New perspectives for air transport performance

Cook, A.J., Tanner, G., Cristobal, S. and Zanin, M.

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A. Cook and G. Tanner
Department of Planning and Transport
University of Westminster
London, United Kingdom

S. Cristóbal and M. Zanin
The Innaxis Foundation & Research Institute
Madrid, Spain

***Abstract*— The average delays of flights and passengers are not the same. The air transport industry is lacking passenger-centric metrics; its reporting is flight-centric. We report on the first European network simulation model with explicit passenger itineraries and full delay cost estimations. Trade-offs in performance are assessed using passenger-centric and flight-centric metrics, under a range of novel flight and passenger prioritisation scenarios. The need for passenger-centric metrics is established. Delay propagation is characterised under the scenarios using, *inter alia*, Granger causality techniques.**

Keywords–delay propagation; passenger-centric; metric; flight prioritisation; Granger causality

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I. INTRODUCTION

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 in Europe 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 and understand the associated trade-offs in the context of delay propagation?

In the 'POEM' (Passenger-Oriented Enhanced Metrics) SESAR Workpackage E project, we have built 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. We compare the effects of novel flight and passenger prioritisation scenarios on new passenger-centric and flight-centric metrics, which assess not only delay but also a range of costs associated with delay. The propagation of delay through the network is also investigated, using complexity science techniques to complement classical metrics.

TABLE I. PRIORITISATION SCENARIOS

Type, level	*Designator*	*Summary description*
No-scenario, 0	S_0	No-scenario baselines (reproduce historical operations for baseline traffic day)
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 are prioritised based on the number of onward flights delayed by inbound connecting passengers
AO, 1	A_1	Wait times and associated departure slots are estimated on a cost minimisation basis, with longer wait times potentially forced during periods of heavy 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 are reaccommodated based on prioritisation by final arrival delay, instead of by ticket type, but preserving interlining hierarchies
Policy, 2	P_2	Passengers are reaccommodated based on prioritisation by final arrival delay, regardless of ticket type, and also relaxing all interlining hierarchies

Table I summarises the prioritisation scenarios investigated. They were designed in parallel with the new metrics. 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. The policy-driven scenarios P_1 and P_2 are bolder than the current scope of European regulations. It is essential to explore the context of the model and the metrics in terms of future developments such as Airport Collaborative Decision Making (A-CDM) and, regarding flight prioritisation, the User Driven Prioritisation Process (UDPP). These technical contexts, in addition to the evolving socio-political landscape, are discussed in Section III. This includes a review of the European Union's underpinning regulatory instrument for air passenger compensation and assistance (Regulation 261, [1]), of high-level political objectives, of the Single European Sky performance scheme, and of recent ATM delay performance. A full discussion of the design of our metrics has recently been published [2], whereby a complementary approach is proposed to the understanding of network performance. This is reflected in the cross-section of results presented in Section IV. We turn first to a review of the start of the art.

II. OVERVIEW OF POEM MODEL AND EXISTING MODELS

A. Existing modelling – the state of the art

Using large data sets for passenger bookings and flight operations from a major US airline, it has been shown [3] 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.

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: [5].

Based on a model using 2005 US data for flights between the 35 busiest airports, [4] 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 ([5], [6]).

Using US historical flight segment data from 2000 to 2006 to build a passenger flow simulation model to predict passenger trip times, [5] 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 [7], 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 [7].

Analysing US flight data for 2007 between 309 airports to estimate passenger-centric delay metrics showed [6] 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 [8] 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, [9] 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.

