Data-driven modelling of the Tree of Reactionary Delays

The way primary delay disruptions are handled determines the extension and pattern of the knock-on effect

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***Abstract*— In spite of the relevance of Reactionary delays for air traffic performance, the research effort to understand the origin and handle this kind of delays is in practice limited. While being critically important due to its contribution to the total cost of delay, it is the primary cause which must be identified if effective action is to be taken. The SESAR WP-E project TREE (data-driven modeling of network-wide extension of the tree of reactionary delays in ECAC area) aims at characterizing and forecasting the propagation of reactionary delays through European Network taking into account the influence of the aircraft, crew and passenger links. Thus, the project proposes the use of innovative modelling techniques to explore new solutions that are not currently addressed by previous works.**

Reactionary Delays; Complexity Science; Diruption Management; Network Performance;

I. Introduction

According to CODA Digest 2011 and 2012, reactionary or propagated delays are one of the largest delays causes in Europe. Among all the causes, Airlines related are the ones with highest contribution to the total delay. Due to the complexity of the recording of precise origins of reactionary delays, Airlines find collecting all the primary delays as effective way to monitor operational performance.

In case of unexpected events in the form of disruptions, airlines disruption management processes involve making decisions during operations to minimize additional operating costs while getting back on schedule as quickly as possible. Measures such as flight cancelations, flight holds, aircraft swaps, crew rotation and passenger re-accommodation are used as part of the disruption management process. Because the airline system operates as a closely interconnected network, it is subject to propagated effects, this means, a disruption in one airport can quickly propagate to multiple other parts of the air transport network.

TREE proposes the use of a model to understand the European Air Transport System response to airlines disruption management strategies linked to delays propagation and to assess strategies to handle these disturbances. The delays are characterized by aircraft links, crew links and passenger connections. Each branch of the delay-tree monitors the global metric of reactionary delay due to a particular type of flight link.

Additional measures can provide local values for each branch or even airline specific values: which percentage of the delay of airline ‘A’ suffered at the end of the day has been due to reactionary delays type ’crew-link’. Which type of links could provoke more delays? Moreover, capturing the reactionary impact per airline allows monitoring if airline-driven criteria give emergence to negative effects that come back to the same airline.

This paper presents the work that is being performed in the frame of SESAR WP-E TREE project which, based on promising results obtained in previous research works carried out by the project team members for both USA and European networks, brings up the study of delays propagation linked to local strategies applied by the airlines for disruption management.

