A data-driven method to assess the causes and impact of delay propagation in air transportation systems

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Abstract

Air transportation systems are exposed to disruptions, which have significant impact on operations. Airlines operate tight schedules to maximise resource utilisation, however, the lack of sufficient buffers often result in propagating delays. Thus, understanding how likely it is to experience delays, why they keep happening and what is their impact on airline operations are important steps for the management of the disruptions they cause. In this paper, we propose a data-driven method to empirically analyse how delays propagate and their impact on an airline schedule. Our multi-layer network method captures different variables that are influenced by schedule disruption, namely aircraft (tail), crew, passengers and their interfaces. The method is tested on the schedule disruptions of a hub-and-spoke airline where we empirically demonstrate that incorporating information in this multi-layered manner results in a more robust assessment of delay propagation. The method along with the empirical results of this study can support aviation system planners gain additional insights into flight delay propagation patterns and consequently support their resource allocation decisions while improving overall system performance.

Keywords: transport, delay propagation, airline operations, multi-layer networks

1. Introduction

Air transportation systems are subject to disturbances, in which unexpected events such as mechanical problems, severe weather, air space congestion, prevent services to continue as planned and cause delays [1, 2]. Air transportation delays are both common [3] and create a substantial annual cost [4] which reached $60 billion in 2016 [5]. Moreover, delays cause a number of adverse effects such as lower utilization rate for aircraft, susceptibility to decreased demand, increased airfares for future flights, complaints from passengers and difficulties in airport operations [6, 7]. In the future, as the number of airline passengers are estimated

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to double by 2034, the potential for delays cannot be underestimated, especially if the infrastructure is not to be adapted to future traffic levels [5]. The complex nature of air transportation systems only adds to the delay problems, as delays affecting any one of its components can create a knock-on effect, delaying other dependent components [8]. In particular, the phenomenon of one (delayed) flight delaying another flight, known as *delay propagation*, plays a significant role in delay generation [2, 9], as it has accounted for 30%–60% of all delays in the US [10] and Europe [3]. Similar effects of propagated disruptions are also common in other transport network [11] and supply chains more generally [12].

The contribution of this study is twofold. Firstly, we introduce a data analysis method that allows us to study the effect of delay propagation on airline schedules from the viewpoint of an airline operator utilising data typically found in airline management software. The data-driven method uses a *multi-layer airline schedule network* perspective which means incorporating tail, crew and passenger information in our analysis. Using this method, we can develop a more holistic view to air transport delays in contrast to previous studies utilising delay propagation trees [10, 13] which are only a subset of the airline schedule network thus enhancing decision making. Moreover, we argue about the importance of taking a multi-layer perspective to study the delay propagation phenomenon by examining the role of individual connection layers. We observe rare cases of significant delay propagation, resembling cascading failures, which are not visible without the passenger layer. In doing so, we contribute to existing literature analysing transportation systems from a network science perspective [14, 15, 16, 17].

Secondly, we analyse how flight delays propagate —in a case study with a particular hub-and-spoke airline operator— and what impact they have on its operations, thus also demonstrating the applicability of the method. The hub-and-spoke model is widely used nowadays by airlines around the world [18] and has recently attracted attention due to the effects of the pandemic in airlines [19, 20] and other transportation systems [21]. Our analysis is possible because of the use of the aforementioned novel data analysis method coupled with extensive operational data. The data enables us to accurately estimate buffers for each connection, hence accurately evaluate which flights caused delays to propagate further. Accurate buffer estimation has been an important issue in relevant literature [22] as previous studies often limit their analysis to aircraft information only [23, 24], use aggregated passenger information [15], or simulate passenger connections [25, 26]. We find that two out of three root delays are not amplified (i.e. they do not lead to an even greater total caused delay), and they do not usually propagate to more than one or two flights. However, we observe situations where delays cause significant impact to multiple flights over a long period of time.

From a managerial perspective, using the method proposed here can help better understand how delays propagate and what impact they have. This is particularly important as [2, 10, 27, 28, 29, 30]:

- empirical results can be incorporated in recovery optimisation models to enhance the quality of proposed recovery solutions, or in robust planning in order to better allocate resources to minimise propagation effects, since in both cases the knock-on effect of alternative plans can be estimated the network;
- the method and the empirical results it can produce can be used alongside delay propagation prediction models to support the explainability and interpretation of the results produced by such models;
- airlines can take measures to tackle the cause of delays having a higher impact on their operations, as they can track not only the frequency and size of root delays but also the impact root delays have on various downstream flights in their networks.

The remaining of this paper is organised as follows. Section 2 reviews the relevant literature. In Section 3, a method to study the delay propagation phenomenon is presented. Section 4 presents an in-depth case study with a hub-and-spoke airline. Section 5 discusses the implications of this study for research and practice along with future work paths.

2. Related work

Academic literature has investigated flight delays and delay propagation mainly from three perspectives. Firstly, from a structural perspective looking at how structural characteristics of an air transportation network affect its susceptibility to delays. Secondly, taking a dynamics perspective, examining the delay propagation phenomenon as it evolves in a network. Thirdly, investigating why delays occur in the first place, and in particular focusing on causes of root delays. We review relevant literature in each of these areas in the sections that follow.

2.1. Structural characteristics

Delays in an air transportation system are difficult to examine because the system consists of multiple interconnected components such as airports, runway systems, passengers, aircraft and baggage [8]. Delays affecting any one of these can create a knock-on effect, delaying other dependent components. Thus, examining an air transportation system as a network of interconnected components has been a logical representation and frequent subject of research. for example by representing the system via an *airport network* with different levels of granularity [15, 31].

A network's topology has been shown to have close connections to a system's susceptibility to disruptions [32, 33, 34] in a range of domains including protein-protein networks [35], power grids [36], and air transportation systems [37]. In order to study a network's vulnerability to disruptions from a topological perspective, *percolation* has been the most popular approach. In a percolation study setting, nodes and links are systematically removed to measure how the network's connectivity is affected in the process. The literature reports that airport networks do not loose connectivity if airports and their connections are removed at random. However, airports quickly become isolated when the removal is guided by centrality metrics, especially betweenness [37, 38], degree and Bonacich centrality [16]. This suggests that airport networks on the global and national level are over-reliant on the large hub airports. Since hubs play a role of connectors between deeply hierarchical airport clusters, the network is highly fragmented once they are removed [39]. Similarly, airline networks are susceptible to targeted removals guided by degree centrality [40]. Looking at recovering from disruptions, re-opening airports with the highest centrality metrics can be the best strategy to faster come back to the pre-disruption performance [41].

Despite a wide variety of air transportation networks being studied (e.g. airport, sector, air route networks), their topologies have been considered separately. However, the structural properties of an aggregated airport network have been shown to differ from properties of the individual layers [42]. Moreover, considering an aggregated network might cause mis-identification of critical airports [43]. Hence, numerous studies advocate extending network topologies with additional layers to achieve a better picture of network robustness [43, 44, 45, 46, 17].

2.2. The dynamics of delay propagation

The structural characteristics of an airport network alone are not enough to fully capture the system's vulnerability to delays [47]. Because of this, several studies emerged to simulate airline operations dynamics, using agent-based modelling [25, 26, 48, 49, 50, 51], queuing models [52], and epidemic modelling [13, 53]. Modelling dynamics of the entire system enables one to estimate a system's behaviour and performance under different operational characteristics, for example, when an airport's capacity is lowered, instead of removing components from a network as it is the case in percolation studies.

Delays propagate when there is not enough buffer to absorb delays from previous flights [54]. It has been observed that a delay not only can cause downstream delays but also upstream delays [52]. This is attributed to the fact that when a destination airport is congested it might not be able to allow incoming flights to land, thus affecting their ability to take off from the airport of origin. Recent studies [49, 50] observed that both arrivals of flights and flight delays exhibit a *bursty* behaviour; peaks of activity in a short period of time. This is especially exacerbated by hub-and-spoke operations since multiple flights are arriving and departing at the same time to accommodate connecting passengers. Moreover, it has been observed that delays can be absorbed over the course of the night (during “resting time”) [48].

The most crucial factors that contribute to delays propagating are connecting crew members and passengers, reduction in airport capacity, and regional differences [25, 48, 51]. Connecting crew members and passengers have much higher impact on causing delay propagation than decreased airport capacity, since it has been estimated that a decrease in airport capacity by 50% is needed to observe significant delay propagation effects [25, 48]. Regional differences also have an impact on delay propagation. The European airspace system has been shown to be more efficient than the U.S. network due to European Air Traffic Management priority slots working better than U.S. first-come first-serve policy [51]. Similar observations have been made for the Chinese network, where priority-based strategies outperformed first-come first-served policy [26]. Nevertheless, the U.S. airspace system has been reported to be more flexible and well-connected, whereas Chinese network maintains the same structure and runs either fully utilised or not at all [55].

2.3. Causes of delay propagation

It is of high economic relevance not only to understand how delays propagate, but also what is causing them [51]. Scheduling slack to account for delays without addressing their root-causes is seen as not adequate to create a robust schedule [56, 27]. There are multiple factors that contribute to delays, for example weather, aircraft type, turnaround buffer time, cargo and mail handling, technical and aircraft equipment, passenger and baggage handling, time and seasonality [27, 57]. However, finding causes of delays is not equivalent to finding root-delays of delay propagation. A *root-delay*, or *newly formed delay* is defined as "the delay that occurs during the immediate upstream operation (which can be either a flight or turnaround)", whereas delay propagation is "the delay that is rooted upstream" [28]. An early approach to model root-causes resulted in defining delay propagation trees [10]. A *delay propagation tree* is a network that has nodes representing flights and links representing aircraft turnaround and crew connections through which delay propagated. Authors track how a single root-delay propagates across the airline schedule by calculating how much delay was absorbed by the buffer and how much propagated through connections. They found that the majority of root-delays do not propagate across the network, being absorbed by the slack. However, if propagation has been observed, its impact is usually significant (likely to double the original root-delay). Additionally delays are localised, meaning that they do not spread far geographically. It has been reported that keeping aircraft and crew members together can significantly contribute to reducing the delay propagation effect [10].

