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Managing airlines: the cost of complexity

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Abstract

This paper is dedicated to the structure of airline networks as a sink of efficient airline operations. Parameters of complexity were derived and mirrored on level of service as well as efficiency parameters. Airlines usually consider an operational overhead to predict the total flight operation cost. This parameter includes the expected cost for disruptions and delays. When an airline has to mobilize an aircraft in a base for recovering the service or for breaking an emergent dynamic, then it is running extra costs. The cost of managing complexity in the airline industry has a direct impact on profit and loss account. Therefore, this paper presents an integrated approach to evaluate this cost, based on padding and aircrafts dedicated to recover disruptions. Finally, some additional indicators are derived to evaluate reliability improvement as part of complex performance.

Keywords: Airline, network, cost, complexity, reliability, delay, propagation, performance.

1. Introduction

Complex systems have always existed, but complexity has gone from something found mainly in large systems, such as cities, to something that affects a lot of common things and organizations. Systems that used to be separate are now interconnected and interdependent, which means more complexity in many cases. Furthermore, technology revolution has been a factor to increase level of complexity.

Complex organizations are far more difficult to manage than merely complicated ones. It is harder to predict what will happen, because complex systems interact in unexpected ways. Also, it is harder to make sense of things,

because the degree of complexity may lie beyond cognitive limits. And it is harder to place bets, because the past behavior of a complex system may not predict its future behavior. In a complex system the outlier is often more relevant than the average.

On one hand, complicated systems have many dynamic components, but they operate in patterned ways. It is possible to make accurate predictions about how a complicated system will behave. For example, flying a commercial airplane involves complicated but predictable steps. On the other hand, complex systems, in contrast, are imbued with features that may operate in patterned ways but whose interactions are continually changing.

Three properties determine the complexity of an environment. The first, multiplicity, refers to the number of potentially interacting elements. The second, interdependence, relates to how connected those elements are. The third, diversity, has to do with the degree of their heterogeneity.

It is possible to understand both simple and complicated systems by identifying and modeling the relations between the components of the network; the relations can be reduced to clear, predictable interactions. It is not possible to understand complex systems in this way, because all the elements are interacting continuously and unpredictably.

This chapter aims to develop an analysis of the airline network from the point of view of complexity science. It is structured in three sections. The first includes an introduction to complex theory and its applications to airline industry. The second section addresses a network analysis by applying complexity indices is presented. Finally, a methodology of reliability estimation and cost associated to delay propagation is developed.

The main objective of this paper is to describe a network in terms of complexity and to estimate the cost of managing this complexity. Based on the overall objective more specific objectives are addressed:

- To propose a set of indices to describe airline network complexity based on previous works.
- To apply these indices to a real airline network and derivate network properties.
- To understand the reliability of network in terms of delay propagation and estimate the cost.

2. State of the art

Network analysis has a long history in operations research and quantitative social science research, where the spatial configuration of networks was put in the center of empirical investigation. It appears that in the past decades many social, spatial and economic systems show an organized pattern characterized by network features, such as transportation, telecommunication, information or energy systems. As a consequence, much attention has recently been paid to the study of network properties emerging in many social, spatial and economic fields, as witnessed by the vast amount of literature published in the past years (Barthélemy, 2003; Gorman and Kulkarny, 2004; Reggiani and Nijkamp, 2006).

Air transport shows indeed clear network features, which impact on the way single airline carriers operate (Button et al., 2000). The abundant scientific literature on airline networks has addressed this topic in terms of theoretical modeling and empirical measurements on different typologies of airline network configurations. This strand of recent research aimed to measure the network structure in relation to the new trends in airline business strategies denoted as ‘low cost’ principles. Low cost carriers developed rather fast after the deregulation policy, by acquiring a competitive network advantage on traditional airlines, which consequently seemed to reorganize rapidly their airline network to respond to the new market dynamics.

In this context, research has emerged that mainly addressed the issue of describing and classifying networks by means of geographical concentration indices of traffic or flight frequency (Caves et al., 1984; Toh and Higgins, 1985; Reynolds-Feighan, 1994, 2001). These measures, such as the Gini concentration index (Gini, 1912) or the Theil index, provide a proper measure of frequency or traffic concentration of the main airports in a simple and well-organized network. However, if a real-world network structure is complex, including multi-hub or mixed point-to-point and hub-spokes connections, the concentration indices may record high values for all types of structure, but fail to clearly discriminate between different network shapes (Alderighi et al., 2007). There is a need for a more appropriate measurement of connectivity structures in complex networks.