II. Literature Survey On Delays Propagation

The focus of this literature survey are works studying delay propagation patterns in air transport networks as well as the influence of different factors on these patterns. There are two main lines of study of delay propagation in air transport: mathematical static studies and modelling and simulation attempts to reproduce flight operations. For both lines, most literature is focused on USA data and network, even if the investigation is undertaking by European organizations and researchers. On one hand, several studies analyzed static data to find cause-effect relations between air transport schedules and the reactionary delays distributions in the network. A prolific field of study is the algorithmic optimization of airline schedules with the general objective of having better delay propagation pattern. In [1] a model was developed for producing robust crew schedules with the objectives of minimizing the crew cost and maximizing the number of move-up crews, i.e. the crews that can potentially be swapped in operations. An algorithmic approach was also used in [2], [3] and [4] for airline scheduling, focusing respectively on maintenance routing constraints, redistribution of existing slack in the planning process and multi-objective optimization. All these theoretical studies showed promising results in reducing propagated delays and improving the robustness of the network. Propagation trees [5] [6] are another tool useful tracking for individual flight delays propagation through the network and studying the impact of airline schedules on delay propagation. While pioneering study [6] pointed out to the early reduction of primary delays as a key to control delay propagation [5]deepened in the tree analysis to conclude that even with root delays of up to 180 minutes, nearly 40% of the flights have no propagating effect. The work identified as the key “buffers” limiting the propagation of delays: crews going off-duty, crews and aircraft remaining together (preventing one delay from causing two subsequent downstream delays), and periods of decreased activity in the network. Extensive data mining provided valuable results in [7] and [8]. The thesis by Jetzki [7] was one of the few attempts to analyze European airline planning and traffic data in search of delay propagation patterns. Results showed that over the observed four seasons, on average 50% of delays in low-cost operations are reactionary delays. Hub-and-spoke operators have the lowest ratio as reactionary delays account for nearly 40% of all delays, and point-to-point operations lie in between with around 45% of reactionary delay. Data mining was performed in [8] as a previous step to develop a model that reproduces delay propagation in the USA airport network. There have been several attempts to model delay spreading. The inherent complexity of the mechanisms that produce delay propagation motivate that different modelling techniques were proposed. A representative line of research focused on simulating the air traffic system as a network of queues [9][9]. Using as metric the propagated delay profile per flight and hop at each airport, the proposed model was used to estimate slack and flight time allowance needed to compensate for the root delays at airports and en-route. The stochastic nature of the air transport network performance is taken into account in [10] to develop a strategic departure delay prediction model for a single airport. Departure delays are split in three components: seasonal trend, daily propagation pattern and random residuals, addressing in this way the uncertainty in flight's departure time. The linkage between flights is an essential feature of the networked structure of the air traffic system, and therefore the propagation dynamics cannot be understood without referring to the underlying complex structure. The use of network theory to characterize air transportation describes the system as a graph formed with vertices representing commercial airports and edges direct flights between them. NeCo 2030 project [11] proposed a high level assessment of the behavior and stability of the highly congested European 2030 air transport network. The tool used was a macroscopic model conceived to capture the emergence of network properties such as performance degradation, behavior predictability, amplified impact of external events and geographical stability. The ability of the model to measure reactionary delays and their propagation was also explored. The model was later on evolved and customized to analyze the impact in terms of network-wide performance and delay propagation of local departure prioritization strategies [12], [13]. In this very recent work, it was observed how First Come First Served provides better performance picture at global level than any of the studied departure prioritization criteria, whereas in few cases slight improvements were detected at airport level in specific timeframes. As general conclusion, it was proved the suitability of the mesoscopic modelling framework for analyzing the multi-component air transport network and, in particular, for obtaining straightforward performance results associated to specific prioritization rules applied to flights. A related approximation for analyzing the USA airport network was a stochastic and dynamic queuing model based on the Approximate Network Delays concept (AND-concept) [14]. The analytical macroscopic model computed the propagation of delays within a network of airports, based on scheduled itineraries of individual aircraft and a First Come First Served queuing system for each airport based. The metrics were local and of system-wide (propagated) delays over a 24 hour period. The authors used a stochastic and dynamic queuing engine to estimate local delays and a network decomposition approach to propagate delays through the network. The model’s results were sensitive to different parameters, such as the setting of the ‘‘slacks’’ in ground turnaround times and promising results were obtained in reproducing trends and behaviors that are observed in practice in the USA system.

III. Characterization of Delay Propagation In The US Network

TREE modelling approach builds upon previous work done on the US airport network by P. Fleurquin, J. J. Ramasco and V. M. Eguiluz [17][18][19]. Indeed, the notable capacity to evaluate the risk of development of system-wide congestion and to assess the resilience of daily schedules to service disruptions showed by the US model is one of the main reasons why the TREE project is expected to be able to deliver interesting and useful results. In the following sections US model description and a summary of simulation results are provided:

A. *Input Data*

The model follows an agent-based approach, with aircrafts as the basic entities, and is data-driven in the sense that the real daily schedules and (optionally) primary delays for the aircrafts are used as input. These were reconstructed from Airline On-Time Performance Data, built with flight statistics provided by air carriers that exceed one percent of the annual national revenue for domestic regular service, which can be downloaded from the website of the Bureau of Transport Statistics (BTS) [20]. The database comprises information accounting for 74% of all the flights operated in the US during 2010. For each flight includes real and scheduled departure and arrival times, origin and destination airport, airline and tail number. It is worth noting that the schedules used for modelling are based on real events, so they do not coincide with the original schedules planned by the airlines in the cases where canceled, diverted or rescheduled flights are involved. Such flights, however, represent less than 2% of all flights in the database, so their effect is expected to be negligible. An in-depth analysis of the data can be found at [17].

