: US – "aircraft arriving late" [2]; Europe – [3] and [4] (see main text).

d. Source: [5]; diverted flights not shown. Sample: 16 reporting carriers.

e. Sources: on-time [3], [4]; delayed [4]. Sample: 68.6% of ECAC flights.

f. Adjusted to correct for cancelled flights; diverted flights not shown.

g. Approximate value [6].

Comparing European and US air traffic management contexts, the latter area is approximately 10% smaller and handles some 57% greater flight activity, as measured by operations or flight hours [1]. Despite the different operating settings, both in terms of internal factors such as flow management methods and system integration, and externalities such as weather, several indicators of operational performance are comparable between the two regions. (See [1] for a comprehensive comparison.) Table I offers an overview of key performance data for 2013 (note that variations in reporting exist between various sources).

In Europe, the average arrival delay (all causes) in 2013 was 9 minutes per flight; in the US, it was 13 minutes per flight (based on data from reporting airlines [4, 5]). The rotational[1] reactionary delay in 2013 is practically equal in the two regions, at approximately 42% of all delay. Since 2010, the corresponding trends are rather moderately upwards in the US (not plotted) and relatively flat in Europe (Fig. 1). Let us explore the high-level European data further, to set some context for the analyses to follow. Plotting average departure and arrival delay[2], delay proportion comprised of total reactionary delay, and total traffic, and normalising these values to 2004 data (Fig. 1), demonstrates that reactionary delay correlates weakly with departure or arrival delay ($r^2 \approx 0.0$) and somewhat less weakly ($r^2 \approx 0.5$) with total traffic.

European punctuality in 2010 was at its worst since 2001. Although subject to a high number of cancellations (due to the Eyjafjallajökull ash cloud in April and May, strikes in France and Spain, and bad winter weather), this had a limited effect on punctuality *per se* [7]. Nevertheless, the relative proportion of reactionary delay was fairly insensitive to this change in performance. Nor can the relative stability (or persistence) of the reactionary ratio be attributed to any substantial changes in schedule buffers over this period [3]. (Compare also

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[1] [2] reports rotational reactionary delay; for comparison, the European value is thus adjusted from total reactionary delay [3], of which 90% is rotational [4].

[2] Minutes per flight, all flights; delays counted from first minute, earlies counted as zero. Arrival punctuality in Europe is mainly driven by departure punctuality, with relatively small variations in the gate-to-gate phase [3].

comprehensive US work [8] demonstrating, perhaps unexpectedly, that departure delay plays only a minor role in setting scheduled block-times.)
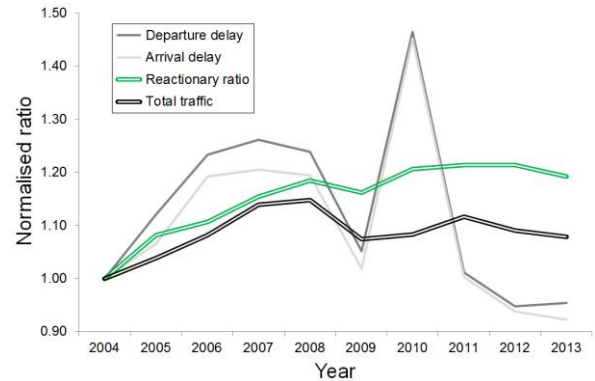

Figure 1.   European high-level performance trends, 2004 – 2013.

Source: data provided by EUROCONTROL's Central Office for Delay Analysis and Performance Review Unit, and taken from Network Manager Monthly Summaries.

Whilst the ratio of reactionary delay seems to weakly follow traffic volumes, and may thus reflect system stress to some extent, these correlations are far from establishing causality. Furthermore, whilst most reactionary delay is recorded as simply rotational, it is likely that this cause is substantially over-reported, due in large part to the difficulty of assigning and tracking true causality through the operational day. For example, an aircraft awaiting late passengers early in the day may be late on every subsequent rotation, with all but the first erroneously recorded as pure rotational from a true causality perspective (a subject to which we shall return later in this paper). From high-level data, we are thus left with a degree of oversight, but with a stronger conviction that we are missing substantial insight.

B. Wider policy context

Air traffic management reform in Europe (through SESAR) and the US (through NextGen) is set in the wider policy context of improving service delivery to the passenger. NextGen is implementing new technological and procedural capabilities to make the US National Airspace System (NAS) safer whilst mitigating impacts on the environment and reducing delays (e.g. targeting a 41% reduction in delays by 2020) [9]. The FAA published a new strategic plan in 2011, 'Destination 2025', streamlining strategic goals. Mindful of the passenger, these include goals that will "serve the needs of the traveling public and the aviation industry to provide unencumbered access to the aviation system" and "enhance aviation's value to the public by improving travel throughout the National Airspace System, and beyond" [10]. Since the FAA Modernization and Reform Act came into force in 2013, the FAA has been required to track and report on twelve specific metrics in order to measure the impact of NextGen. These have been harmonised with existing NAS-wide

performance metrics to ensure alignment with FAA targets and goals [11].