Unfortunately, estimating delay propagation is a difficult task [58] due to lack of data to accurately calculate empirical buffers [28, 57]. In order to address this issue, researchers started to look at the causality of delay time-series between two airports [44, 59, 60]. This results in a *functional network*, where nodes represent airports and a directed link indicates that arrival delays in a source airport cause delays in the target airport. It has been shown that delays usually propagate from small regional airports and medium airports [44, 59]. Additionally, only about a quarter of all airports in a global airport network are involved in delay propagation and a small set of airports contribute the most changes on a daily basis [59] .

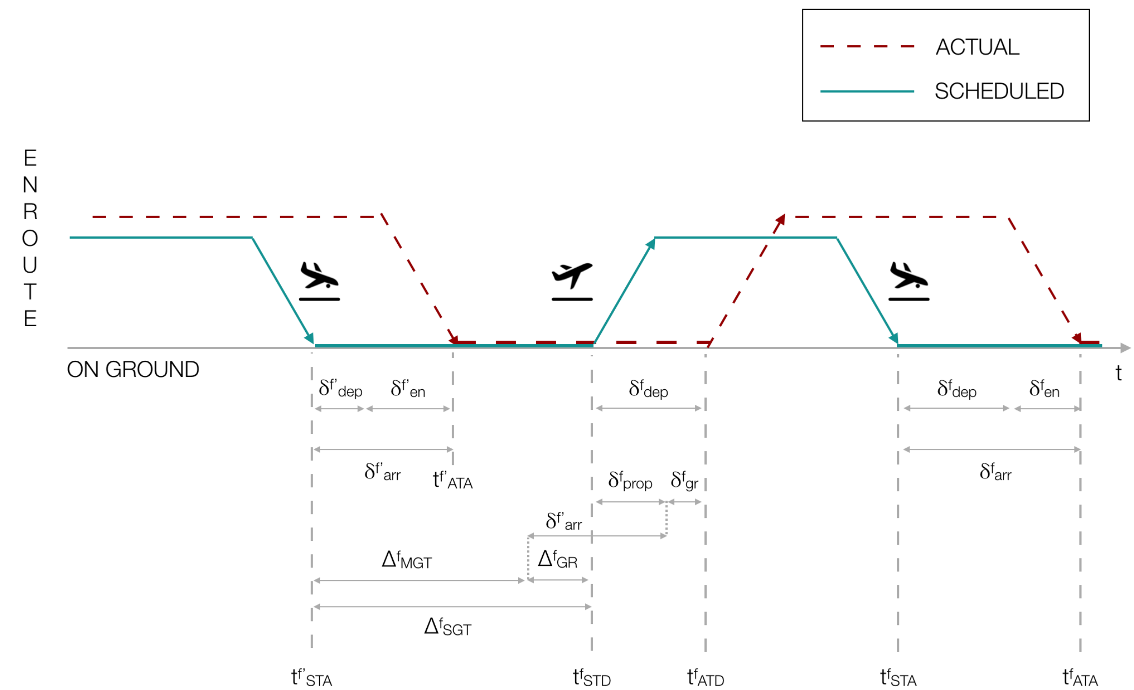


Figure 1: Delay propagation model diagram.

3. A method to study delays and their propagation

We take a network perspective to develop a data-driven method to study the delay propagation phenomenon. This is because modelling delay propagation through aircraft (tail), crew and passenger connections can be achieved naturally by using a network of flights as nodes and connections as links [10, 13]. The method consists of two stages: the first one models the airline schedule network and the second extracts delay propagation patterns and root-causes. Each stage will be discussed in separate sections below.

3.1. Modelling the multi-layer airline schedule network

We start by formalising the airline data used as an input to the method. These data are typically collected by airline operators and refer to scheduled and actual connections of tail, crew and passengers along with operational parameters such as ground slack and minimum connection times. This is necessary in order to properly define the concept of a 'delay' and 'delay propagation'. For a visual aid please refer to Figure 1, which illustrates dependencies between scheduled and actual variables used to define delay propagation.

Let us denote a flight $f \in F$, where F is a set of all flights of an airline. A flight f is late, when its arrival delay is greater than zero. Equation 1 defines an arrival delay (δ^f_{arr}) as the difference between the actual time of arrival (t^f_{ATA}) and the scheduled time of arrival (t^f_{STA}). The actual time of arrival is recorded when the flight arrives at the destination gate.

$$\delta^f_{arr} = t^f_{ATA} - t^f_{STA} \tag{1}$$

An arrival delay can be composed of two parts: *a*) a departure delay, in case a flight departed after its scheduled time, and *b*) a en-route delay, in case the a flight stayed en-route longer than initially planned. More specifically, a departure delay (δ^f_{dep}) is defined as the difference between the actual time of departure (t^f_{ATD}) and the scheduled time of departure (t^f_{STD}) in Equation 2.

$$\delta^f_{dep} = t^f_{ATD} - t^f_{STD} \tag{2}$$

The actual time of departure is recorded when the flight pushes back from the departure gate. The en-route delay is the delay that occurs during off-block time, where off-block time refers to the time aircraft is not positioned at the gate i.e. taxiing out, taking-off, airborne, landing, taxiing in. An en-route delay (δ^f_{en}) can be derived from the arrival and departure delays (Equation 3).

$$\delta^f_{en} = \delta^f_{arr} - \delta^f_{dep} \tag{3}$$

Note that a delay, as it is defined above, can take a negative value; this is intentional so that the model can keep track of those flights arrived/departed early along with how much earlier they arrived/departed. Now, let us denote a flight $f' \in F'$, where $F' \subset F$ and F' is a set of all flights that connect to flight f through the same tail, crew member, or passengers and happen before flight f. The *scheduled ground time* ($\Delta^{f',f}_{SGT}$) is the difference between the scheduled time of departure of the flight f and the scheduled time of arrival of the flight f'.

$$\Delta^{f',f}_{SGT} = t^f_{STD} - t^{f'}_{STA} \tag{4}$$

As discussed previously, in practice, airlines incorporate slack into their schedule in order to reduce the impact of events that could cause a flight to departure late [28]. Such events include delays in airport operations, congestion at the departure airport, weather issues, delays of previous flights, late passengers etc. However, the slack is an artificial construct that represents the difference between expected and scheduled times. Moreover, there is no universal way to observe or estimate slack using empirical data [28]. We argue, that the slack magnitude can be approximated using minimum turnaround and connection times internal to an airline, which means that it is usually not available publicly to study.

The *ground slack* ($\Delta^{f',f}_{GR}$) incorporated into the schedule is unique for a pair of flights f' and f and is calculated as the difference between scheduled ground time and minimum ground/connection time. *Minimum ground time* (Δ^a_{MGT}) is the minimum time on the ground needed to prepare an aircraft p for departure at the airport a, also known as a minimum turnaround time. A *minimum connection time* (Δ^a_{MCT}) is the minimum time required for passengers or crew members to change airplanes at airport a, and is usually given for each airport. Given the multi-layered structure of the airline schedule, it is possible that there are multiple types of connections between two flights. This will affect the amount of slack available, which we define as the smaller value among all connection types. Equation 5 formally describes a ground slack.

$$\Delta^{f',f}_{GR} = \begin{cases} \min\{\Delta^{f',f}_{SGT} - \Delta^{p,a}_{MGT}, \Delta^{f',f}_{SGT} - \Delta^a_{MCT}\} & \text{if connecting through tail, pax and crew} \\ \Delta^{f',f}_{SGT} - \Delta^a_{MGT} & \text{if connecting through tail only} \\ \Delta^{f',f}_{SGT} - \Delta^a_{MCT} & \text{if connecting through crew or pax} \end{cases} \tag{5}$$

The ground slack plays a role of an absorbent. This means that whenever an arrival delay occurs the ground slack compensates for the delay. In practice, ground slack ensures that if the flight is delayed there will be no further delay to the next flight, i.e. there will still be enough time for the crew and the airport to perform any necessary preparation for the timely departure of the next flight. However, only a certain amount of the delay can and is limited by the magnitude of the ground slack. A propagation delay from flight f' to f ($\delta^{f',f}_{prop}$) occurs when the ground slack is not able to fully absorb the arrival delay of the previous flight, and is denoted by Equation 6:

$$\delta^{f',f}_{prop} = \max\{0, \delta^{f'}_{arr} - \Delta^{f',f}_{GR}\} \tag{6}$$

If the ground slack is greater than the arrival delay of flight f', the delay is fully absorbed and $\delta^{f',f}_{prop} = 0$. Based on suggestions made in the literature [28], we assume that the arrival delay is absorbed first and determines how much delay propagated to the next flight. There is a lower bound on the propagation delay because if the delay is fully absorbed and there is still some ground slack left, this does not necessarily mean that the aircraft will depart before its scheduled time. This is because for an aircraft to depart before time there are set of conditions that need to be met, including passengers on board and clearance from the Air Traffic Control. The concept of delay propagation through tail is presented in Figure 1. The concept is identical for crew and passenger connections, however the term Δ^a_{MGT} is replaced by Δ^a_{MCT}. Since a flight might be delayed by more than one flight, we set the propagated delay to flight f (δ^f_{prop}) as the maximum