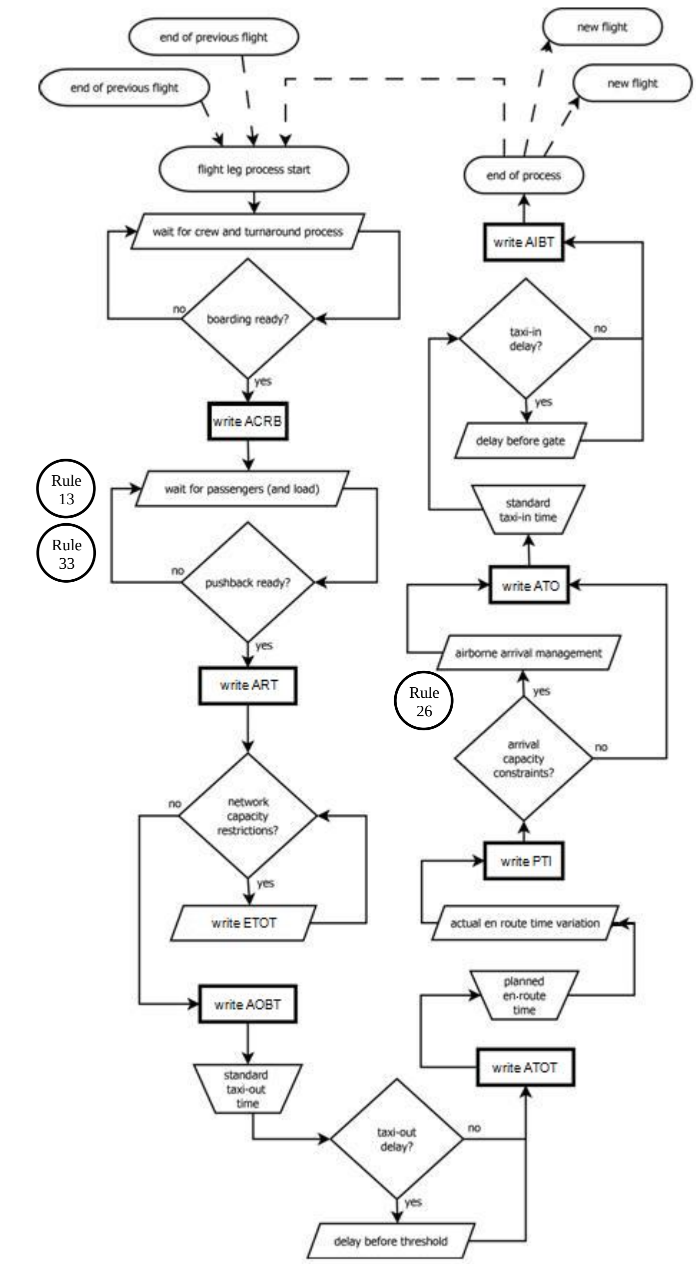
An analytical queuing and network decomposition model – Approximate Network Delays (AND) – studied [10] delay propagation for a network comprising the 34 busiest airports in the US and 19 of the busiest airports in Europe. The model treats airports as a set of interconnected individual queuing systems. 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.

Covering 305 US airports in 2010, an agent-based model reproduced [11] 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.

Almost no current models use explicit passenger data, although this is planned for the AND model (*ibid*.). Also, actual passenger transfer numbers have been used in numerical simulations of a major US hub, where it was demonstrated [12] 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. (As part of our work in SESAR Workpackage E, we are also preparing publications focused on actual transfer passengers at a major European hub.)

B. The POEM model – an overview

POEM models the busiest 199 European Civil Aviation Conference (ECAC) airports in 2010, having identified [13] 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. The core flow structure is shown in Fig. 1. Each simulated process is governed by one or more rules (as detailed extensively in [13]). Two airline case studies, including on-site visits and workshops, focused on developing and testing specific aspects of the model rules in an operational context.



Key: ACRB: aircraft ready for boarding; ART: actual ready time; ETOT: estimated take-off time; AOBT: actual off-block time; ATOT: actual take-off time; PTI: passing time over Initial Approach Fix (IAF); ATO: actual time on; AIBT: actual in-block time.

Figure 1. Model core flow structure and selected rules.

Designator	Rule 13 Wait for boarding	Rule 26 Airborne arrival management	Rule 33 Passenger reaccommodation
N_1		•	
N_2		•	
A_1	•		
A_2	= A_1	•	
P_1			•
P_2			•

Figure 2. Selected rules by scenarios.

Fig.2 shows the key rules that are modified from their baseline behaviour under the various scenarios introduced in Table I. 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 – see below). 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 IAF. 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 (see Fig. 2), 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.