Social and political priorities in Europe are shifting in further favour of the passenger, as evidenced by high-level position documents such as 'Flightpath 2050' [12] and the European Commission's 2011 White Paper ('Roadmap to a Single European Transport Area', [13]). SESAR's 'Performance Target' [14] refers frequently to the concept of society and the passenger. The 'societal outcome' cluster of key performance areas[3], is defined as being of "high visibility", since the effects are of a political nature and are even visible to those who do not use the air transport system. The 'operational performance' cluster[4] is also specifically acknowledged as impacting passengers. Notably, the Performance Target [*ibid.*] not only significantly refines the fifteen minute historical threshold for defining arrival and departure delay in Europe (and the US, as observed above), the new European threshold being ±3 minutes, but also sets a target reduction in reactionary delay of 50% by 2020, relative to 2010. NextGen currently has no reactionary delay target.

In parallel, the Performance Scheme is a central element of the Single European Sky initiative. It is defined across various reference periods (RPs). Performance targets are set at various levels before each period and are legally binding for European Union (EU) member states. With RP2 running from 2015 to 2019, any incorporation of passenger-centric metrics into the scheme would need to be considered for RP3 (2020 - 2024). Currently, however, neither NextGen nor SESAR has metrics oriented *specifically* to the passenger. As we shall develop within this paper, examination of such specific metrics is of particular value to performance assessment.

C. Regulation 261 in Europe

At the centre of established and indeed, evolving, EU regulation in this context, is the underpinning regulatory instrument for air passenger compensation and assistance (Regulation 261, [15]). Already a key factor in determining airline costs incurred due to delayed passengers, this regulation is currently undergoing a process of review [16], due to several problems with regard to its implementation and interpretation. There have been numerous qualifying and clarifying court rulings and appeals, often substantial in impact, by national government (e.g. [17]) and the Court of Justice of the European Union (e.g. [18]). Proposed changes could become law by 2016-2017, subject to approval by member states. Key proposed changes are to: (i) initiate passengers' right to care and assistance after two hours of delay, regardless of the length of the flight; (ii) require an airline to re-route passengers onto other carriers (already much commoner in the US) if it cannot re-route onto its own services within 12 hours; (iii) offer passengers the same rights for delays relating specifically to connecting flights. The impacts of such changes on the airlines are often considerable, e.g. not only increasing the scope (e.g. [18]) but also greatly extending the time period permissible for

retrospective claims (e.g. [17]). Tools for exploring the (cost) implications of such regulatory changes are noticeable by their absence − a gap we have attempted to begin filling with the POEM model.

III. PREVIOUS MODELLING AND DATA AVAILABILITY

A. Previous modelling

Using large data sets for passenger bookings and flight operations from a major US airline, it has been shown [19] that passenger-centric metrics are superior to flight-based metrics for assessing passenger delays, primarily because the latter do not take account of replanned itineraries of passengers disrupted due to flight-leg cancellations and missed connections. For August 2000, the average passenger delay (across all passengers) was estimated as 25.6 minutes, i.e. 1.7 times greater than the average flight leg delay of 15.4 minutes.

Based on a model using 2005 US data for flights between the 35 busiest airports, [20] concurs that "flight delay data is a poor proxy for measuring passenger trip delays". For passengers (on single-segment routes) and flights, delayed alike by more than 15 minutes, the ratio of the separate delay metrics was estimated at 1.6. Furthermore, heavily skewed distributions of passenger trip delay demonstrated that a small proportion of passengers experienced heavy delays, which was not apparent from flight-based performance metrics [21, 22].

Using US historical flight segment data from 2000 to 2006 to build a passenger flow simulation model to predict passenger trip times, [21] cites flight delay, load factors, cancellation (time), airline cooperation policy and flight times as the most significant factors affecting total passenger trip delay in the system (see Table II).

An "inherent flaw in the design of the passenger transportation service" has been pointed out [23], in that service delivery to the passenger did not improve in 2008 in the US, despite the downturn in traffic. One in four US passengers experienced trip disruption (due either to delayed, cancelled or diverted flights, or due to denied boarding). Recovery mechanisms in place for disrupted passengers, such as transfer to alternative flights or re-routing, require seat capacity reserves. However, the airline industry wishes to maximise economies of scale, optimise yield management, maximise load factors, and (thus) to minimise seat capacity reserves. In 2008, as airlines reduced frequencies to match passenger demand, higher load factors severely reduced such reserves [*ibid.*].

TABLE II. PREDICTED PAX TRIP DELAY BY PERFORMANCE CHANGES

Performance change	Predicted pax trip delay change
15-minute reduction in flight delay	-24%
Improved airline cooperation policy in re-booking disrupted passengers	-12%
Flights cancelled earlier in the day	-10%
Decreasing load factor to 70%	-8%

Source: [21].

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[3] Environment, safety, security.

[4] Capacity, cost effectiveness, efficiency, predictability, flexibility.

Analysing US flight data for 2007 between 309 airports to estimate passenger-centric delay metrics showed [22] that the average trip delay for passengers over all flights was 24 minutes, whilst for passengers on flights delayed by at least fifteen minutes, the average delay was 56 minutes.

Flight-centric and passenger-centric metrics have also been examined [24] by comparing different rationing rules in a model US ground delay programme rationing rule simulator, exploring the trade-off between flight and passenger delay, and also between airline and passenger equity. (We shall return to these results later.)