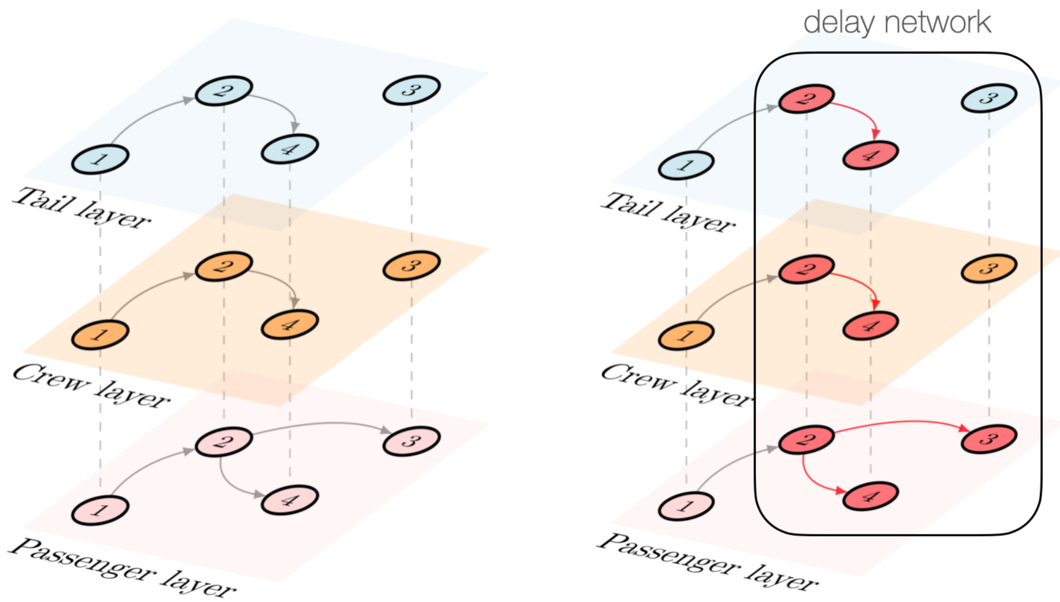


Figure 2: An example of a multi-layer airline schedule network (left); and a delay network as a subset of the airline schedule network (right). In this example, if passenger layer is not considered, the influence of flight 2 on delay of flight 3 might be overlooked.

magnitude of the propagated delay for all its inbound flights [2].

$$\delta^{f}_{prop} = \max_{f' \in F'} \delta^{f',f}_{prop} \tag{7}$$

We can now use the departure delay and propagated delay to calculate ground delay (δ^{f}_{gr}), as presented in equation 8. Ground delay occurs due to problems that delay an aircraft while on the ground. If a flight is delayed by both delay propagation and ground delay, their magnitudes might help to unveil what was the main cause of the flight to departure late. For example, if a ground delay has a larger magnitude than propagated delay it might mean that the connecting flights were not the main cause of this late departure.

$$\delta^{f}_{gr} = \delta^{f}_{dep} - \delta^{f}_{prop} \tag{8}$$

Having formalised the flight data and the delays associated with it in Equations 1–8, *airline schedule networks* can be created to illustrate this information. Due to the richness of our dataset, the airline schedule networks created here are not limited to tail connections only but allow links to represent connecting crew members and passengers, giving rise to a multi-layered topology (Figure 2). We divide our network into multiple layers that correspond to different connection types. We distinguish between connecting tail (T), crew members (CM), and passengers (P), where each type of connection is placed in its corresponding layer.

3.2. Extracting delay propagation patterns and their root-causes

In this second stage of our method we extract delay propagation patterns and their root-causes from airline schedule networks. We begin by formally defining delay propagation. The concept of a *delayed* flight can be troublesome, as when the word *delay* is used, it is not always clear if it refers to the arrival or the departure of a flight. Similarly, the concept of *delay propagation* tends to be ambiguous. We use the following definition here: in order for a flight f' to *cause* flight f to be delayed, assuming that flight f' connects to flight f through either tail, crew or passengers, the following condition needs to be met:

$$\delta_{prop}^{f',f} > 0 \tag{9}$$

Even though Equation 9 is necessary for a delay to propagate, it is not sufficient. Even if a propagated delay is positive the flight might still not be delayed. This is because an airline or an airport knowing that there is a delay potential in flight f might allocate resources in a way that prioritise flight f, and therefore prevents the late departure of this flight regardless of delays. As a result, the departure delay needs to also be greater than 0 for a causal delay relationship to occur (Equation 10).

$$\delta_{dep}^{f} > 0 \tag{10}$$

In this paper, we study delayed flights by looking at cases where the delayed arrival of one flight causes the delayed departure of another flight. This follows arguments in the academic literature that looking only at the delayed arrival of a flight tends to underestimate how delays actually propagate [61].

We now define a*delay network* as a subset of an airline schedule network which contains only these consecutive flights that departed or arrived late. A node represents a delayed flight and a link indicates that the late arrival of one flight caused late departure of a next flight. Examples of an airline schedule network and a delay network are presented in Figure 2. The multi-layer perspective is necessary to understand the impact of delays on airline schedule as individual layers tend to underestimate how delays propagate.

The idea of modelling flights as nodes and connections as links is not new in literature and has been proposed through *delay propagation trees* [10]. Building on this idea we develop delay networks for two reasons. Firstly, delay networks are extended to multiple layers allowing us to evaluate how different connectivity types contribute to delay propagation, whereas delay propagation trees only consider an aggregated view. Secondly, delay propagation trees have so far been used to study delay propagation by delaying one flight and then evaluating how a delay propagates across the schedule. Conceptually, this approach instinctively implies that there is a single root-delay and that this is the only delay for a flight. It also does not take into account other types of flight delays that are not related to delayed upstream flights. In reality, airline networks can have multiple flights delaying a downstream flight whilst this very flight can face its own delays. We argue that networks are a better representation of this concept, while we acknowledge that this is not the only possible modelling option.

In order to extract delay networks from airline schedule data, we propose the Delay Network Algorithm (Algorithm 1). An airline schedule network S is extracted from the dataset D, where S consists of set of nodes F and set of connections L. Each node $f \in F$ is labelled with a unique flight id and there is a directed link $v(f', f) \in L$ from flight f' to flight f if either crew members, passengers or a tail are connecting. Next, all flights that were delayed are extracted from an airline schedule network and stored in a network n with respective causal relationships. The time complexity of the algorithm is equal to $O(|F| + |L|)$ as the algorithm traverses each node and link only once. An algorithm for finding weakly connected components needs to be applied to network n in order to separate it into set of networks N which include only consecutive flights ($findWeakConnComp(n)$ in Algorithm 1). Finding weakly connected components is carried out as described in [62].

Networks generated this way have an interesting property: if a node within the network does not have any incoming connections, it indicates that this flight must be the root-cause of the delay propagation within this network. Finding all such flights would be equivalent to finding all root-causes of airline delays. Coupled with delay codes, one could also infer the true cause of the root-cause delay by looking at the delay code of the flight with no incoming connections.

However, this is a simplistic view as two connected flights might be delayed by two distinct disruptions. For example, let's denote two flights f' and f, where f' connects to f through the same tail. Flight f' was delayed by a 10-minute weather delay at the destination airport, causing a 5 minute delay propagation to flight f. However, if flight f also had a mechanical breakdown causing a departure delay of 50 minutes, this mechanical breakdown will be the main cause of flight f to departure late. Looking purely at a structure of resulting networks, the weather delay would be identified to be the cause of the mechanical breakdown, which is not accurate. A situation like this indicates that there are more than one disruptions embedded in the network structure and there needs to be a mechanism that allows one to decompose such situations.

To address this issue we propose a procedure based on community detection that will remove connections that are deemed to be unlikely to be the cause of the next flight departing late. Network community is a structure in which nodes are tightly connected to each other within a community, and loosely connected to nodes that are not a part of the same community [63]. By separating flights into communities we aim to find a set of flights that heavily delay each other. If such a set exists it would include flights that are likely to belong to the same disruption; and hence carry a set of related root-causes. Then, we keep the intracommunity links and remove inter-community links, thus keeping only these connections that significantly contributed towards propagating delays. There are various algorithms in the literature to identify groups that naturally occur in a network structure, the most popular being: the Girvan-Newman algorithm [63, 64], algorithm optimising modularity using heuristics [65], and an algorithm optimising modularity using leading eigenvalue[66]. We have chosen modularity maximisation algorithm in [65] because of the following reasons:

1. It is suitable for large networks. The algorithm has a complexity of $O((|L| + |F|)|L|)$. This is an important criterion since we expect to apply the algorithm to a large number of delay networks, with some of them including a lot of nodes and links. This criterion has disqualified Girvan-Newman [63] since it has complexity of $O(|L|^2|F|)$ which is slow.

2. It is able to naturally divide the network into an odd number of communities, whereas [66] gradually divides the whole network into two, resulting in better even than odd splits [62]. In our case, in order to find more accurate root-causes it is important not to favour any particular type of community split.

The algorithm aims to maximise the modularity metric Q in a weighted directed graph:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i^{in} k_j^{out}}{2m} \right] \delta_{c_i, c_j} \tag{11}$$

where A_{ij} is the adjacency matrix, where i, j^{th} element denotes weight of the link from node j to node i (in our case it is the magnitude of delay propagation); k_i^{in} is the in-degree of the node i, k_j^{out} is out-degree of node j. The algorithm was developed using python, the code was verified by replicating results obtained by [65] and validated on the artificially generated airline data.