B. *Model Description*

The model tracks the state of each aircraft as daily schedules are performed, with a temporal resolution of one minute; the simulation ends once all aircrafts have completed their schedules. In case this happens after the selected day has ended, flights scheduled for the next day are not considered. At the beginning of each simulation run, connections between eligible pairs flights are established randomly. Two flights are eligible for connection if the arrival airport of the first coincides with the departure airport of the second, and the scheduled departure time of the second lies within a 3 hours window starting at the scheduled arrival time of the first. Each eligible pair is connected with probability proportional, with a factor α, to the flight connectivity level provided by the BTS for the airport where the connection takes place. The other parameter, β, affects airport capacities: each airport has an hourly capacity given by β times its hourly scheduled arrival rate and incoming aircrafts exceeding this capacity are put on hold in a queue on a "First In-First Served" basis, thus accumulating delay. If a normal day of operation is to be modeled, both α and β are supposed to have a single value for the whole day and for all airports. However, they can be selectively modified for subsets of airports and/or specific time windows in order to mimic external events such as extreme weather or labor issues. Other details to account for external perturbations can be easily added. Flight connectivity and finite airport capacity can be turned on/off separately to explore the relevance of each sub-process in leading to network-wide congestion. Naturally, aircraft rotation is intrinsic to the schedule and cannot be removed, although an artificial schedule could be used in place of a real one to study its properties. Finally, aircrafts are not allowed to recover from delay by increasing their flight speed, so delay can only be absorbed at airports when aircrafts arrive late but still in time for their next scheduled flight (the minimum turn-around time is set to 30 minutes for all aircrafts and airports). A more detailed description of the model is available in [18].

C. *Comparison of Model Predictions with Real Data*

An airport is considered congested if the average delay of its departing flights over a certain period of time exceeds 29 minutes, which is the average delay of all flights in the database. By building an airport network for each day of data, it is possible to assess whether congested airports are organized in connected clusters – a sign of spatiotemporal correlation of congestion – or not.

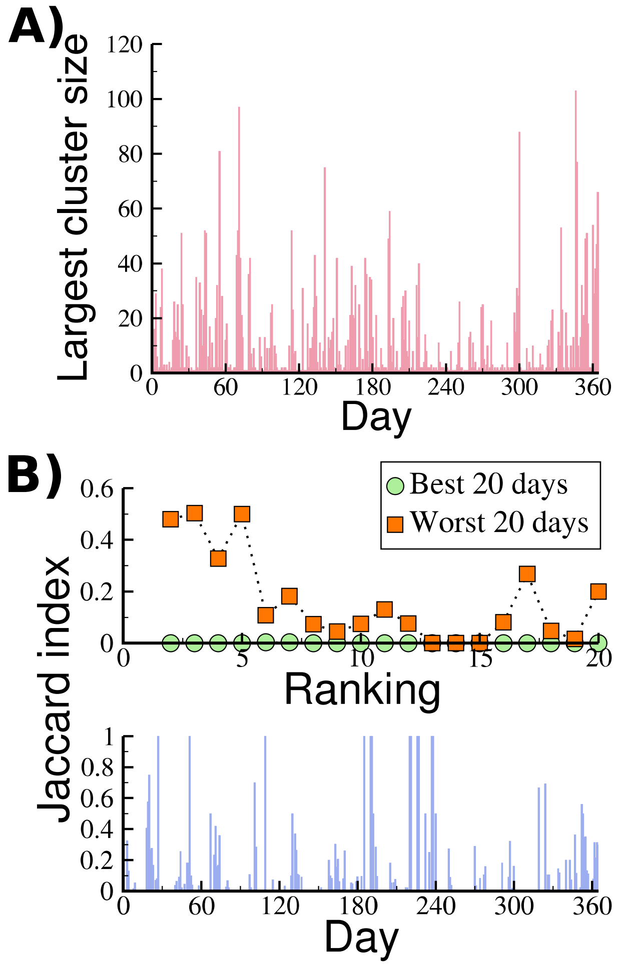

Figure 1 Largest cluster size for each day of 2010 (A) and Jaccard index for consecutive days and between the best (lower average delay) and worst (higher average delay) 20 days of the year.

As can be seen in Figure 1, the scenario dramatically changes from day to day: in some days the largest cluster can include a significant part of the network, while in other days it only consists of one or two airports. The overlap of the sets of airports in the largest cluster is measured by the Jaccard index, the ratio between the number of elements in the intersection and in the union of two sets. By calculating the Jaccard index between the largest clusters in consecutive days or for the top 20 worst and best days of the year, it can be concluded that the same airports are not consistently part of the largest cluster.

To compare empirical data and model predictions, it is possible to use the temporal evolution of the largest cluster. In order to do this the model is run with the following parameters: primary delays from real data, β = 1 (which amounts to the assumption that the capacities are the same as originally scheduled) and α obtained by imposing that the largest cluster size is as close as possible to the one seen in the data.