However, indices derivated from spatial network analysis are static and often a dynamic perspective of network is necessary. One of the main problems in the field of airline management is delay propagation. Delays have a strong impact on operational reliability and these impacts directly on profit and loss account and passenger experience.

Delay propagation is the result of different factors, including the lack of coordination of airline flight schedules, finely tuned airline flight schedules with little slack to dampen delay propagation, high levels of congestion preventing re-accommodation of delayed flights, or high aircraft load factors preventing timely re-accommodation of passengers who misconnect or whose flights are cancelled. All delay causes combined create passenger disruptions and lengthy passenger waiting times that create new flight delays.

According to Eurocontrol (2014) there were 1.7% more flights per day in the reference area than in 2013. However, data received directly from airlines by CODA describing delays from all-causes illustrated a stable situation for the network during the year. First, the average delay per delayed (ADD) flight of 26 minutes per flight; this was a small decrease of 2.6% compared to 2013 where the ADD was 26.7 minutes. Second, this small improvement was offset by a small increase of 1.3% to 37.4% of flights delayed on departure (≥ 5 minutes). Third, the share of reactionary delay was 44% of delay minutes reported compared to 45% in 2013. Finally, regarding arrival delay, the average delay per delayed flight on arrival from all-causes was 27.2 minutes per flight in 2014. Then, the percentage of delayed flights increased by 0.7% to 34.3% and operational cancellations remained stable at 1.5% of planned flights.

Delays cause immense losses to the Air Traffic System, a situation that will worsen in the near future if traffic increases. Models and methods allowing stakeholders to characterize mechanisms behind delay propagation, to forecast network congestion, and to optimize planning and operational practices to mitigate delays are thus of great relevance.

Researchers who have been studying the performance of ATM have done a significant effort to identify the causes for initial or primary delays (Rupp, 2007). These primary delays can in turn trigger a cascade of secondary delays as was noted in (Beatty et al., 1999; Jetzki, 2009) by the introduction of a ripple effect. Because of the inherent complexity of the mechanisms that produce and boost delay spreading, different modeling techniques were proposed. A first line of research focused on simulating the air traffic system as a network of queues without considering information on aircraft schedules (Schaefer and Miller, 2001). A second line of research was devoted to analytical approximations for modeling the airport as a dynamic queuing system with varying demand and service rate (Malone, 1995). Another analytical queuing model was used in (Pyrgiotis et al., 2013). In this work, airports were modeled as dynamic queues and implemented in a network. The authors ran the model in a network of 34 airports with a specific algorithm that accounts for downstream propagation of delays. An additional body of work uses statistical tools to predict the delay patterns observed in the data. Such techniques could be classified into traditional linear regression models (Churchill et al., 2007), artificial neural networks (Sridhar et al., 2009) and Bayesian networks (Xu et al., 2005).

Deutschmann (2012) proposes a method to predict off-block delays based on assumptions of non-linear physics and knowledge of airport dynamic characteristics, applying this method to several US airports. Later, the author (Deutschmann, 2013) carried out an analysis and development of models to understand the airport as a dynamic system, applying the concept of harmonic oscillating system.

Trapote-Barreira (2015) proposes a complete analysis of airline network configuration, integrating static perspective through a set of complex indices and dynamic perspective with a delay propagation algorithm. This work is the foundation of this paper.

Technologically driven transport systems are characterized by a networked structure connecting operation centers and by dynamics ruled by pre-established schedules. Schedules impose serious constraints on the timing of the operations; they condition the allocation of resources and define a baseline to assess system performance. Technical, operational or meteorological issues affecting some flights give rise to primary delays. When operations continue, such delays can propagate, magnify and eventually involve a significant part of the network. Metrics have been defined to quantify the level of network congestion. The results indicate that there is a non-negligible risk of systemic instability even under normal operating conditions. Passenger and crew connectivity were also identified as the most relevant internal factor contributing to delay spreading.

3. Analysis of network complexity

This section aims to investigate the scientific potential and applicability of a series of network connectivity and concentration indices, in order to properly typify and map out complex airline network configurations. Specifically, several network indicators will be adopted and tested to describe the main properties of airline systems.

The goals of this section are further: first, to detect the extent to which the real network configuration is close to typical network models that evolved over time and, secondly, to examine how concentration measures can point to the different network topologies.