The final output of the Delay Network Algorithm is a set of delay networks (DN), which encode both significant delay propagation patterns and their root-causes. Once generated, delay networks can be then analysed by standard network theory metrics such as degree distributions, average path length, clustering etc., for which detailed description can be found in [62]. Application of network theoretic measures to our case is powerful because it enables airlines to understand the susceptibility of their operations to disruptions.

4. Case study: An international hub-and-spoke airline

4.1. Approach

We will now use the method introduced in the previous section in an in-depth case study. The aim of the case study is twofold: Firstly, to demonstrate the applicability of the method to the airline industry, utilising data that are commonly available in airline systems. Secondly, to draw results that can be applicable to

Algorithm 1 $dna(F, L)$ (Delay Network Algorithm)

$n \leftarrow \emptyset$
for each node $f \in F$ **do**
  if $\delta^{f}_{arr} > 0$ **then**
    $n \leftarrow n + f$ *% add node f to network n*
  end if
end for
for each link $v(f', f) \in L$ **do**
  if $\delta^{f',f}_{prop} > 0$ and $\delta^{f}_{dep} > 0$ **then**
    if f' not in n **then**
      $n \leftarrow n + f'$
    end if
    if f not in n **then**
      $n \leftarrow n + f$
    end if
    $n \leftarrow n + v(f', f)$ *% add directed link from f' to f to network n*
  end if
end for
$N \leftarrow findWeakConnComp(n)$ *% find weakly connected components*
$DN \leftarrow communityDetection(N)$ *% remove insignificant connections*
return DN

other hub-and-spoke airlines interested in understanding the delay propagation phenomenon. The airline under consideration is an international hub-and-spoke airline, operating short and long-haul flights from several airports including both domestic and international flights.

The case study makes use of data extracted by various software systems used by the anonymous case airline to manage its airline operations (fleet scheduling, crew management, passenger itineraries). The collected empirical, proprietary dataset covers six months worth of airline operations and includes flight, crew and passenger information. In total, we collected information for 96106 flights. The data is then used as an input to the method described in Section 3. The method is implemented in a software tool written in Python that automatically analyses the input data.

We report the results from applying the proposed method to the schedule of the airline under consideration in Section 4.3. More specifically, we first study the topological properties of the hub-and-spoke airline schedule to understand how it might affect network robustness. Then, we show how many flights are typically affected by propagating delays and the importance of considering all layers of connectivity in order to understand the impact of delays on airline schedule. Our analysis continues by measuring the impact of everyday delays on an airline schedule by proposing two metrics: root arrival delay and total caused arrival delay. Finally, we report which root-causes that have the highest impact and we suggest improvements.

4.2. Data input

We use flight data for aircraft (tail), crew and passengers along with some necessary operational parameters. More specifically, for each flight, the collected dataset includes information about the departure airport, arrival airport, flight number, tail number and aircraft type. Additionally, for each flight the scheduled time of departure, the actual time of departure, the scheduled time of arrival, and the actual time of arrival are reported. In case of a delay, a delay code —internal to an airline— for each flight is given. In practice, delay codes are used to report flight delays (primarily departure delays) and are collected by airlines of commercial flights after a delay takes place [67]. Delay codes reported by the case airline are related to passengers, airport capacity and resource allocation, turnaround time, weather and aircraft defects. For cases, where there are more than one delay code reported for a certain flight, we scale the impact proportionally to magnitude reported by the airline. For example, if it is reported that delay codes P1 and A3 are responsible for six and four minutes of delay respectively, then we will attribute 60% of downstream impact to P1 and 40% to A3.

Crew data includes information about what cabin and cockpit crew served which flight. In the dataset, crew members are recognised by anonymised crew ID numbers. For each crew ID number, the flights they served on in this six-month period is collected and identified by a flight number, the scheduled time of departure and arrival, departure airport and arrival airport. Passenger data is collected in the form of flight pairs passengers connect from and to, connection status and number of connecting passengers. For the flight that the passengers connect from we collect: flight number, arrival airport, scheduled and actual time of arrival. For the flight that the passengers connect to, we collect: flight number, departure airport, scheduled and actual departure time.

Other operational parameters are also collected. In particular, for each aircraft type and airport pair, minimum ground times for aircraft type and airport pairs is reported describing the minimum time, i.e. the time required to prepare an aircraft for its subsequent departure. Similarly, minimum passenger and crew connection times are also given. These describe the minimum time needed for passengers and crew to move between flights, respectively. The latter are independent from the airport for the case airline. Moreover, following airline policies, we define a connection as a situation when the same aircraft or crew member serves two consecutive flights or when a passenger flies on two consecutive flights within 24h.

The dataset was cleaned and any errors were removed. Specifically, we removed:

- instances of two consecutive flights with mismatching landing and take-off airports, i.e. the arrival airport of the first flight does not match with departure airport of the second flight;
- instances of two consecutive flights with violating landing and take-off times, i.e. the actual arrival time of the first flight is after the actual departure time of the second time;

Table 1: Topological characteristics of an airline schedule. T denotes transitivity, l average shortest path length, μ_k average node degree and their respective standard deviations σl and $\sigma\mu_k$.

Layer	L	T	l	σl	μ_k	$\sigma\mu_k$
Tail	94 006	0.0	61.68	59.26	1.95	0.21
Crew	57 937	0.0	14.66	12.15	1.21	1.79
Passenger	935 317	0.0	0.90	0.29	19.46	18.88
Aggregated	1 060 022	0.0	74.42	49.11	22.06	18.78

- crew and passenger connections, when these referred to a pair of flights that did not occur in the dataset.

4.3. Results

4.3.1. Topological characteristics of the airline schedule affecting robustness

As discussed earlier, network connectivity patterns play a significant role in defining network robustness. As a result, in this section we analyse topological properties of the multi-layer airline schedule network to discuss how it might affect potential delays. The collected data resulted in an airline schedule network with 96106 nodes (equal to the number of flights in the dataset) and $L = 1060022$ links for the aggregated network (showing a connection between two flights via tail and/or crew and/or passengers). The number of corresponding links per layer are reported in Table 1. The airline operates under a hub-and-spoke model, hence the vast amount of passenger connections is not surprising.

Table 1 presents transitivity T, average shortest path length l, and average node degree (μ_k) for aggregated and individual layers. Transitivity is defined as a property of the network, where given nodes v, u and w, if node v is connected to both nodes u and w, then relations between these nodes are transitive if u and w are also connected (also known as *clustering coefficient*). In simpler words, transitivity measures number of connected triangles in a network [62]. All layers have T equal to zero because of temporal and spatial characteristics of the network: i.e. given that there are already two connections between three flights, it is unlikely for a third connection to exist to form a triangle since the connection would not have matching airports[1]. The tail layer has a high l because a single aircraft is likely to operate multiple flights without a break longer than 24h to maximise the schedule utilisation. The average path length is lower for crew members since there are regulations in place to ensure that airline employees have sufficient rest time between flights. It is worth noting that despite long average path lengths the tail and crew layers have low average degree, which

[1] Given that there is a connection from flight A to B, and from flight A to C, it is unlikely for flights B and C to be connected and hence to form a triangle, since certain conditions would need to be met: 1) departure airport of flight C would need to be the same as arrival airport of flights A and B, while 2) departure airport of flight B needs to be the same as the arrival airport of flight A. There is only one possibility of that happening i.e. flight B has to depart and arrive at the same airport, while it still needs to arrive *before* flight C departs.

indicates that if the flight is delayed it can propagate only to few consecutive flights. Low l for a passenger layer is a result of "bursts" of connectivity during waves at the hub airport. However, we can observe high average degree, which indicates that passengers are likely to simultaneously connect to multiple flights. If all layers are aggregated, both average path length and average degree significantly increase. It creates a potential for delay propagation because it joins long paths but sparse connections of the tail and crew layers with short paths but dense connections of the passenger layer. It is worth nothing that standard deviations for l and μ_k are high for aggregated network and individual layers. There are two network properties contributing to this high variation of network statistics: 1) this is a hub-and-spoke network, where network connectivity patters will vary depending on whether tail/crew/passengers are connecting in the spoke, or in the hub, and 2) the network has a few large weakly connected components and a number of small sub-networks; for which these connectivity patterns differ.

We plot airline schedule network's degree distribution for individual and aggregated layers in Figure 3. Interestingly, the degree distribution of the airport schedule does not seem to exhibit power-law nor Poisson degree distribution. There are two clear peaks where one peak corresponds to the passenger layer, and the other to tail and crew connectivity. It is not surprising that there is a high overlap in degree distribution for crew and tail connectivity as these tend to often travel together in a hub-and-spoke operating model. Observed peaks indicate that the degree distribution of the airline schedule is bimodal. This observation was also statistically confirmed by the Hartigan's dip test, which returned a p-value less than 0.001. Theoretical considerations suggest that a bimodal degree distribution emerges when the optimisation objective is to increase robustness of networks to both random and targeted attacks [68, 69]. Hence, it suggests that airline schedule must also be robust against both targeted and random attacks. In the next section, we study how delay propagates on an airline schedule network in practice.

4.3.2. Dynamics of delay propagation

As described earlier, our method enables us to use airline schedule data to find delay propagation instances and their root-causes in a form of a delay network. We show that delay networks do not always exhibit a tree structure and in fact are better represented as an acyclic graph than a tree. This has significant implications because it is possible that there is more than one root-cause that resulted in delays propagating.