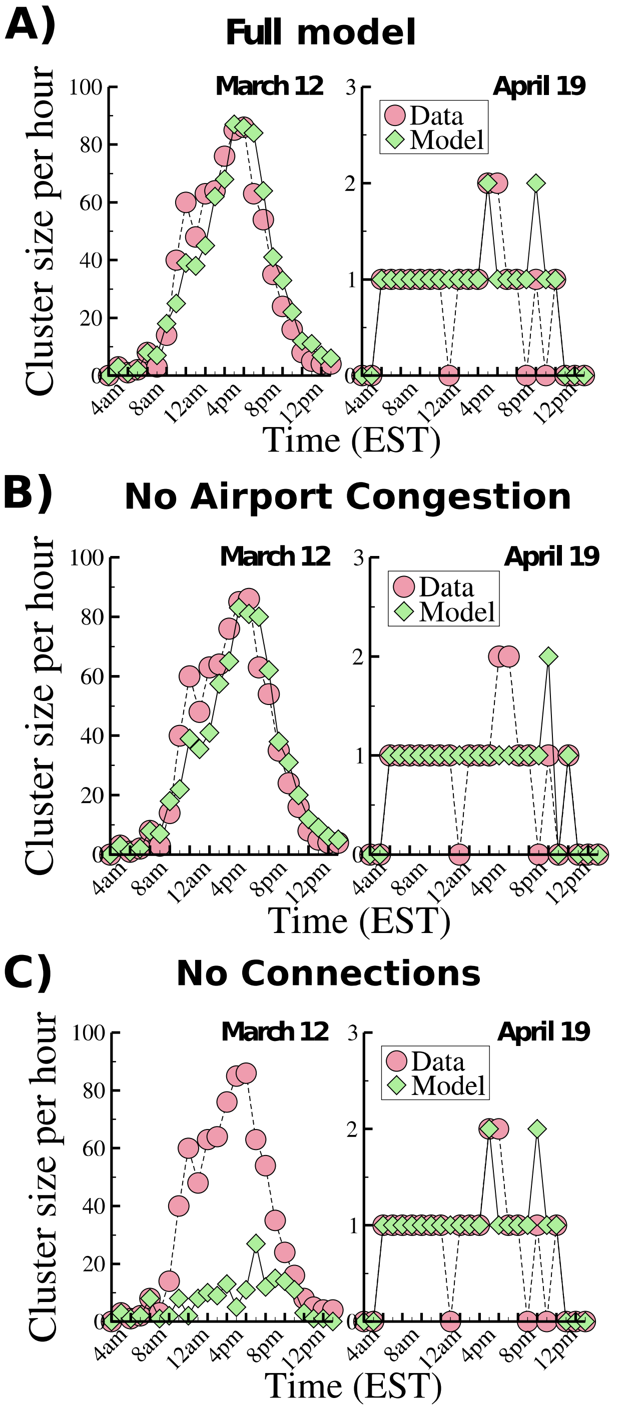

Figure 2 Temporal evolution of the largest cluster size for real data and simulations with different settings: regular model with connecting flights and finite airport capacities (A), infinite capacities (B) and no connecting flights (C).

Figure 2 shows the results for March 12 and April 19; similar plots for other days, as well as other details about the comparison between model and real data omitted here, are available in [18]. While the fit of α is necessary to get the maximum of these curves, the cluster size evolution follows remarkably well that of the real data and almost 60% of the airports in the real cluster are correctly identified by ranking airports by probability of congestion. Furthermore, by fixing α, the model can predict with 66% accuracy if a day will develop a large congested cluster from the schedule alone. Figures 2B-C shows the results of turning off airport congestion and flight connectivity; it is evident that the latter is the most important factor. The impact of varying β, not shown here, is modest: a reduction of the capacities of around 50% is necessary in order to trigger new primary delays that later on will spread in a cascading effect. Using initial delays different from the real ones, it is possible to assess the resilience of a schedule to unforeseen events. In Figures 3, a fraction of randomly selected flights are delayed by a fixed amount of time. The results are displayed for the schedules of the same days used for Figure 2.