Many economic activities are currently characterized by network characteristics with a high degree of complexity, since their processes and outcomes depend not only on the choices of the single agents but also on the dynamic – often nonlinear – interactions between them in a continuous dynamic environment (Reggiani and Nijkamp, 2006). A clear example of a complex spatial-economic network is the geographical network of the air transport industry: understanding its peculiarities and responding to these features can bring about substantial advantages for both consumers and producers (Button and Stough, 2000). The focus of this work is not the whole air transport industry; really, it is focused on one airline and how indices can provide information for decision-making processes.

Modeling complex networks is also a great challenge: on one side, the topology of the network is governing the complex connectivity dynamics; on the other side, the functional-economic relationships in such networks might also depend on the type of connectivity structure. The understanding of these two interlinked network aspects may be instrumental for capturing and analyzing airline network patterns.

The analysis and representation of complex systems as complex networks has been a growing trend in the last years (Strogatz, 2001). However, one of the most relevant contributions was done by Gini (1912) at the beginning of last century. Moreover, complex networks have been crucial in order to understand many emergent phenomena in systems with a large number of interacting actors. Such formalism has been successfully applied to the study of many transportation systems: railways (Kurant and Thiran, 2006), subways (Latora and Marchiori, 2002) and air transport (Zanin and Lillo, 2013).

There are some standard metrics that are usually considered when a network has to be characterized and some of them are presented in following subsections. Also, the paper presents an empirical and short case study, applying indices of complexity to real data. Due to an agreement of confidentiality the identity of these airlines are not revealed. Then, Airline 1 is a short-medium haul low cost carrier; and it is a small and start-up project. This airline manages a point-to-point network, but very concentrated in three bases around Europe. It is operating more than 300 flights in one week and more than 60 airports. For this reason, the number of flights for one day is large but not comparable with number of flights that airline 2 manages. Airline 2 is a large low cost carrier, focused on short and medium haul, and one of the most important LCC in Europe. It manages more than 180 airports (more than 70 bases) and more than 2,000 relations each day.

3.1. Indices of complexity

Airline networks may exhibit simple or complex topologies. Networks have been given several definitions in the framework of graph theory. In this context it is useful to outline some indicators most frequently used to represent the network shape (Barrat et al., 2004). Table 1 synthesizes a set of indices of complexity.

Figure 1 shows the degree index and strength index for airline 1 and Figure 2 shows them for airline 2. The level of concentration is higher than concentration of airline 1 and it is due to the fact that airline 2 dominates some markets and it supplies high frequencies in some routes very profitable.

It is not surprising that both low cost airlines show distributions relatively concentrated despite of the fact they manage routes point to point. First of all, from a business point of view, airlines have the need to concentrate main operations in a few bases because it is easier to control the cost. Furthermore, it is easier to give reliability to the network. Second, one of the critical aspects it is to not provide connections for passengers, this issue allows managers to not transfer delays in connection times. In practice, low cost airlines manage the best indices of punctuality.

Table 1. Indices of complexity.

Indicator	Equation	Definition
Degree Index (Barrat et al., 2004)	$k_i = \sum_j a_{ij}$	Measure of centrality, level of connectivity of each node in terms of links (adjacency matrix). Matrix of incidence, $A=\{a_{ij}\}$ for $i, j = 1 \dots n$.
Strength Index (Barrat et al., 2004)	$s_i = \sum_j w_{ij} a_{ij}$	Measures connectivity of each node in terms of flights (weight w_{ij} for relation a_{ij}).
Vertex Degree Index (Candarelli, 2007)	$P(k) = \frac{N(k)}{n}$	Measures connectivity in terms of probability of finding nodes with k links. $N(k)$ is the number of airports with k connections.
Cluster Coefficient (Kaiser, 2008)	$C_i = \frac{E_i}{k_i(k_i - 1)}$	Gives information about the spatial structure and depends on number of triangles in the network.
Average Nearest-neighbors Degree (Barrat et al., 2004)	$k_{nn,i} = \frac{1}{k_i} \sum_j k_j$	Gives information about correlation of the degrees of connected nodes (nodes with high degree tend to connect with high degree nodes).
Weighted Average Nearest-neighbors Degree (Barrat et al., 2004)	$k_{nn,i}^w = \frac{1}{s_i} \sum_j A_{ij} w_{ij} k_j$	Idem, with weights related to flights.
Gini Index (Gini, 1912; Cento, 2006)	$G = \frac{\sum_i \sum_j f_i - f_j }{2n \sum_i f_i}$	Measures geographical concentration of flights

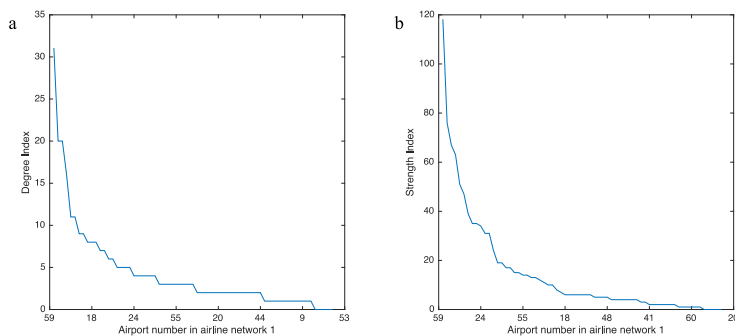


Fig. 1. (a) degree index; (b) strength index for Airline 1.