Cost estimations are with respect to delay costs to the airline, since it is these that drive airline behaviour. Costs considered are: passenger hard and soft costs to the airline, fuel, maintenance and crew costs [13]. In order to improve the cost optimisation for the airlines, without running the entire model to estimate the implication of each decision, pre-computed cost functions were developed. These were implemented as complementary procedures to the dynamic cost functions in the scenario modules by calculating delay propagation costs based on scheduled times, i.e. without dynamic data or stochastic assessment. These functions work recursively (i.e. backwards from the end of the simulation day) using entire propagation cost trees based on discrete delay values (0, 5, 10, 15 … minutes of delay, up to 6 hours).

The two principal datasets used to prepare the input data for the model were IATA's PaxIS passenger itineraries 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). 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).

III. SOCIO-POLITICAL AND TECHNICAL CONTEXTS

A. *Socio-political context – the passenger imperative*

SESAR's 'Performance Target' [14] refers frequently to the concept of society and the passenger. The 'societal outcome' cluster of KPAs[1], 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[2] is also specifically acknowledged as impacting passengers.

Social and political priorities in Europe are now shifting in further favour of the passenger, as evidenced by high-level position documents such as 'Flightpath 2050' [15] and the European Commission's 2011 White Paper ('Roadmap to a Single European Transport Area', [16]).

However, it has been accepted that there are currently several problems with regard to the implementation and scope of Regulation 261. A roadmap for the revision of the Regulation was published in late 2011 [17]. After various consultations, a memo was released in 2013 [18] detailing key proposed changes, which could become law by 2015, subject to approval by member states. In summary, the key 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, and to extend such rights to compensation for long delays (including arrival delay) caused by any reason; (iv) introduce new obligations (currently none exist) regarding information on delayed or cancelled flights; and, (v) better define 'extraordinary circumstances' that exempt carriers from paying passenger compensation (although proposed changes to the compensation rights will make these more complex, allowing the carriers more time to avoid cancelling flights, for example).

The baseline scenario (S_0) rules of the POEM model reflect airline costs typically imposed by Regulation 261 and common practice regarding care and rebooking during disruption [13]. Under the P_1 and P_2 scenarios, current constraints on airline practice are successively relaxed and the impacts are examined, as presented in Section IV.

B. *ATM delay performance and model alignment*

Table III compares key statistics for 2010 (the year from which the POEM model's baseline day was taken) and 2012 (the latest year for which such statistics were available at the time of press). It is to be noted that the traffic and passenger numbers are similar. Passenger numbers depend on coverage: whereas data from Eurostat [21] describe a small fall between these periods, EUROCONTROL [20] reports an increase.

TABLE III. KEY PERFORMANCE STATISTICS FOR 2010 AND 2102

Metric	*2010*	*2012*
IFR flights (million)	9.5	9.6
Total pax (million, EU 27)	777	734
Average dep. delay (mins)	14.8	9.5
Arrival delays > 15 mins	24.2%	16.7%
Reactionary delays	46.7%	45.5%

Sources: [19], [20], [21].

Whilst 2010 suffered from 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* [19]. Nevertheless, punctuality in 2010 was at its worst since 2001, even with traffic below 2007 levels after modest growth on the previous year [19]. The average departure delay values include all flights, with delays counted from the first minute and early departures counted as zero delay. The percentage of arrival delays greater than 15 minutes in 2012 reached an all-time low of 16.7% – the changes in punctuality were largely driven by improvements in en-route ATFM delays [20].

The average departure delay for September 2010, the month from which POEM's baseline was selected, was 13.9 minutes, and the average arrival delay was 13.6 minutes. As we have detailed more fully [13], the model was calibrated partly using these values, with S_0 (baseline) averages of 13.8 and 13.5 minutes, respectively. With similar passenger and traffic volumes already across the two years, the model could also be recalibrated, if required, to reflect the better delay performance of 2012 (or, indeed, for future traffic scenarios).

Fig. 3 shows the sensitivity of the network to primary delay. In 2010, the ratio was approximately 0.9. On average, every minute of primary delay thus resulted in approximately 0.9 minutes of reactionary delay. After peaking in 2010, the ratio improved in 2011 and 2012. Reactionary delay in September 2010 averaged 46%, with the POEM model S_0 value calibrated at 49%.