Turning to more recent work, [25] presents a closed-form, aggregate model for estimating passenger trip reliability metrics from flight delay data from US system-wide simulations. Metrics were derived from the probabilities of delayed flights and network structure parameters. A particularly appealing finding was that the average trip delay of disrupted passengers varies as the square of the probability of a delayed flight and linearly with respect to rebooking delays.

An analytical queuing and network decomposition model – Approximate Network Delays (AND) – studied [26] delay propagation for a network comprising the 34 busiest airports in the US and 19 of the busiest airports in Europe. The model treats airports as a set of interconnected individual queuing systems. Due to its analytical queuing engine, it does not require multiple runs (as simulations do) to estimate its performance metrics and can evaluate the impacts of scenarios and policy alternatives.

Research in this area, employing complexity science methods, is rather uncommon (see [27] and [28] for reviews). Applying such techniques to the characterisation of actual European passenger trip itineraries, we previously investigated network topologies and vulnerabilities [27] and will refer to this work briefly, later.

Covering 305 US airports in 2010, an agent-based model reproduced [28] empirically observed delay propagation patterns. Estimated passenger and crew connectivities were identified as the most relevant factors driving delay propagation. The probability of such connections were modelled as proportional to flight connectivity levels at each airport. Investigating how congested airports form connected clusters, it was found that the same airports were not consistently part of such clusters, implicating daily scheduling differences in delay propagation patterns. It was noted that being in the same cluster was a measure of correlation but not necessarily a sign of a cause and effect relationship. Notably, only two major hubs, Newark and San Francisco, were present in the top ten for persistence in the largest congested clusters ([*ibid.*]; "Supplementary information").

This work was later developed in the European context [29] for characterising and forecasting delay propagation (preliminary results showing promising agreement with empirical flight performance data) and to study large-scale weather disruption on US delay propagation [30]. With regard to the latter, by computing the evolution of the largest congested clusters, empirical and modelled results agreed well when weather impacts and cancelled flights were considered as input variables. The continuing value in research of identifying delay-multiplier airports and the role that schedule buffer and turnaround times play in delay propagation is also taken up in [31]. Here, an analytical model is used to calculate propagated delay using US on-time performance data for first quarter of 2007. The optimal timing of buffers during the day and varying airline strategies, even within airlines across airports, regarding buffer application are discussed – see also [8] for a comprehensive US study in this field.

Almost no current models use explicit passenger data, although this is planned for the AND model (*ibid.*) and [29]. Also, actual passenger transfer numbers have been used in numerical simulations of a major US hub, where it was demonstrated [32] that each metric studied – terminal transit times of passengers, aircraft taxi times and gate conflict durations – outperformed observed values through the use of a balancing objective function. (The 'CASSIOPEIA' project in the SESAR Exploratory Research programme is also preparing publications focused on actual transfer passengers at a major European hub.)

B. Data availability

Much of the data employed in the US research outlined above may be sourced from the US Department of Transportation's Bureau of Transportation Statistics (BTS). Table III summarises three databases with particular relevance to passenger-based studies (e.g. estimating passenger itineraries and modelling delay propagation). These do not provide explicit passenger connections that are linked to flights, although the DB1B database provides a sample of passenger itineraries (see also [33]). These US databases are publicly available, with no comparable (free) sources available in Europe.

The two principal datasets used to build the flight-specific passenger itineraries for the POEM model were IATA's PaxIS passenger data and EUROCONTROL's PRISME traffic data. Extensive data cleaning of the source traffic data was required, especially with regard to unreliable taxi-out data and scheduled times, missing taxi-in data and aircraft characteristics (including registration sequencing) [34]. This model is outlined next.

TABLE III.   BUREAU OF TRANSPORTATION STATISTICS' KEY DATABASES

Database	Summary	Available
DB1B: Airline Origin and Destination Survey	10% sample of airline tickets from reporting airlines; includes origin, destination and other passenger itinerary details	Quarterly
T-100: The Air Carrier Statistics	Contains domestic and international airline market and segment data; includes carrier, origin, destination, aircraft type and load factor	Monthly
AOTP: Airline On-Time Performance Data	Scheduled & actual departure & arrival times reported by major US airlines with at least 1% of domestic scheduled pax revenues; includes origin, destination, flight number, cancelled and diverted flights	Monthly

IV. THE POEM MODEL

A. Model overview

POEM comprises a European network simulation model with explicit passenger itineraries and full delay cost estimations. A baseline traffic day in September 2010 was selected as a busy day in a busy month – without evidence of exceptional delays, strikes or adverse weather. The baseline model represents a normative day and the simulation results reflect schedule robustness (e.g. with respect to passenger reaccommodation). The busiest 199 European Civil Aviation Conference (ECAC) airports in 2010 are included, having identified [34] that these airports accounted for 97% of passengers and 93% of movements in that year. Routes between the main airports of the (2010) EU 27 states and airports outside the EU 27 were used as a proxy for determining the major flows between the ECAC area and the rest of the world. This process led to the selection of 50 non-ECAC airports for inclusion of their passenger data. The assignment of passengers to individual flights, with full itineraries and calibrated load factors, was a fundamental component of POEM. All the allocated connections were viable with respect to airline schedules and published minimum connecting times (MCTs). Dynamically, the full gate-to-gate model then explicitly manages passenger connectivities. There are approximately 30 000 flights in each day's traffic and around 2.5 million passengers distributed among 150 000 distinct passenger routings. Using a cloud-computing platform, each full day's simulation took approximately two minutes. As a stochastic model, statistically stable results were produced typically after ten runs (although the results presented are based on fifty runs). A model flow structure, overview of recursive cost optimisation and model calibration methods were presented in [35].