The Delay Network Algorithm identified 26308 delay networks, where 70.6% did not include delay propagation effects and 29.4% which included delay propagation. Out of all flights, 20% departed late because of delay propagation. In total, we counted 30526 connections causing delay propagation (denoted by $Lprop \in L$). We count a connection only once if delay propagation occurred across multiple layers. We can further separate those according to the connection type ($Lprop_x \in Lprop$). We can now use two metrics to

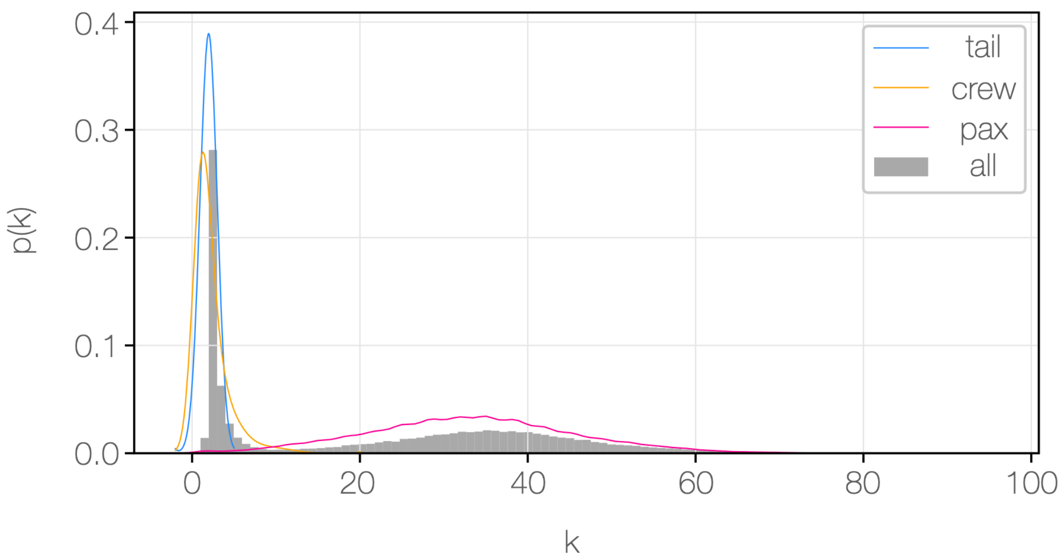


Figure 3: A degree distribution $P(k)$ of an aggregated airline schedule network and the individual layers. Tail, crew and pax distributions were estimated using Kernel Density Estimation with bandwidth = 1.

Table 2: Connection types causing delay propagation, where (x) is a connection type, $|L_x|$ is total # of connections, $\frac{|Lprop_x|}{|L_x|}$ corresponds to Metric 1 and $\frac{|Lprop_x|}{|Lprop|}$ to Metric 2

(x)	$\lvert L_x\rvert$	$\lvert Lprop_x\rvert$	$\frac{\lvert Lprop_x\rvert}{\lvert L_x\rvert}$ [%]	$\frac{\lvert Lprop_x\rvert}{\lvert Lprop\rvert}$ [%]
CM	38 833	7	0.0	0.0
T	67 398	6035	9.0	19.8
P	926 558	19 685	2.1	64.5
CM + T	18 474	4575	24.8	15.0
CM + P	625	0	0.0	0.0
T + P	8129	224	2.8	0.7
CM + T + P	5	0	0.0	0.0
Total	1 060 022	30 526		

study how the type of connection affects delay propagation: *i*) the probability that a particular connection type will cause delay propagation (i.e. $\frac{|Lprop_x|}{|L_x|}$); and *ii*) the probability that —when a delay propagates— it has a certain connection type (i.e. $\frac{|Lprop_x|}{|Lprop|}$). These two metrics are shown in Table 2.

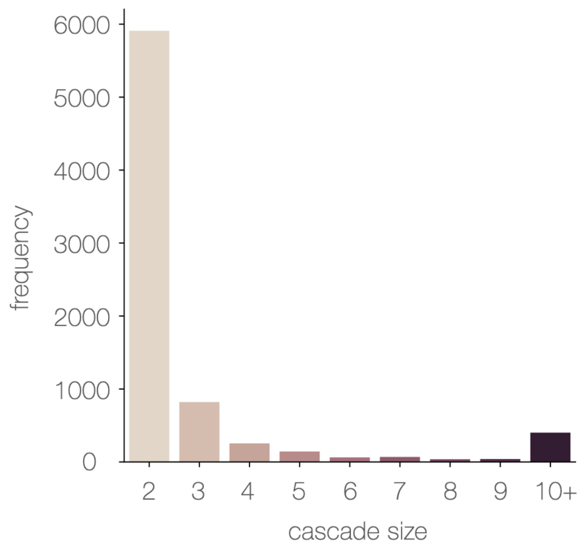
Looking at the results for Metric 1, one can see that when both tail and crew members are connecting the chance that a delay will propagate is the highest among other connection types (24.8%). Moreover, almost one in ten tail-only connections propagated a delay. For other connection types the chance of leading to delay propagation is relatively small, not exceeding 3%. This is not surprising for an airline operating a hub-and-spoke network. In practice, when an aircraft and crew members fly from hub to spoke they often return together to the hub. If a flight leaving the hub is delayed it is likely that this delay will affect the consecutive flight back to the base.

Interestingly, it is rarely the case that crew-only connections cause delay propagation, given how many such connections exist. This can be explained by hypothesising that usually when crew members connect to another flight without staying on the aircraft they do it in the hub. The hub for a hub-and-spoke airline plays the role of a crew base and possibly the airline has reserve crews available to cover when facing a delay. On the other hand, when crew members move between aircraft in the spoke, they most probably have longer connection times scheduled as opposed to when they stay on the aircraft to return to the hub.

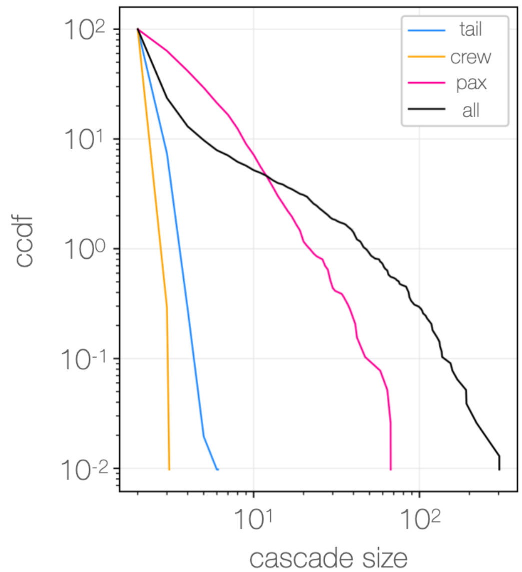
A first observation by looking at Metric 2 is that most delayed connections are due to passengers moving from one flight to another. This gives a first indication that these connections might be prone to delay propagation. Indeed, in absolute numbers, the number of passengers connections that cause delay propagation is significantly higher than another other type of connection. In fact, more than half of all delay propagation connections were of type passenger-only (64.5% in Metric 2). This is because connecting passengers is the essence of hub-and-spoke operations. This results in: *i*) a lot of passenger-only connections; and *ii*) unlike crew or tail connections, there are usually many passengers connecting between multiple flights during a single wave, resulting in a higher delay propagation potential when a flight is delayed. Additionally, Table 2 shows that one in five cases when delay propagated included a tail-only connection, and almost one in seven cases include crew and tail connecting together. This can be again explained by tail and crew members causing delay propagation to the flight coming back to the hub when connecting at the spoke. Moreover, while it is likely that the airline has reserve crew in the hub, it is less likely that there are reserve aircraft. This might explain why crew-only connections are less prone to delay propagation than tail-only connections.

Additionally, we are interested in estimating the impact that a single disruption has on the airline schedule. We found that among cases when delay propagation was triggered, in only 5% the delay propagated to 10 or more flights. To measure the impact of a delay propagating across consecutive flights we count the number of flight nodes present in the delay network, which we call a *cascade size*. Figure 4a shows a histogram of the cascade size.

The above results indicate that the airline is quite robust to disruptions, as suggested by the bimodal topology of the airline schedule network. However, if the system is stressed the effects of delay propagation can be significant. We found 22 cases of large delay networks, where number of affected flights exceeded 100. The large size of observed delay networks resembles a phenomenon called *cascading failures*, whose occurrence is a result of multiple failures of interlinked and dependent entities [70]. However, the impact of delay propagation was possible to be observed only when all airline schedule layers were aggregated. If we consider individual layers, delay propagation becomes underestimated and only a fraction of connections that enabled delays to propagate is visible. Moreover, we find that the passenger layer is crucial in understanding how delays propagate through the airline schedule. Without this layer the observed cascades do not reach



(a)



(b)

Figure 4: (a) a histogram of a number of consecutive flights delayed through delay propagation (including root flight), which is effectively a size of the delay network with aggregated layers; (b) a complementary cumulative distribution function (ccdf) of the cascade size across multiple layers.

sizes higher than 10 flights. We show this in Figure 4b, where we plot complementary cumulative distribution function of the cascade size for the aggregated schedule network and across multiple layers. This supports our findings from the previous section, since aggregation of all layers results in joining long but sparse connections of the tail and crew layers with short but dense connections of the passenger layer.

The biggest disruption we observed in the data was the severe weather condition in the hub airport. The severe weather persisted for a few days and created a large knock-on effect which was difficult to recover from and lasted for 12 days. This case is depicted in Figure 5, with different colours showing different delay networks. Each delay network encodes an arrival or a departure wave to and from the hub with the corresponding root-cause flights that were responsible for propagating the delay further. If the delay network was initiated by set of flights that were part of an arrival wave, they were usually delayed due to en-route delay since they were not able to land on time. Delay networks that were initiated by flights which were part of a departure wave, were stuck at the hub airport and the reason for their late departure is severe weather conditions at the hub. The first wave that was delayed is denoted by a yellow delay network on the left, the consecutive waves progressed from left to right. The severe weather incident lasted for four days, followed by a knock-on effect phase that lasted for eight days. The recovery phase is seen on the top-right side of the Figure 5, and connections between flights are visibly less dense.