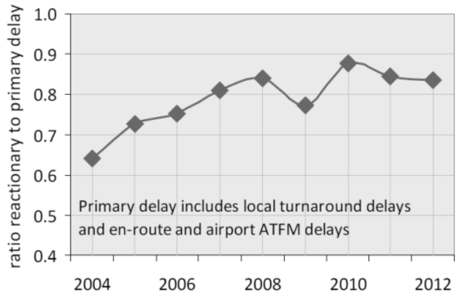


Figure 3. Reactionary delay trend to 2012.
Source: adapted from [20].

A key advance made possible through the POEM model is the detailed analysis of the effects of the various scenarios on reactionary delays and the associated trade-offs with other

[1] Environment, safety, security.

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

metrics, as will be illustrated in Section IV. The persistence of reactionary delays illustrated through Fig. 3 underlines the continuing importance of research into these effects.

C. *The SES performance scheme and model flexibility*

TABLE IV. SES PERFORMANCE SCHEME REFERENCE PERIODS

Reference period	*Applicable years*
RP1	2012 - 2014
RP2	2015 - 2019
RP3	2020 - 2024

EUROCONTROL is designated the Performance Review Body (PRB) of the Single European Sky (SES). The performance scheme is managed by the PRB and is a central element of the SES initiative. It is defined across various reference periods (RPs), as shown in Table IV. Performance targets are set at various levels before each period and are legally binding for EU member states.

Several en-route RP1 targets have been set [22] at the European level. For capacity, average ATFM en-route delay per flight has a binding EU-wide target of 0.5 minutes by 2014. Encouraging intermediate reporting has been published for performance in 2012 [23]. RP2 sets out to extend the performance scheme to cover the full gate-to-gate scope, with target setting for four of the International Civil Aviation Organization's eleven KPAs: capacity, environment, cost efficiency and safety [24]. The PRB has recently published [25] its proposed EU-wide targets for RP2. For capacity, this is an average of 0.5 minutes of ATFM en-route delay per flight for 2015-2019. According to PRB analysis (*ibid*.), this target corresponds to more than 98% of flights not being constrained by ATC. (Not a focus of our research to date, the POEM model does not yet have sufficient fidelity for assessing en-route ATFM delays *per se*, although this module is a target for future refinement.)

Setting challenging targets for 2020, SESAR's Performance Target [14] significantly refines (see Table V) the fifteen minute historical threshold for defining arrival and departure delay in Europe and the US. Whilst the SES performance scheme focuses on improving air navigation service (ANS) provision, and hence uses ATFM delay in its capacity KPAs, the SESAR targets are broader in scope.

TABLE V. SESAR PERFORMANCE OBJECTIVES AND TARGETS

SESAR metric	*Target for 2020*
departure punctuality	≥ 98% of flights departing as planned ±3 mins other 2%: average delay ≤ 10 mins
arrival punctuality	> 95% of flights arrival delay ≤ 3 mins other 5%: average delay < 10 mins
reactionary delay	50% reduction by 2020, *cf.* 2010
cancellations	50% reduction by 2020, *cf.* 2010
variation in block-to-block times	block-to-block σ < 1.5% of route mean[a]

a. For repeatedly flown routes using aircraft with comparable performance.

Airline punctuality is a poor metric for assessing ANS performance *per se*, since such punctuality is driven to a considerable extent by airline scheduling decisions. Such punctuality metrics remain pertinent in terms of service delivery to the passenger, however, and it is clear that a complementary set of metrics is needed by the industry. Whilst evidence [6] suggests that delays of less than 15 minutes are less important in terms of passenger connectivities, increasing pressures on utilisation and lower connecting times add to the importance of more exacting targets.

For the POEM model results, we focus in Section IV on the trade-offs between flight-centric and passenger-centric metrics, including costs, reporting on the corresponding reactionary delay effects at the disaggregate level, in addition to the impact on the high-level target of Table V. With RP2 now matured, incorporation of passenger-centric metrics into the SES performance scheme would need to be considered for RP3.