B. Model prioritisation scenarios and rules

Table IV summarises the prioritisation scenarios. For convenience, they are broadly classified according to the agency of the instigating stakeholder. For example, only airlines are currently likely to be able to estimate their own delay cost data in A_1 and A_2. Cost estimations are with respect to delay costs to the airline: these drive airline behaviour.

TABLE IV. PRIORITISATION SCENARIOS

Type, level	Designator	Summary description
No-scenario, 0	S_0	No-scenario baselines: reproducing historical operations
ANSP, 1	N_1	Prioritisation of inbound flights based on simple passenger numbers
ANSP, 2	N_2	Inbound flights arriving more than 15 minutes late prioritised based on number of onward flights delayed by inbound connecting passengers
AO, 1	A_1	Wait times and associated departure slots estimated on cost minimisation basis; longer wait times potentially forced during periods of heavy air traffic flow management (ATFM) delay
AO, 2	A_2	Departure times *and* arrival sequences based on delay costs – A_1 is implemented *and* flights are independently arrival-managed based on delay cost
Policy, 1	P_1	Passengers reaccommodated based on prioritisation by final arrival delay, instead of by ticket type; preserves interlining hierarchies
Policy, 2	P_2	As P_1, now also relaxing all interlining hierarchies

TABLE V. SUMMARY OF EXAMPLE RULES

Rule 13 takes account of inbound passenger arrival times, MCTs and prevalent ATFM conditions to determine how long a flight should wait for inbound connecting passengers. The baseline rules are driven by implicit cost considerations (passengers' onward haul and ticket types; percentage of expected passenger loading completed) in the context of ATFM slot availabilities. Under A_1 and A_2, explicit costs are traded in the wait rules (by passively running Rule 33). During heavier congestion, the flight either waits an extra hour, or departs. Under less heavy congestion, costs are calculated for increments of 15-minute waits, and the minimum cost alternative is adopted.

Rule 26 models arrival management based on airport capacities, applying spacing from the Initial Approach Fix. Under baseline conditions, this is operated on a first-come, first-served basis. Under N_1 and N_2, flights are prioritised based on minimising total passenger inbound delay and onward flight delays, respectively. Whilst inactive under A_1, under A_2 Rule 26 arrival-manages flights based on delay costs – independently with Rule 13.

Rule 33 governs realistic decision-making for missed passenger connections due to delays and cancellations. It incorporates dynamic passenger reaccommodation onto aircraft with free seats, using detailed fleet and load factor data, and integrates with the tail-tracked aircraft wait and turnaround (recovery) rules. This rule allows for the investigation of the policy-driven scenarios P_1 and P_2, relaxing current airline practice to explore potential future policy outcomes.

Costs considered are: passenger hard and soft costs to the airline, fuel, maintenance and crew costs [34]. The baseline scenario (S_0) rules reflect airline costs typically imposed by (the current) Regulation 261 and common practice regarding care and rebooking during disruption [*ibid*.]. Under the P_1 and P_2 scenarios, current constraints on airline practice are successively relaxed. These policy-driven scenarios are bolder than the current scope of European regulations.

Each simulated process is governed by one or more rules, with examples thereof above, and details in [34]. Two airline case studies, with on-site visits and multi-stakeholder workshops, focused on developing and testing specific aspects of these rules in an operational context. Further validation with stakeholders is anticipated in on-going development work.

V. MODEL RESULTS

A. Classical and new metric results

Fig. 2 presents the core results across various flight-centric and passenger-centric metrics, by the various scenarios. The values indicated[5] are scenario values minus the corresponding baseline (S_0) value. Flight prioritisation scenarios (N_1 and N_2) operating during arrival management based simply on the numbers either of inbound passengers or on those with connecting onward flights, were ineffective in improving performance. The policy-driven scenario (P_1) represents putative conditions not driven by current airline or ATM objectives but which may nevertheless benefit the passenger. This scenario, rebooking disrupted passengers at airports based on minimising delays at their final destination, produced very weak effects when current airline interlining hierarchies were preserved. When these restrictions were relaxed, under P_2, marked improvements in passenger arrival delay were observed, although at the expense[6] of an increase in total delay costs per flight, due to passenger rebooking costs.

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[5] Differences shown are statistically significant ($p < 0.05$; z-tests) and exceeded a minimum change threshold applied to avoid reporting artefactual results (typically set at approximately 2% of the baseline mean values; not applied to the ratio metrics).