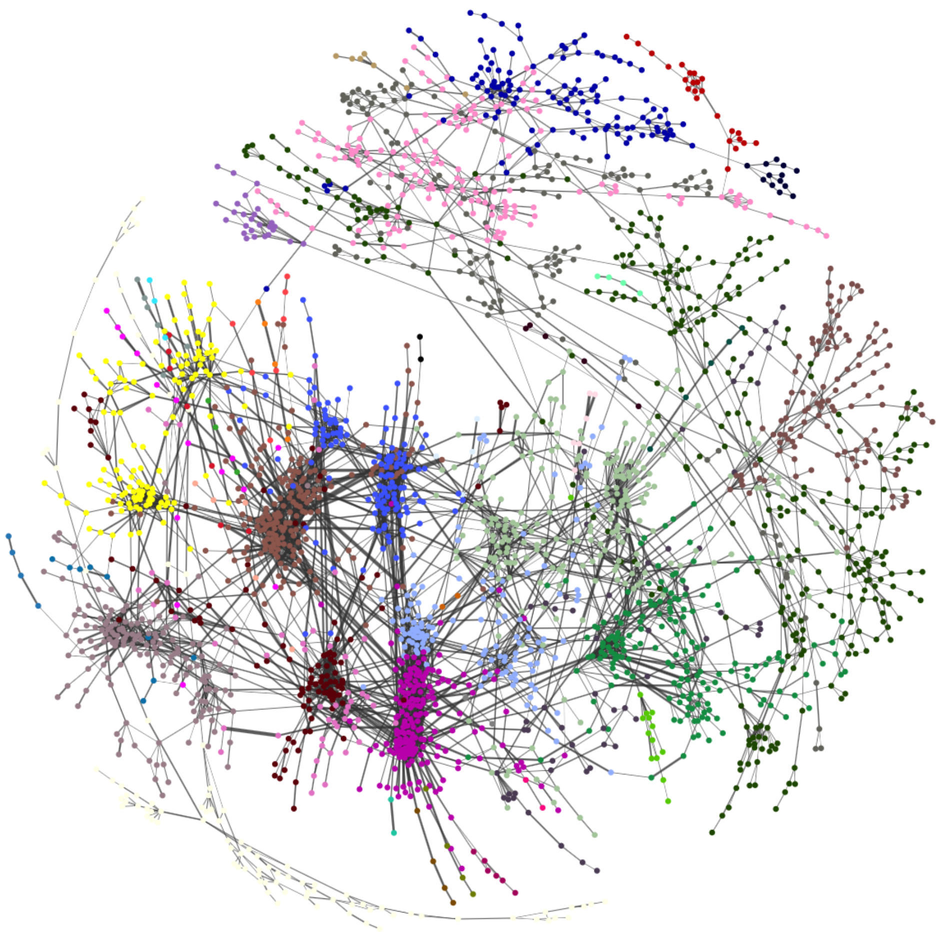


Figure 5: The largest disruption found and its 45 delay networks. The amount of delay that propagated is denoted by width of the link.

4.3.3. Absorption and amplification of root delays

We focus on everyday delays as they are usually the focus of an airline's operational disruption management efforts, compared to low-frequency, high-impact delays that are often managed more strategically.

We do this by looking at each delay network separately ($dn \in DN$) and we define a *root arrival delay* (δ_{rad}^{dn}), as the sum of arrival delays for flights that initiated delay propagation in a delay network dn (Equation 12).

$$\delta_{rad}^{dn} = \sum_{f_{dn}} \delta_{arr}^{f_{dn}} \cdot \alpha_{f_{dn}} \tag{12}$$

Here, f_{dn} is a flight that belongs to a delay network dn, $\alpha_{f_{dn}}$ is equal to 1 when flight f_{dn} has in-degree $k_{f_{dn}}^{in}$ equal to 0 within a delay network dn. Similarly, we denote the *total caused arrival delay* (δ_{tcad}^{dn}) as the sum of arrival delays for flights in a delay network dn that were delayed due to delay propagation

(Equation 13).

$$\delta_{tcad}^{dn} = \sum_{f_{dn}} \delta_{arr}^{f_{dn}} \cdot \beta_{f_{dn}} \tag{13}$$

Here, $\beta_{f_{dn}}$ is equal to 1 when flight f_{dn} has in-degree $k_{f_{dn}}^{in} \neq 0$. An interesting property emerges when we compare root arrival delay to total caused arrival delay. If δ_{tcad}^{dn} is greater than δ_{rad}^{dn}, it implies that the root arrival delay has been *amplified*. If δ_{tcad}^{dn} is less than δ_{rad}^{dn} it implies that the root arrival delay has been mainly *absorbed*. Figure 6 plots δ_{rad}^{dn} vs. δ_{tcad}^{dn}.

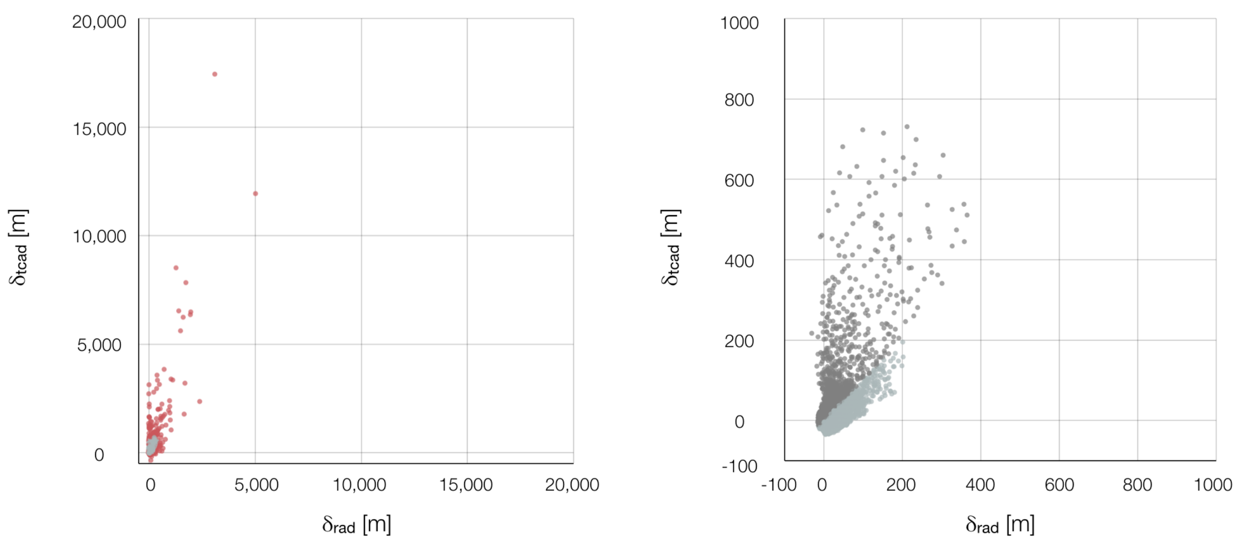


Figure 6: Root arrival delay for (δ_{rad}) plotted against total caused arrival delay (δ_{tcad}). The plot of the left includes all delay networks, where grey includes 95% and red indicates 5% networks identified as outliers by Local Outlier Factor method. The plot on the right zooms into those cases that are not outliers. Darker grey indicates amplified, lighter grey indicates absorbed delay propagation.

As our aim is to assess impact of everyday delays, we apply outlier detection on the network size to remove extreme cases. We do this using the Local Outlier Factor method [71, 72] as it is implemented in the *scikit-learn* library.[2] As extreme cases we understand situations when delay was significantly amplified (rare disruptions) and situations when airline recovered very well. We marked these as red points on the Figure 6, which counts for 5% of all networks. We found that for the airline under study, the majority of networks fall into the absorbed category. In fact, excluding outliers, these consist of 68.8% of all observations. The delay absorption can be caused by proactive and reactive approaches taken by the airline including: 1) scheduling enough ground and en-route slack, 2) aircraft speed-up during the flight, and 3) speed-up of ground operations. There are 31.2% observations which belong to the amplified category. This can relate

[2] `https://scikit-learn.org/stable/auto_examples/neighbors/plot_lof_outlier_detection.html`, $n\_neighbors = 100, contamination = 0.05$. These values were decided after experimentation and validation with industry experts.

to many problems including: 1) scheduling not enough ground slack between two flights, 2) joined impact of multiple root-causes occurring at the same time, and 3) root-causes creating other issues e.g. missing take-off slots.

We can look at both absorbed and amplified categories under four quadrants. The 1^{st} quadrant, where the positive δ_{rad} causes positive δ_{tcad} and this is the most frequent scenario. The 2^{nd} quadrant, where negative δ_{rad} causes positive δ_{tcad}, and means that even if the flight arrived early it still caused delay propagation to another flight. This is mainly caused when the Δ_{SGT} is less than Δ_{MGT} for a set of flights. Usually the scheduling phase would not allow this to occur. However, we noticed that the difference is often small and we hypothesise that a decision like this might have been made during the recovery phase in form of tail/crew swap as a necessity to mitigate delay of another flight. The 3^{rd} quadrant relates to the scenario when negative δ_{rad} causes negative δ_{tcad}, and might be explained similarly to 2^{nd} quadrant. Please note that for 3^{rd} quadrant it is possible that there are still some flights delayed, however the majority of flights arrived early. Finally, the 4^{th} quadrant implies that positive δ_{rad} causes negative δ_{tcad}. It relates to a case when airline recovery performed exceptionally well or schedule fully absorbed the delay, and resulted in flights being able to arrive before scheduled time.