In 2014, traffic is expected to increase by 2.8%, finally reaching the 2008 pre-economic crisis levels again by 2016 [20]. Future traffic samples could also be used as inputs into the POEM model, which would be interesting to stress-test the scenarios. (Explicit passenger assignments would have to rebuilt using the dedicated algorithms.) It would be feasible, and instructive, to observe the impacts on modelled performance compared with some of the SES / SESAR targets.

D. *Flight prioritisation and SESAR ConOps*

At the core of the POEM model simulations are the flight and passenger prioritisation scenarios. These need to be considered in the context of the SESAR Concept of Operations (henceforth 'ConOps'). Is there a future role for such mechanisms? If so, over what timescale and at what level of prominence? The SESAR ConOps is mapped into three steps – Step 1: time-based; Step 2: trajectory-based; and, Step 3: performance-based. Key components of these steps are UDPP and Demand and Capacity Balancing (DCB). UDPP is a CDM-based process carried out for DCB purposes, which allows airlines to request a priority order for flights affected by restrictions arising from unexpected capacity reductions. The desired priority order is that which "best respects the business interests" [27] of the airspace users.

Indeed, ConOps Step 1 extends [26] the previous scope of UDPP. Previously, the emphasis of UDPP was on implementation after DCB had failed to reach an acceptable solution. Its current scope, however, embraces strategic, pre-tactical and tactical phases and will be available in any 'normal' situation, although with a particular applicability during capacity constraints with an early focus, once the design has sufficiently matured, on the pre-departure phase (but ultimately including en-route and arrival phases). The Step 1 deployment phase is from 2014 to 2025. Furthermore, in the second edition of the ATM Master Plan [28], the prominence of UDPP in the implementation of Step 3 is also apparent: ""Performance-based Operations" is realised through the achievement of SWIM and collaboratively planned network operations with User Driven Prioritisation Processes (UDPP)."

Clearly, there is a well-defined place for flight prioritisation strategies within the SESAR ConOps. Already aligned with A-CDM implementation plans, UDPP is a perfect vehicle for the inclusion of cost- and passenger-focused prioritisation mechanisms. In the next section, we demonstrate how the impacts of the POEM (flight) prioritisation scenarios are reflected through appropriate metrics and analytical tools.

IV. KEY RESULTS FROM THE POEM MODEL

A. *New metric results*

Fig. 4 presents the core results across various flight-centric and passenger-centric metrics, by the various scenarios. The values indicated[3] 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 of an increase in total delay costs per flight, due to passenger rebooking costs. (Trade-off results have also been observed in a US model [8]: 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.)

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. 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.

Under A_2 (results not shown) the addition of independent, cost-based arrival management (see Table I) apparently foiled the benefits of A_1 due to lack of coordination between departures and arrivals. This was also reflected through the finding that A_2 caused increased dispersion (standard deviations) of all the core metrics, and produced the highest reactionary delay ratio of 58%.

[3] 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).

Core metric	Units	N_1 & N_2: Inbound prioritisation based on simple pax numbers, or on onward flights delayed	P_1: Passenger reaccommodated based on delay at final destination … … preserving interlining hierarchies	P_2: … relaxing interlining hierarchies	A_1: Departures times based on cost minimisation (& consideration of ATFM delay)
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 4. Summary of core results.

Comparably, it has been shown [29] using US data, that arrival queuing delay at certain airports is associated with a net reduction of delay in the network as a whole, whilst queuing at others is associated with a net increase. Non-linear relationships were demonstrated. Arrival queuing may thus have a delay multiplier effect in the network.

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 II.

The importance of using passenger-centric metrics in fully assessing system performance is clearly made through the results shown in Fig. 4, 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*

Reactionary delays and their causes are determined *a posteriori*. 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.

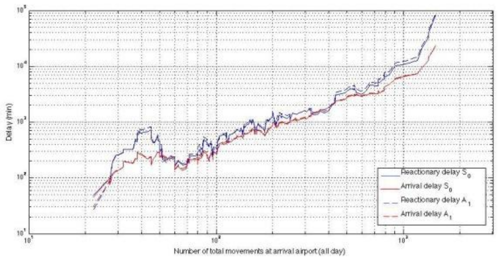


Figure 5. Arrival and reactionary delay, by airport size.