[6] Trade-off results have also been observed in a US model [24]: compared to the traditional ration-by-schedule rule, rationing by aircraft size (three priority queues: 'heavy', 'large' and 'small' aircraft) was shown to decrease the total passenger delay by 10%, with a 0.4% increase in total flight delay. Rationing by passengers on-board decreased total passenger delay by 22%, with only a 1.1% increase in total flight delay.

Core metric	Units	N1 & N2	P1	P2	A1
		Inbound prioritisation based on simple pax numbers, or on onward flights delayed	Passenger reaccommodated based on delay at final destination …		Departures times based on cost minimisation (& consideration of ATFM delay)
			… preserving interlining hierarchies	… relaxing interlining hierarchies	
Flight departure delay	mins / flight		no significant changes in current flight-centric metrics: stresses need for passenger-centric metrics		
Flight arrival delay	mins / flight				
Departure delay of departure-delayed flights	mins / flight				
Arrival delay of arrival-delayed flights	mins / flight				
Pax departure delay	mins / pax	no significant changes under simple inbound scenarios driven by passenger numbers, or by numbers of delayed onward flights	revised passenger re-booking rules produce only weak improvements whilst current airline interlining rules are preserved, c.f. →	=	+0.4
Pax arrival delay	mins / pax			-0.4	-1.6
Departure delay of departure-delayed pax	mins / pax			=	=
Arrival delay of arrival-delayed pax	mins / pax			-2.2	-9.8
Passenger value of time	Euros / pax			-0.2	-0.7
Non-passenger costs	Euros / flight			=	=
Per-flight pax hard cost	Euros / flight			+26	-40
Per-flight pax soft cost	Euros / flight			=	=
Total flight cost	Euros / flight			+26	-39
Total flight cost per minute of departure delay	Euros / min			=	-7.8
Reactionary delay ratio	ratio			49%	51%

Figure 2.   Summary of core results.

The prioritisation process A_1, assigning departure times based on cost minimisation, markedly improved a number of passenger delay metrics and airline costs, the latter determined by reductions in passenger hard costs to the airline. One of the very few negative outcomes associated with A_1 was an increase of two percentage points in overall reactionary delay. (Actual reactionary delay in September 2010 averaged 46%, with the model S_0 value calibrated at 49%.) This was manifested through relatively few flights and was introduced purposefully by airlines through the cost model (i.e. waiting for late passengers) such that the overall cost to the airlines decreased.

A_1 also performed well when increased delay and simple cancellations were modelled; in contrast, A_2 was generally unsuccessful (results not shown; see [35]). For A_2, the addition of *independent*, cost-based arrival management apparently foiled the benefits of A_1 due to lack of coordination between departures and arrivals. This was also reflected in that A_2 caused increased dispersion of all core metrics and the highest reactionary delay ratio of 58%.

The ratio of arrival-delayed passenger over arrival-delayed flight minutes (both pertaining to delays of greater than 15 minutes) was 1.5 for the S_0, P_1 and P_2 simulations for the baseline traffic day and the high delay day, rising to 1.9 for S_0 on the high cancellation day. Notably, A_1 for the baseline traffic day resulted in a minimum value of this ratio of 1.3. These values compare well with the range 1.6 − 1.7 cited in Section III(A).

The importance of using passenger-centric metrics in fully assessing system performance is clearly made through the results shown in Fig. 2, since the changes were not expressed through any of the currently-used flight-centric metrics at the common thresholds set. Scenario A_1 appears to hold particular promise and will be studied in particular, along with the corresponding baseline (S_0) results, in the next sections.

B. Delay propagation and causality

(i) During the simulations, reactionary delays and their causes are determined retrospectively. If several passengers were connecting from different flights and all of them were late, we only considered the most restrictive connection (in actual minutes) as the reason for the reactionary delay being induced. In this sense, one flight can delay many others, but any given flight can only be delayed by one previous flight (the most restrictive one). This graph is thus a (propagation) tree.

Although large airports are associated with more reactionary and arrival delay, there is a considerable relative difference between these delay types at the smaller airports. For some of the forty smaller airports arrival delay was doubled (or even tripled) into reactionary delay. This is due to reduced delay recovery potential at such airports, for example through: flexible or expedited turnarounds; spare crew and aircraft resources (as yet not explicitly modelled in POEM); and, whether a given airport has sufficient connectivity and capacity to reaccommodate disrupted passengers. In practice, the business model of airlines operating at airports also influences these effects. Similar findings have been reported in some literature [36, 37].

Back-propagation (where an aircraft's outbound delay propagates back to an airport one or more times later in the day) was found to be an important characteristic of the persistence of delay propagation in the network. Paris Charles de Gaulle, Madrid Barajas, Frankfurt, London Heathrow, Zürich and Munich all demonstrated more than one hundred hours of back-propagated delay during the modelled (baseline) day. The prevalence of hub back-propagation has also been reported in the literature ([26], [37, 38]). Asymmetries of the general phenomenon have been reported in the US [39]. One minute of delay per flight in the three New York airports causes 0.07 minutes of delay per flight in the other (major) NAS airports; conversely, one such system minute generates 0.28 minutes of delay in New York.