Comparing δ_{rad} and δ_{tcad} reveals information about airline's schedule susceptibility to delay propagation. Robustness to delay propagation can be observed when the majority of cases fall into absorbed category and this is indeed the case for the airline under study. The more absorbed delays are closer to the centre of the plot, the more robust the airline schedule is to everyday disruptions. Moreover, we can infer the performance of airline recovery by looking at extreme values of δ_{rad} and δ_{tcad}. These are cases when the airline was exposed to difficult disruptions. High δ_{rad} resulting in high δ_{tcad} implies that the airline had problems to recover, and therefore a set of root-causes resulted in high delay propagation. And indeed we can observe this for the airline under study by looking at Figure 6. There are multiple high δ_{rad} corresponding to significantly high δ_{tcad}, implying lower recovery performance. However, whether better recovery solutions were possible at the time when airline was exposed to a disruption is an open question.

4.3.4. Causes and impact of root delays

We now turn our attention to root delays, i.e. those delays that initiate delay propagation in each delay network identified by our methodology. Each root delay can be linked to one or more delay codes captured by the airline, describing the reason or cause of this delay (as described in Section 4.2). Delay codes can be divided in different categories: related to airport capacity and resource allocation (A1–A7), passenger related (P1–P8), turnaround time related (T1–T3), weather related (W1), and aircraft defects (F1). Table 3 presents the twenty most frequent delay codes appearing in root delays, sorted by frequency. It also reports

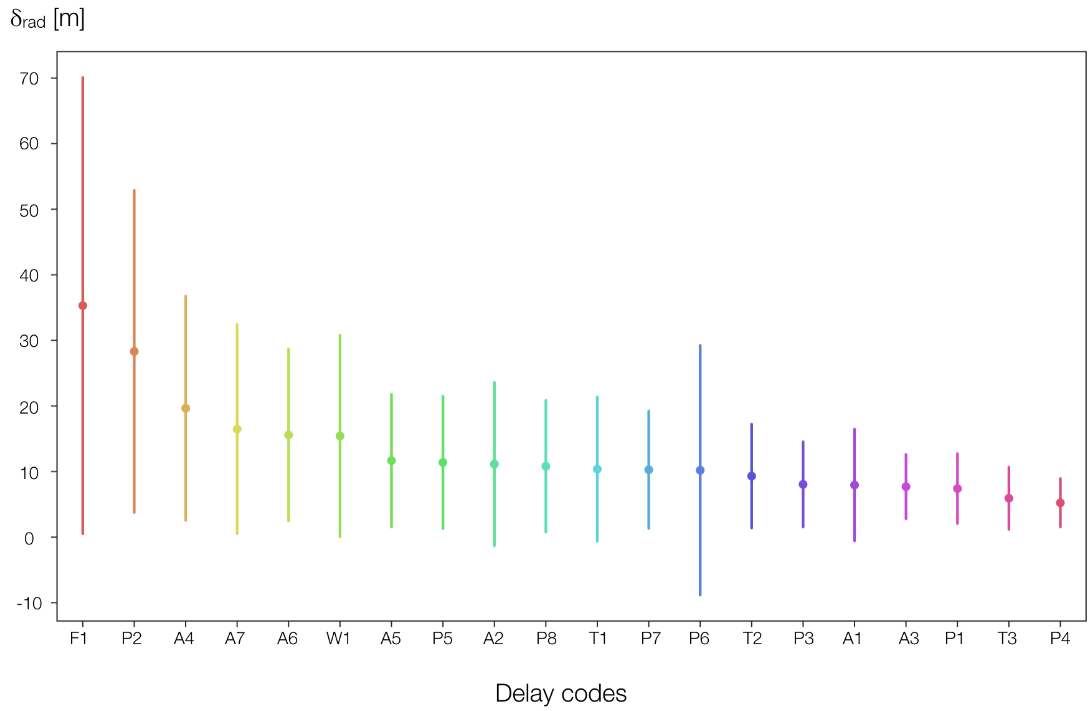
Table 3: Delays codes reported in root delays

DC	Meaning	Occurrences #	Occurrences %	Root airport Type	Root airport %
A1	awaiting pushback clearance	2507	25.15	Hub	92
A2	air-traffic control problems	1046	10.49	Hub	54
P1	offloading pax baggage	955	9.58	Hub	93
A3	airport runway congestion	445	4.46	Hub	98
P2	handling pax due to medical reasons	426	4.27	Hub	71
P4	reloading pax baggage after offloading was initiated	334	3.35	Hub	96
P3	late collection of excessive hand-baggage at gate	332	3.33	Hub	98
F1	aircraft defect requiring repair	311	3.12	Hub	69
T1	late completion of loading or unloading	216	2.17	Hub	80
A6	mandatory security check	208	2.09	Hub	85
P5	late collection of excessive hand-baggage at gate	174	1.75	Hub	99
W1	aircraft de-icing	146	1.46	Spoke	21
A4	awaiting towing clearance	136	1.36	Hub	100
T3	late completion of cabin security checks	121	1.21	Hub	81
A5	airport facilities failure or limitation	120	1.20	Hub	66
T2	difficulty in loading or unloading of ULD	118	1.18	Hub	86
A7	loading bridge or parking stands not available	102	1.02	Hub	81
P8	passenger special handling	87	0.87	Hub	80
P6	prolonged pax dis-embarkation on arrival	80	0.80	Hub	60
P7	passenger searching for missing property/document	78	0.78	Hub	91

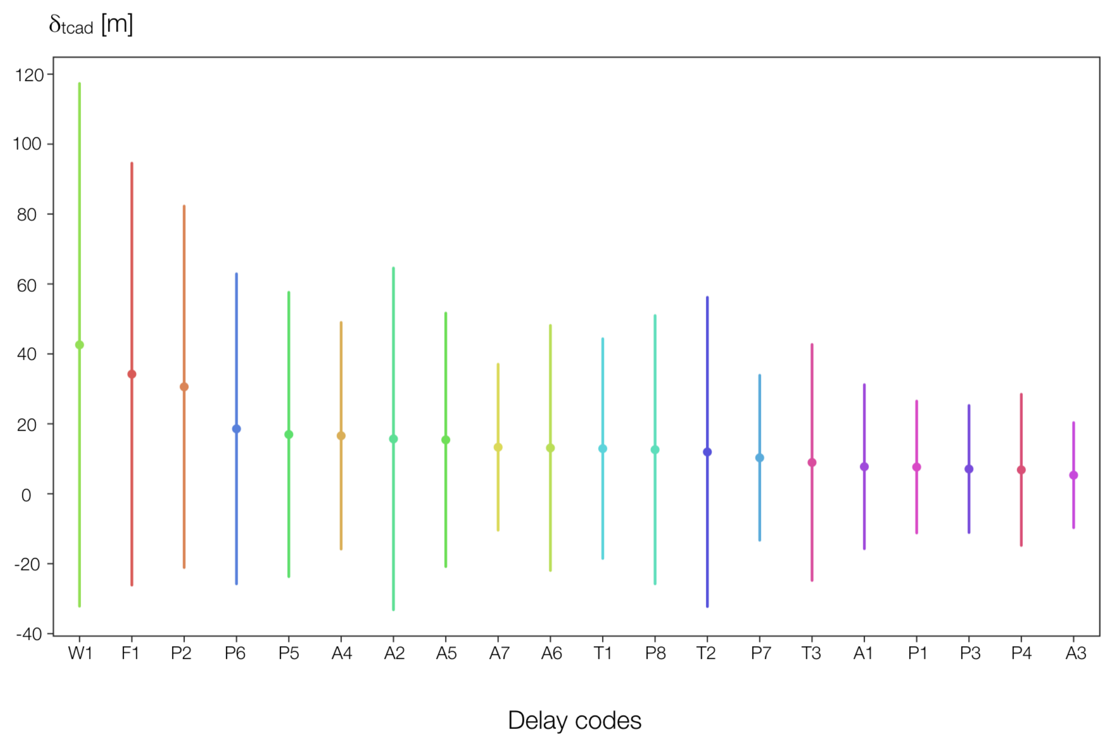
(in the last two columns) the airport that the particular delay code appears most frequently in –differentiating between the hub and a particular spoke— along with that frequency.

Looking at the most frequent delay codes we can observe that the majority of incidents are related to airport capacity and resource allocation issues. This includes runway congestion, awaiting pushback/towing clearance, slot allocation problems, and airport facilities failure or limitation. More than 75% of these problems originate from the hub, and might come from high hub congestion. Another large group of delays is related to passengers, where more than 80% of delays within this group originate from the hub. Delay codes point to the problems with late passengers and baggage processing issues. Since the airline operates a hub-and-spoke network this type of delay might have different reasons: error-prone luggage processing at the hub airport, complex terminal layout that makes it difficult for passengers to effectively travel from arrival to departure gates, or gate allocation that results in long distances that need to be travelled by passengers between connecting flights. Additionally, only the aircraft de-icing delay code did not appear most frequently to originate from the hub but from a specific spoke. Around 21% of de-icing comes from a specific airport and it is not surprising that is a frequent root delay code since our dataset included winter months.