Fig. 5 shows total (daily) reactionary and arrival delay as a function of airport movements. 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 ([30], [31]). Better integration of passenger disruption recovery into A-CDM practice is an important area for future research.

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 ([10], [31], [32]).

C. Granger causality directed network analysis

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, on the other hand, is held to be one of the only tests able to detect the presence of causal relationships between different time series. It is an extremely powerful tool for assessing information exchange between different elements of a system, and understanding whether the dynamics of one of them is led by the other(s). It was originally developed by Nobel Prize winner Clive Granger [33] and although it was applied largely in the field of economics [34] it has received a lot of attention in the analysis of biomedical data ([35]-[37]).

A network reconstruction was computed for the flight and passenger layers for the S_0 and A_1 scenario simulations of the baseline traffic day, i.e. four reconstructions in total (the two baseline networks are shown in figures 6 and 7). The colour of each node represents its eigenvector centrality, from green (low centrality) to red (most central nodes). The size represents the out-degree, i.e. the number of airports that a given airport Granger 'forces' in terms of delay. The 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.

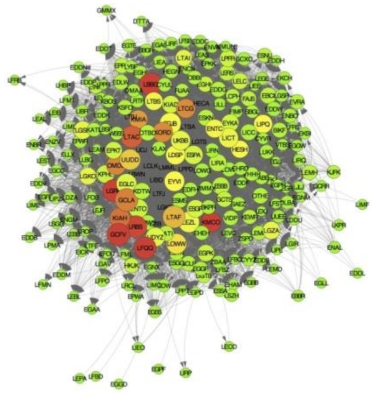


Figure 6. Flight delay causality network for S_0 simulation.

Comparing eigenvector centrality rankings through Spearman rank correlation coefficients showed [13] that all four network layers 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 lists for in-degree, out-degree and eigenvector centralities was evident. Indeed, the largest airports present in these rankings were Athens, Barcelona and Istanbul Atatürk. We previously reported similar findings in a network vulnerability analysis [2].

Investigating how congested airports form connected clusters in the US 2010 network, it was found [11] 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 ([11]; "Supplementary information").

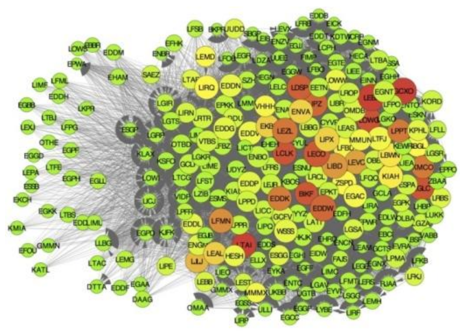


Figure 7. Passenger delay causality network for S_0 simulation.

D. Robustness under disruption

The POEM model represents a normative day and the simulation results thus reflect schedule robustness (e.g. with respect to passenger reaccommodation). Exploring the robustness of our prioritisation rules under disruption, two disrupted days were derived from the baseline traffic. This allowed like-for-like comparisons between the disrupted days and the baseline day. One disrupted day imposed 1 extra minute on the average departure delay (making a new average of 14.9 minutes across all flights). The other disrupted day imposed just under 1% of additional cancellations on morning operations. Comparing the model outputs for the disrupted days showed them to be well modelled in that changes to the core metrics were as expected and reflected operational experience (e.g. with regard to relatively low impacts on flight punctuality metrics during periods of higher cancellations). Compared with the baseline day, the prioritisation rules performed similarly under disruption, demonstrating a degree of robustness in terms of their efficacy under perturbation [13].

V. Future Research

An examination of 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. The results we have presented, building the first explicit passenger connectivity simulation of the European air transport network, show 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. These furnish insights into such performance, in addition to oversight. 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 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). It could also be readily adapted to include impacts on emissions. These factors may be examined not only at the network level, for example in the context of SES (RP3) and SESAR high-level targets, but also for airline route clusters and airports.

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