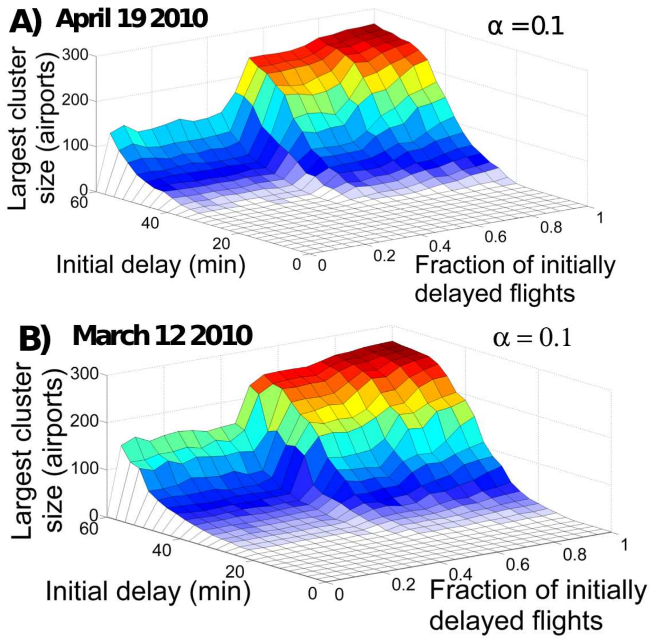

Figure 3 Largest cluster size as a function of the fraction of initially delayed flights (chosen at random) and initial delay.

While April 19 was a normal day with low average delay, March 12 had the second largest average delay of the year, despite the fact that no major disruptive event was reported in the news. This implies that the network-wide propagation of delays was likely caused by internal mechanisms of the system; this conclusion is also supported by the fact that the surface representing the largest cluster size for March 12, compared to the one of April 19, is displaced toward smaller values of the initial delay intensity or fraction of delayed flights, indicating a higher susceptibility of the schedule to disruptive perturbations. Another remarkable property is that, regardless of the schedule, a non-negligible risk of systemic congestion can always be introduced by sufficiently strong primary delays. A picture where the initial delays are distributed randomly is not very realistic, since the direct impact of events such as storms, air controllers' strikes or political riots is likely to be localized. To address this issue, simulations can be run with the real initial delays randomly shuffled between flights. The result, not shown here, leads to the conclusion that random perturbations can damage the system with much more ease than localized ones, probably because more airports are affected and a heavier burden is put on the smaller airports, which have a much more limited ability to react.

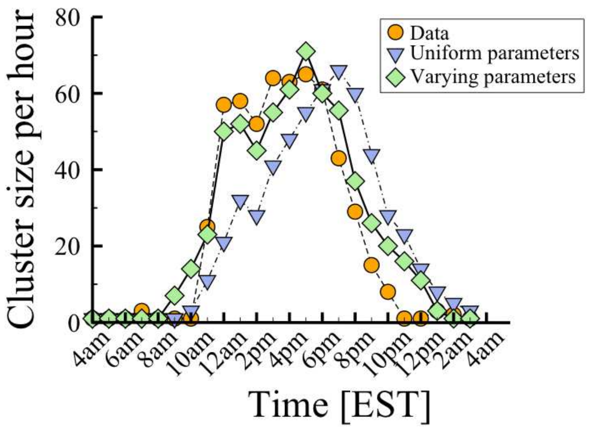

Figure 4 Evolution of the largest cluster for October 27. The blue dots represent the model run with alpha equal to 0.26 and b equal to 1 for all airports during the whole day. The green dots represent the model run with reduced connectivity and capacities in the time and zone where the weather disturbance took place.

For the worst day of the year, October 27, the extreme congestion was caused by meteorological conditions, which according to the news reports affected at least Hartsfield-Jackson airport in Atlanta and the three main airports of the New York-New Jersey area: John F. Kennedy, La Guardia and Newark [21]. Average flight departure and arrival delay amounted to respectively 54 and 53 minutes, and the largest congested cluster contained 88 airports.

An in-depth analysis of this day can therefore provide useful insights on the resilience of the schedule to external perturbations and on the proper way of modeling such events. Some of the results obtained are shown in Figure 4, with more details available on [19].

Without taking into account the perturbation, the evolution of the largest cluster obtained from the simulation is significantly different from the real one (although the qualitative features are reproduced), but this can be notably improved by just introducing changes in α and β localized in space and time.

Finally, the question arises of whether the large congestion of October 27 was mainly caused by the weather, or intrinsic inefficiencies in the schedule played a significant role.