(ii) After the simulations, delays were studied *a posteriori* using topological reconstructions of the flight and passenger networks (or 'layers'). Such networks were constructed for the S_0 and A_1 scenario simulations of the baseline traffic day, i.e. four reconstructions in total. For these networks, causality needed to be established in a different way. Classical statistical instruments such as correlation analysis are only able to assess the presence of some common (equivalent) dynamics between two or more systems. However, correlation does not imply causality. Granger causality [40], on the other hand, is held to be one of the few tests able to detect the presence of causal relationships between different time series. (See [35] for further details of how this methodology was applied.)

Comparing eigenvector centrality[7] rankings through Spearman rank correlation coefficients showed [34] that all four topological networks were remarkably different from each other $(r_s: 0.01 - 0.07)$. These rankings demonstrated that different airports have different roles with regard to the type of delay propagated (i.e. flight or passenger delay) and that these were further changed under A_1. Indeed, a trade-off was introduced under A_1: the propagation of delay was contained within smaller airport communities, but these communities were more susceptible to such propagation. The absence of major hubs in the top five ranking list was evident. We previously reported similar findings in a network vulnerability analysis [27] and such results resonated with the findings of [28], reported above. These findings were explored further using percolation theory.

C. Toplogical percolation analysis

Percolation is a theme that has been extensively studied in complex networks, e.g. in the initial work of [41] and subsequent research of [42, 43]. Given an initial network, a percolation study involves deleting links (or nodes) at random, and studying how its topological properties are modified as a function of the fraction of links removed. Universalities are typically found, as for instance with phase transitions and various other critical phenomena [44]. Such analyses have often been applied to transportation and communication networks, in which the percolation itself represents a series of random attacks (or random failures) on the infrastructure. It is thus of interest in understanding how much change the network is able to absorb, before significantly disrupting its functioning. In our analyses, the links represent the propagation of delay (they are not flights). Link deletion thus represents the removal of propagated delay between the corresponding pair of airports. (Node deletion, possible in other study contexts, is thus not sensible in this context, as it would imply the actual removal of airports.) As we disrupt the network in this way, we are interested in disrupting its structure as soon as possible, as this would indicate that small changes in the system could yield important benefits.

TABLE VI.   PERCOLATION METRICS

Metric	Mainly characterises	Definition
Maximum degree	Worst element of the system	Number of connections of the most connected node in the network
Size of the giant component	Size of the delay propagation core.	Number of nodes comprising the largest set of nodes (or subgraph) in which any two nodes are connected to each other by at least one path, and which are not connected to any other node of the original graph
Efficiency	Information flow (here, delay propagation)	Mean value of the inverse of the geodesic distance between all pairs of nodes, i.e. of the distance (length) of the shortest path connecting them; this represents the ease of information flow between pairs of nodes [45]
Normalised information content	Network organisation / structure	Assesses the presence of any mesoscale structure, by evaluating the information lost when pairs of nodes are iteratively merged together; this quantifies how random the network is [46]

Panel A: maximum degree (flights).   **Panel B**: giant component (flights).

Panel C: efficiency (flights).   **Panel D**: information content (flights).

Panel E: efficiency (pax).   **Panel F**: information content (pax).
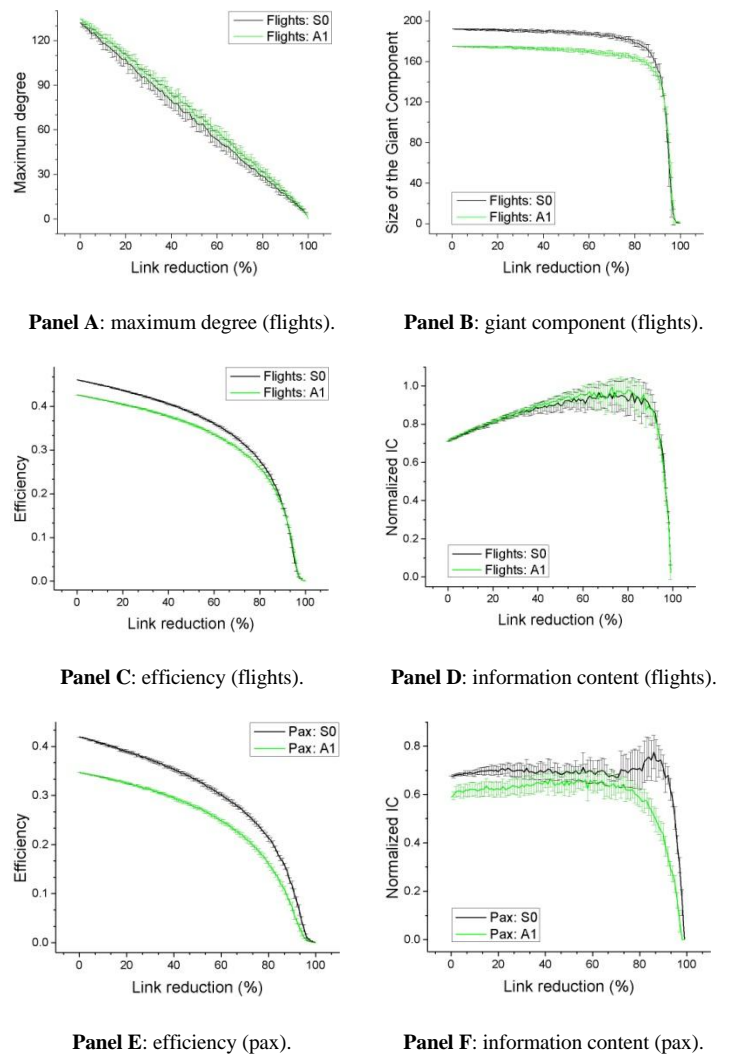
Figure 3.   Randomised network attacks.