We assessed the impact of each delay code through the root arrival delay (δ_{rad}) and total caused arrival delay (δ_{tcad}) for each root delay code (presented in Figure 7). The highest root arrival delay have aircraft technical failure (F1), handling passenger due to medical reasons (P2), air traffic control problems (A4),



(a) root arrival delay mean ($\overline{\delta_{rad}}$) and standard deviation ($\sigma_{\delta_{rad}}$)



(b) total caused arrival delay mean ($\overline{\delta_{tcad}}$) and standard deviation ($\sigma_{\delta_{tcad}}$)

Figure 7: Bar plots showing the mean and standard deviation in a) root arrival delay and b) total caused arrival delay.

loading bridge or parking stands not available (A7), and mandatory security checks (A6). The highest total caused arrival delay have aircraft de-icing (W1), aircraft technical failure (F1), handling passenger due to medical reasons (P2), prolonged passenger dis-embarkation on arrival (P6), and late collection of excessive hand-baggage at gate (P5).

From the graphs, we can make two important points. Firstly, the highest root arrival delay and one of the highest total caused arrival delay is caused by the aircraft technical failures. This is not surprising because when an aircraft breaks down it is expected to have high implications on the schedule. It also highlights the importance of maintenance and repair practices adopted by airlines. Secondly, a high root arrival delay does not imply that the delay will propagate significantly to other flights. For example, prolonged passenger dis-embarkation does not have the highest magnitude, however it often causes high delay propagation. This results from the fact that it might cause further delays even when the aircraft has landed on time, and it does not give the airline time to react. As a result of the above, an airline needs to look at both measures when prioritising their delay management efforts.

5. Conclusions and Implications

5.1. Implications for research

In this paper, we propose a novel data-driven method to study robustness of an air transportation system. The method makes uses of a novel *multi-layer airline schedule network* and enables us to discuss potential and empirical susceptibility of the hub-and-spoke airline schedule to delay propagation, and pinpoint root-causes of delays in the airline under study. An important contribution of this work is that it empirically demonstrates the value of incorporating extra layers of information for the analysis of delay propagation. We observed that all the layers of the schedule network need to be considered in order to have a better visibility over delay propagation. Unlike previous studies that indicate that the aggregation of consecutive layers is an oversimplification [44, 43, 45, 46], in our case it is a necessity. Without the passenger layer, the size of delay networks is relatively small and cascading failure effect is not visible. Hence, understanding the full extent of delay propagation is only possible by aggregating all layers.

Applying our method to empirical data enables us to recreate delay propagation patterns for the hub-and-spoke airline. Generally, the airline schedule is robust to everyday delays. However, there are extreme cases indicating there is a threshold after which the network 'collapses' and it is hard to recover, which resembles a phenomenon of *cascading failures* [70]. This phenomenon happens rarely but has a surprisingly large impact [73], and has been observed in a number of systems [74, 75], including other logistics transportation systems [76, 34], and supply networks [77], Moreover, we find that it is not uncommon for delays to "spill over" to the next day in a large hub-and-spoke airline because there is not clear sense of day and night when the airline operates globally. In fact, we show an example of a severe weather disruption that lasted for days.

We show that the delay propagates in a pattern that does not necessarily resemble trees [10], but rather an acyclic graph. This is an important observation because it shows that there might be more than a single root-delay causing delay propagation. Our results show that the majority of root-causes come from the hub, contrary to previous research [44]. Even though a large number of delays are absorbed by the airline network, our results indicate that about one in three delays are amplified as they propagate to other flights. Moreover, our results partially support statements that passengers and crew members are the main driver of delay propagation [10, 25]. We found that indeed, passengers play a significant role in causing delay propagation. However, crew members do not, unless they stay with the aircraft.

Our topological analysis of the multi-layer airline schedule network revealed that it has a bimodal degree distribution. The bimodality comes from two observed peaks: the first resulting from crew and tail connectivity, and the second resulting from passenger connections. Theoretical studies suggest that a network like this emerges as a result of optimisation and is robust to both random and targeted attacks [69, 68]. The topology of this airline schedule network differs from what has already been observed for other types of air transportation topologies [15, 38]. Airlines use tools to optimise the schedule, which explains why network topology of their schedule is theoretically very robust. However, some of the degree distribution characteristics are likely to be a result of an emergence —due to aspects that cannot be controlled by the airline such as delays and passenger bookings— rather than explicit optimisation efforts. Additionally, we find that tail and crew layers have high average path length and low average degree, whereas passenger layer has low average path length and high average degree. This is an important observation because using our method that aggregates all layers results in a topology that has both metrics high and might be an indication of higher delay propagation potential.

Finally, we note that the results of this study can be of interest to the stream of literature examining the delay propagation phenomenon in other types of logistics and transport networks (e.g. railway systems [78], urban public transport [76], maritime logistics [79] and intermodal logistics [80]. For example, we believe that the multi-layer schedule network approach introduced here can be used in other networks to identify patterns, such as cascading failures, that are not visible via a single layer only. Note, however, that unlike air travel, modes of transport such as trains, buses and ferries do not often wait for passengers to arrive and therefore delays are likely to not propagate a lot via passenger connections. On the other hand, freight transport networks that move inventory from one means of transport to another (e.g. cross docking, intermodal transport) could potentially benefit from replacing the passenger layer of information with a 'freight' one [81].

5.2. Implications for management practice

From a managerial perspective, this study aims to support decisions around airline and airport resource management by enabling airlines to have better awareness of the state of their operations and of the causes and impact of their disruptions. As such, a significant implication of this study for management practice lies with the method proposed here that provides a diagnostic tool utilising post-operations data to examine delay propagation. As similar data are very likely to be collected by software systems used in practice by airline companies, and considering the high levels of automation the method can provide, the method can easily be incorporated into a software data analysis tool that can be used by practitioners for the analysis of their own operations. Analysing large operational datasets including complicated cases, such as the big delay networks presented earlier, can be difficult due to the large number of flights involved; tracking manually every single flight to investigate what happened would be a very labour-intensive process. Moreover, due to the mathematical formalisation of the data input, the method can be easily adapted to the needs of practitioners. For example, the conditions of Section 3.2 can easily be adapted to analyse flights experiencing longer/shorter delays to examine different levels of on 'on-time performance'. Even though the method's full potential is achieved by incorporating different layers of information, it can still provide insightful results if applied to fewer (or even a single) layers. This can be used, for example, to benchmark the operations of a competitor airline using publicly available tail data or to assess the value of each layer in understanding their own operations.

This study demonstrates that when measuring impact of delays on airline operations, both the magnitude of the delay and its knock-on effects on other flights need to be considered to improve awareness. We showed that the airline under study experienced certain delays that did not have the highest magnitude, but did cause significant delay propagation. This can be associated with the very nature of the cause of the delay itself. For example, delays caused by aircraft de-icing are likely to happen early in the morning, hence there is a higher chance of delays propagating to other flights. Another example is when prolonged passenger dis-embarkation on arrival in the hub causes big delay propagation as the airline has limited options to mitigate the delay at that point of time and passengers are likely to connect to multiple other flights.

There are also findings that, even though they are subject to the characteristics of the case airline, can be applied elsewhere, too. Firstly, we found that the majority of irregularity root-causes come from the hub, therefore improving the processes at the hub will lead to significant efficiency gains. Secondly, multiple delays propagate due to passenger connections so improving airport and airline processes related to passenger connections (e.g. passenger and baggage tracking, smart guidance systems) is expected to reduce the impact of delay propagation. Thirdly, when it comes to root-causes of both high frequency and magnitude, our analysis revealed that they concern aircraft technical issues, thus highlighting the importance of effective maintenance and repair. Finally, we observed the impact of certain root-causes that are affecting multiple airline and airport functional areas simultaneously, while at the same time being hard to predict (e.g. severe weather, terrorist threats or union strike actions). An improvement in disruption prediction and recovery capabilities can prepare an airline to deal more efficiently with extreme events, and this might include avoiding network bottlenecks, such as airports and airspace, that can further propagate a delay.

5.3. Limitations and future research

Even though the method introduced here is airline-agnostic, some of the results of this study are, to a certain extent, drawn by the operational characteristics of the case airline. Nevertheless, due to the operational similarities among airlines, we believe that the results (and certainly the proposed methodology) can apply to other operators, especially those using hub-and-spoke networks which are still predominant in industry [18]. In the future, examining different types of airline networks, including those formed by airline alliances, or those for which only public data (such as commercial flight tracking information) are available, could shed more light on the issue of delay propagation. Methodologically, the approach proposed here is a deterministic one, relying on actual data rather than estimations. In practice this is unlikely to be a problem as all data used as an input is collected and stored by airlines. Even when one wishes to study the operations of another airline (e.g. a competitor), the method allows for sensitivity analyses under different estimations for proprietary data such as minimum turnaround times. Future research could look into stochastic version of the approach incorporating estimation intervals or probabilistic values.

Two existing algorithms used in this paper also pose some limitations. Firstly, the community detection algorithm used for the detection of root-causes has its own limitations as it cannot guarantee the identification of the absolute true root-cause. Nevertheless, in practice, the information about whether a certain delay was indeed the root-cause of other delays in the network is not known by any stakeholder. As a result, the best practitioners and academics can aim for is a well-informed proposition drawn by carefully examining historical data and compare plan versus actual. Secondly, the outlier detection algorithm used to prevent unnecessary skewness of the results due to rare disruptions needs to be parameterised by the user based on their own expertise and goals. In practice, this is likely to be done via experimentation and discussion with practitioners. However, the method presented here is flexible enough to allow for other outlier detection algorithms to be used or to be avoided completely as necessary.

In this study, the impact of delay propagation is measured by looking at the number of flights affected and the duration of their delays. Future research can propose different ways to measure the impact of delay propagation introducing monetary metrics that take into account several operational and business model factors such as the number and class of passengers affected, the airport flying from or to, the availability of spare aircraft and crew. The method introduced in this study can also be further extended to enable the prediction (instead of the analysis) of delays as they propagate in a network and be used as a decision support tool on the day of operation.

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