To provide an answer, the same connectivity, capacity reduction and primary delays of October 27 can be applied to the schedule of another day in which no major problem occurred.

Figure 5 illustrates the outcome of this procedure with the schedule of October 20: a large cluster still appears, leading to the conclusion that weather was indeed the main cause of the congestion.

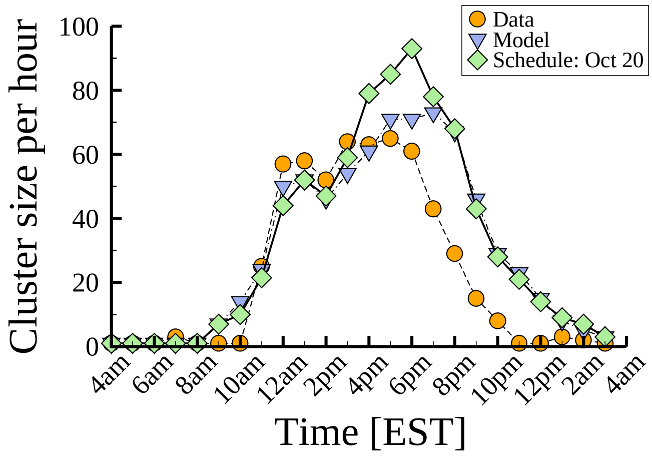

Figure 5 Impact of the perturbation of October 27 on the schedule of October 20

IV. TREE Modelling Approach

The modelling of Complex Systems is still an important challenge in Science. The difficulty increases even further when the object of the models is to do predictions that can be tested against the normal working conditions of systems such as online social networks, pandemic propagation of diseases or cascade failures in transport networks. Since these systems contain a huge amount of heterogeneity and correlations, the only sensible technique to generate realistic simulations and testable predictions is to use a data-driven approach.

In the particular case regarding ATM, these data must include daily schedules for flights and aircrafts in a set of airports. A good part of Western Europe or the full USA are large enough in traffic as to be prone to be subjected to this type of simulations. Smaller subsystems may show severe problems due to its reduced dimensions as larger fluctuations or a decrease in the simulations stability to uncertainty in the input conditions.

The following sections describe how specific concepts and operations intrinsic to the European Air Transport network are being modelled and implemented in TREE. Special attention is paid to the input data as well as the expected simulation results.

A. *Network Nodes and Structure*

The input traffic sample is one-year ECAC traffic sample including the following data for each flight: Callsign, Actual Take Off Time (ATOT), Actual Off Block Time (AOBT), Departure Airport (ADEP), Destination Airport (ADES), flight Duration, Registration, Equipment, Type of Flight (regular/charter), Type of aircraft. The tool reproduces a reduced set of nodes (airports) of the European Air Transport Network. For each node, nominal capacity reflects the actual capacity of the airport, whereas predicted capacity is used to simulate inaccuracies on the information available in the network about the actual capacity of the nodes. The vertices are represented by the aircrafts flying form one airport (node) to another. The propagation of the delays is represented by flight links related to flights using same aircraft, crew or passengers. The advantages in terms of computational tractability of modelling a simplified network are direct. It is an assumption common to most models of real networks that modelling in an explicit manner only the main nodes provides representative results of network performance. As discussed in [15], many empirical complex networks have a skeleton, implying that for developing a dynamical model of an empirical complex network it is enough to simulate only its skeleton, not requiring simulation on (or even knowledge of) the full network.

B. Main features of the tool

1) Aircraft rotations

The model is built using an agent-based approach with aircrafts playing the role of agents that are followed across their rotations. A daily schedule with the plane rotations and the expected departure and arrival time of the flight from/to each airport is thus necessary as an input for the model.

The schedule can be generated artificially, this will be done whenever a theoretical analysis will be performed, but in order to obtain realistic outputs, the schedule must come from real data. Note that there is a difference between the initial daily planning of each airline [16]and the one really implemented recorded in performance databases as CODA (Central Office for Delay Analysis). The former is the plan advanced by the airlines regarding aircraft and crew rotations, while the latter includes all the changes introduced by airline managers to overcome unexpected conflicts such as cancelations due to weather or plan modifications due to mechanical issues. The model can work with any of the two daily plans. It could help even to optimize the pre-established plan in order to reduce delay propagation risks. However, CODA and RITA (Research and Innovative Technology Administration) data typically contain only schedules that were really implemented and these are, therefore, the main model inputs.