We start with the (initial) causality link network and remove links at random. It is important to remind ourselves that this does not imply any change in the operation of the model. This topological analysis is an *a posteriori* process in which delays between two given airports are 'decoupled'. This may be considered *de facto* as generically providing more resources across the link (between the airports), such as might be effected through more aircraft or larger aircraft, thus better managing reactionary delays. Our main concern for now is the topological properties, rather than the mechanics of these processes. In each graph, we simulate a different strategy for allocating such improved resources: we variously try to mitigate those delay propagation links that we think are worse for the system as a whole. Fig. 3 depicts the evolution of four topological metrics (as described in Table VI), showing how the network evolves during this percolation process[8].

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[7] Eigenvector centrality is a metric defined such that this centrality of a node is proportional to the centralities of those to which it is connected.

[8] The passenger analogues of panels A and B are not shown, as they are similar to the flight plots. The error bars reflect the repetition of the randomised attacks over 1 000 runs.

As the number of links deleted increases, the maximum degree decreases (as would be expected; Fig. 3, panel A) whereas the size of the giant component (panel B) is almost constant until a transition point is reached – the so-called percolation threshold. Airports in the giant component (the largest set of airports through which propagation is possible) are thus strongly connected. It is necessary to delete approximately 80% of the causality links to really 'disrupt' the network (and prevent the propagation of delay).

This is similarly reflected through the very slow falls in efficiency until the giant component is compromised. A_1 increases the efficiency reduction for the passenger network (Fig. 3, panel E): it is approximately 0.07 units below S_0 at 80% link deletion (a reduction of some 30%), whereas for the flight network (panel C) the two curves almost coincide by 80%. For the passenger network, the information content is lower under A_1 (panel F), indicating that some mesoscale structure is present (e.g. some modularity, or the presence of clusters of highly connected nodes). This somewhat more modular structure under A_1 is better for the network, in that the propagation of delay is thereby reduced. We may broadly conclude as follows. The S_0 and A_1 networks are fundamentally similar in structure. The modest topological differences observed, however, are greater for the passenger networks, reflecting the quantitative cost savings under A_1, as was shown in Fig. 2.

D. Targeted attack

The preceding analyses may be interpreted as uncoordinated attempts to reduce delay propagation, e.g. through unilateral airline action. Let us now consider, in contrast, the potential for coordinated, centralised action through the network manager, e.g. enabled through both new regulatory measures and new analytical tools to require certain stakeholders to take amelioratory action. This has been extensively studied in complex networks, for example when a communication network is subject to 'targeted' attack by an informed attacker. A large body of theoretical results is thus available, indicating that certain network structures are most vulnerable to specific strategies [47, 48]. (Such an approach has also been successfully applied in other scientific fields, such as the evaluation of the robustness of the brain to different lesions [49].)

Here we report the results of disrupting the causality networks using different types of attack. First, we suppose that (generic) resources are fully allocated to the most connected airport, i.e. the airport with the highest degree, such that all the causal connections of that airport with other nodes are severed (see Fig. 4, panel A, for the passenger network; similar flight network plot not shown). Second, a greedy algorithm [50] is applied to airports: all airports, one at a time, are disconnected from the network, in order to establish the one whose 'removal' yields the largest propagation improvement for the whole network (see Fig. 4, panel B, for the passenger network; similar flight network plot not shown). Finally, a third attack involves applying a greedy algorithm to single links/connections (Fig. 4, panels C and D).

Panel A: Node degree-based (pax).   **Panel B**: Greedy algorithm (pax).

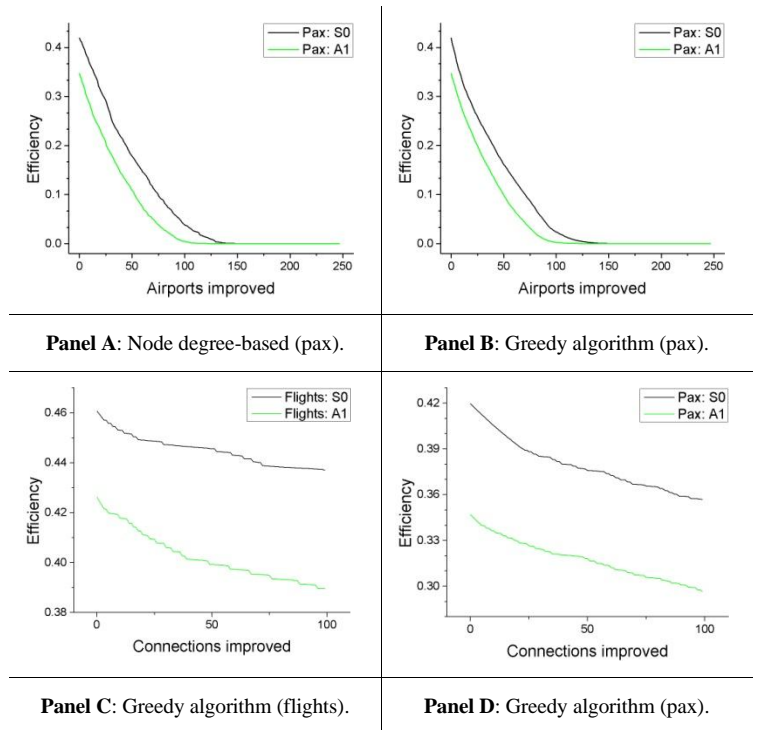**Panel C**: Greedy algorithm (flights).   **Panel D**: Greedy algorithm (pax).