2) Passenger Connections and Crew Rotations

For the USA network, the level of connection between flights in each airport is determined by the statistical information available on the yearly passenger connections in each airport of the network. In TREE, the objective is not only to adapt these ideas to Europe, but also to go beyond by introducing real information on passenger connections. This is important because there exists an important variety in the connectivity level among the flights departing from the same airport. It is not only important in which airport the connection takes place, but also which the destination is and which is the real demand in each connection or route. This information will be included in the model in the moment in which a flight with delay arrives at an airport. This flight has then a certain probability of influencing other flights of the same company in a given time window from its scheduled arrival time. So far, the flights with connections of the passengers or crew were randomly selected, but this mechanism will be substantially improved by using market sector information. As for the crew rotations, it is the objective of TREE to identify a set of strategies applied by the airlines. However, since this is something directly related to airlines business, it is expected that information gathering is one of the challenges to be faced. For this reason, the methodology for the capture of airlines strategies for organizing the crew rotation is being materialised in interviews, distributing questionnaires among airlines and organizing brainstorming sessions among experts. The last was the objective of the workshop on Airlines Disruption Management held in Palma de Mallorca (Spain).

Representatives of all the actors involved in the disruption management process were invited as participants: airline representatives, network manager representatives (CFMU), airport operators, Air Navigation Service Providers, air traffic controllers, ground handling agents and overall ATM experts. Brainstorming sessions were oriented to the identification of airlines specific strategies in case of large disruptions impacting their operations. Thus, different case studies of interest were analysed in detail. These case studies will constitute the basis for implementing modelling scenarios.

3) Airport Operations

The next element to be considered, which affects flight performance, is airport operations. For each airport, if demand exceeds capacity the flights of all the companies departing during a time window get delayed. The delay affects more flights that may have to wait longer to be served or to be allowed to take off due to air space control restrictions. The effect of airport capacity limitation will be included in the model by introducing a queue system. For instance, in most of the US airports where the rule for service or for take-off is based on the protocol “first-arrived, first-served” a single queue system is enough to model airport operations with realism.

In the case of the ECAC area, the operations are more complex due to the existence of ATFCM regulations. Queues for arrival, service and departure will be still used but the order and priorities will be determined by the slot allocation based on those regulations. In the TREE model, all these mechanisms will be taken into account. The slot management will be modelled in order to obtain realistic predictions for delay generation and propagation.

4) Slot Management

First of all, it will be assumed that the schedules obtained from the data correspond to real Airport slot allocation. That is, each flight with a certain scheduled departure or arrival time has Airport slots assigned.

Different schedule allocations could be compared in terms of delay propagation in the system due to disruptions.

For simplification, regulation will only be applied to departure and destination Airports, not to ACC or TMA sectors. Each airport will have a nominal capacity value which will define the maximum number of flights that can be operated per hour. This nominal capacity will be constant for all the simulation.

Depending on the external event (i.e. meteorological event, security checks…) that is simulated, a reduction of the capacity affecting one or several airports will occur over a certain period of time.

If with this reduction of capacity either the departure or the destination airport is not able to cope with the demand then a regulation will be imposed and an ATFM slot will be issued for the flights affected. For the flights not affected by a regulation the “First Planned- First Served” principle will be applied.

When the regulation is activated, the model starts to analyse flight plans. Each flight concerned by the regulation is given a provisional slot based on the order of their Estimated Time Over (ETO) the restricted location (in this case will be the Estimated Take Off Time (ETOT) for departures or Estimated Landing Time (ELDT) for arrivals). This slot is as close to the requested Estimated Time Over (ETO) the restricted location as it is available:

- If that slot is free, it is assigned to the flight, which thus suffers no delay.
- If that slot is already pre-allocated to a flight which is planned to depart or arrive from/to the restricted airport after the new flight, then the latter takes the slot. Of course, the consequence can be a chain reaction, because the flight whose slot has been taken tries to recover another slot, possibly by taking the slot of another flight, etc.
- In case a flight is subject to regulation in both departure and destination airports, the most constraining regulation will prevail.

The slot is an interval of time that goes from -5’ to +10’ of the CTOT (Calculated Take Off Time). The new Estimated Take Off Time of the flight will depend on the Taxi Time of the airport. Two hours before the Estimated Take Off Time the slot is fixed and not subject to modification. A mechanism of Slot Swapping will be implemented only if requested by the Aircraft Operator, with the following conditions:

- The two concerned flights must have a slot issued;
- The two flights must be subject to the same most penalizing regulation;
- Only one swap per flight shall be accepted;
- If an assigned slot could not be achieved by a flight, a new slot will be assigned for it.