Figure 4.   Targeted network attacks.

The reductions in capacity for propagating delays are shown as a function of the number of nodes and links (airports and connections) improved.

Some general conclusions can be drawn. The efficiency drop is always (at least somewhat) higher in the passenger networks when the A_1 prioritisation scenario is applied. Furthermore, such a difference is especially notable when a link-based attack is performed: note also that the gradient of A_1 at lower link deletions is greater than for S_0 (for both networks).

This thus suggests that targeting certain specific links, i.e. assigning more resources to those flights that mitigate delay propagation, may yield important improvements in system performance.

Table VII compares the reduction of the giant component size as a function of A_1 operating alone (first data column) and for the link disruptions described above combined with A_1, or purely on S_0 (values shown as positive, rounded percentages, relative to S_0 without disruption). A_1 is thus hardly improved by a 20% random attack, whereas a 20% targeted link attack in coordination with A_1 has a pronounced effect.

TABLE VII.   GIANT COMPONENT REDUCTIONS BY MODELLED CONDITIONS

Network	No disruption (A_1 only)	20% disruption of …		
		… random links, A_1	… targeted links, S_0	… targeted links, A_1
Flights	9%	9%	13%	22%
Pax	17%	18%	36%	57%

VI. CONCLUSIONS AND FUTURE RESEARCH

Building the first explicit passenger connectivity simulation of the European air transport network, we have shown that passenger-centric metrics, including appropriate network and cost considerations, are necessary complements to existing flight-centric metrics in order to fully evaluate system performance. Applying complexity science techniques, with appropriate corresponding metrics, has afforded additional insights into the propagation of delay through the ATM network. The socio-political, regulatory and technical contexts of European ATM, and of the state of the art regarding current modelling, suggests that there is a role for the continued development of tools to explore the impacts of flight and passenger prioritisation strategies. Building on the POEM model's flexibility, we plan to implement higher fidelity en-route behaviour and ATFM modelling functionalities, and to use the tool to explore: future market trends (such as traffic levels, aircraft size, load factors, service frequencies and hub wave structures); robustness under disruption (including integration with Airport Collaborative Decision Making, A-CDM); and, the trade-offs between various prioritisation and (policy) strategies. The model may be further used by policymakers to better assess the full impacts of future policies (for example changes to Regulation 261 in Europe). It could also be readily adapted to include impacts on emissions. These factors may be examined not only at the network level, but also for airline route clusters and airports.

These types of analyses may help to justify the principle, and support the practice, of the future development of passenger-centric metrics. A number of examples have been demonstrated above. The development of such metrics may be considered in the context of other proposals and investigations. A new consumer protection metric, expected value of passenger trip delay, has been proposed [51] to account for: (i) passenger delays caused by delayed/cancelled flights; and (ii) both the probability of passenger trip delay and the magnitude of the delay. A passenger trip (gate arrival) delay metric is discussed in [20] and [52]. This captures passenger delays due to delayed flights, plus reaccommodation delays due to cancellations and missed connections. Three primary metrics are proposed in [33] to capture passenger trip reliability: annual total passenger trip delay, percentage of passengers disrupted (due to delayed/cancelled/diverted flights or missed connections) and average trip delay for disrupted passengers (expected trip delay experienced by randomly sampled passengers). The timing is opportune to further evaluate such needs in the context of on-going regulatory reform in Europe and of the SES Performance Scheme.

European flight and passenger prioritisation scenarios also need to be considered in the context of the SESAR Concept of Operations. Key components thereof are Demand and Capacity Balancing (DCB) and the User Driven Prioritisation Process (UDPP). UDPP is a CDM-based process carried out for DCB purposes, which allows airlines to request a priority order for flights affected by capacity restrictions. The desired priority order is that which "best respects the business interests" [53] of the airspace users. Already aligned with A-CDM implementation plans, UDPP is thus a perfect vehicle for the inclusion of cost- (and passenger-) focused prioritisation mechanisms, e.g. through implicit airline cost functions.

It is our contention that there are strong synergies to be exploited through the examination of ATM system performance through a complementary application of both classical and complexity science techniques. Established methods in other fields, such as percolation theory and network vulnerability, are starting to afford valuable new insights into the dynamics of ATM performance in general and delay propagation in particular. Combined, these techniques may open new avenues of development towards better disruption management strategies and improved policies.

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