C. Input Data

Passenger and flight traffic data are the key for modelling the skeleton of the air transport network. Aspects such as general connectivity level, primary delays and airport nominal capacities will define the conditions for operation.

The input data are as follows:

- Flight data: data sources like CODA, will provide data on daily flight plans with scheduled arrival and departure times of all the flights, along with the aircraft rotations.
- Market sector data: will determine passenger connections between the different flights arriving and departing from each airport.
- Parameter for the level of general connectivity level: Passenger connections are not the only factor that can produce reactionary delays in outgoing flights. Crew rotation is also important and even though some feedback on the typical airline practices is expected in this sense in the expert consultation, the model will have to include a stochastic mechanism to take into account this type of connectivity with a free parameter to tune its relevance.
- Airports nominal capacity: there are two options for calculating Airports nominal capacity. The first one is based on extracting the information from input traffic samples (schedules). Still, the model will also include a free parameter that will allow us to modify the capacity globally or locally. The tuning of the parameter will make possible the simulation of situations such as bad weather conditions or labour issues affecting some airports. The second one is based on using published data, i.e.: via Airport Corner (web based application of EUROCONTROL) or European Network Operations Plan 2012-2014.
- Primary delays: this information can come from real data as CODA, for instance to validate the model predictions. It can be also fake initial conditions generated to study some particular scenarios. For example, concentrating the delays in a certain airport or flights to test the system resilience by feeding then these primary delays into the model and analysing the unfolding of the corresponding delay trees in the network.

D. Simulation Outputs

The simulation outputs will be comparable to the performance data contained in CODA. Each model realization will generate a pattern of delay propagation from the primary delays on. It will include the list of affected flights, the airports they visited in their rotations as well as the status of each airport in terms of congestion along the day hour by hour. The advantage of the model is that besides this information it also allows for a detailed tracking of which flight causes the reactionary delays in subsequent flights (trees of delays). This extra information will be also part of the output, even though it is different from the actual performance data.

It is important to stress that the results of each realization of the model will be tracking the delayed flights, the status of the airport or the causal relations between flights producing or suffering reactionary delays. However, given the stochastic nature of some of the model components and in order to carry out a serious analysis on the outcome, most of the metrics require the performing of statistics. The median of the different estimators will be considered, but also their fluctuations across model realizations.

V. Next Steps

Next steps are oriented to the implementation of specific operations intrinsic to the European Air Transportation Network into the modelling tool. Then it will be the time to validate the tool to prove the suitability of the TREE modelling framework for analysing and tracking the tree of reactionary delays (making distinctions between delays, i.e. crew links, aircraft links, passenger links). Although some specific case studies of interest were identified during first project workshop, the challenge of capturing airlines strategies for crew and slot swapping remains there. Interviews with airlines representatives and a literature review focused on airlines disruption management will also be performed. Once a set of case studies is identified the experimental plan will be performed. The experimental plan will include the number of scenarios to be modelled, the number of exercises to be tested in each scenario and the list of metrics to be monitored. After simulations, a preliminary analysis of the results will be performed. Experts are expected to be the contributors for the final validation of the results.

VI. CONCLUSIONS

Operating an aircraft within Europe is a very different scenario to that of the equivalent in the USA. The complexity, the vastly diverse cultures, the varied governance, a strong ATC union presence and complicated liaison with differing bordering countries all contribute in stark contrast to the more simplified version of how the Federal Aviation Authority's area of responsibility functions.

Airline Disruption Management process is a transversal problem impacting several airline functions with different kinds of origins and root causes. The robustness of the airline schedule (including turnaround times) influences the propagation of reactionary delays.

Some airlines are very cost sensitive. Financial costs in the current era are of course paramount to how an airline functions and these situations through a variety of experiences were voiced in interesting detail. Crew rotation is another big factor in airline operations and the fact that some airlines split their crews can have a big impact upon delays.

In this sense, the model that is being proposed from TREE would allow different actors testing different strategies giving highly valuable support in problem solving processes.

The integrated approach to a very combinatorial problem based on aircraft, the flights, the airport slots and passenger re-accommodation is the key towards approaching an ideal solution.

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