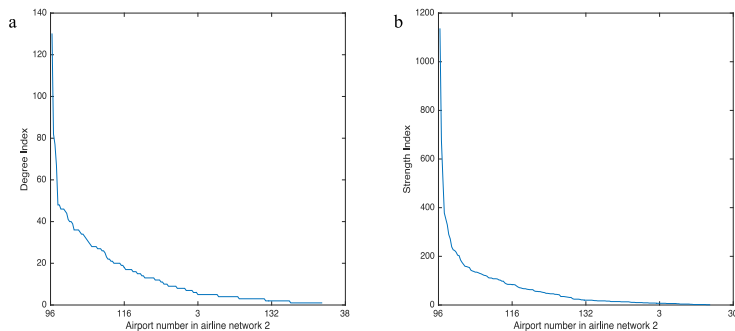


Fig. 2. (a) degree index; (b) strength index for Airline 2.

Cluster coefficients are more interesting for this analysis and comparatively; airline 1 presents a distribution with fewer tendencies to clusterization. The main reason is that this airline manages only a few bases around Europe and less flights than airline 2. With density and radial configurations, these networks tend to create clusters.

Network degree distribution and average nearest-neighbors degree for airline 1 and 2 are presented in Trapote-Barreira (2015). Summarizing, network degree distribution shows an asymmetric level of supply and spatial distribution, especially for large airlines (this fact can be related with the schedule design), and average nearest-neighbors degree allows recognized patterns of concentration much more important for airline 2 than airline 1.

Gini index has been calculated for both airlines, being $G_1=0.6310$ and $G_2=0.6422$. Taking into consideration that they are low cost airlines with point-to-point configurations, the level of concentration is very important. This fact highlights the conclusion that if low cost and point-to-point airlines manage better levels of reliability is due to the fact of not providing connections at their main bases.

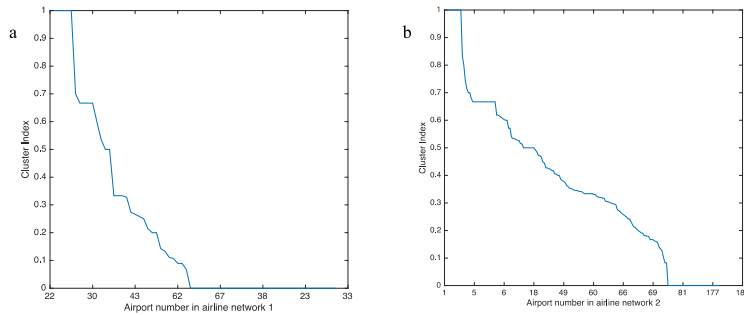


Fig. 3. (a) cluster index for Airline 1; (b) cluster index for Airline 2.

4. Evaluation of operating cost related to improved reliability

Indices of complexity allow understanding the network at strategic level. However, they are a static perspective that cannot be applied to understand the dynamic performance of the operation. For this reason, this section presents an algorithm to control airline planning and to manage delay propagation, taking into consideration the cost of reliability in the operational field.

4.1. Problem statement

Consider a flight scheduling and aircraft routing. This is the basis for a propagation tree scheme. Delays, in this model, follow statistical distributions. First, flight time can present an average delay μ_F , given in minutes per one hour of flight, and a statistical deviation σ_F , considering $N(\mu_F, \sigma_F)=N(1.78, 3.30)$, given in minutes per one hour of flight. Second, turnaround time can be delayed in the same way, with average delay μ_G per one hour of ground time and σ_G statistical deviation, $N(\mu_G, \sigma_G)=N(2.32, 3.43)$ in minutes per hour. This basic assumption improves simplicity and it is consistent from a conceptual point of view.

Airlines can plan or test their flight schedules with characteristic flight and turnaround times (Eq. 1, 2). Where k is the parameter of reliability that they want to consider to hedge their operation. Finally, these expressions are transformed to other ones more useful (involving characteristic delays of design φ, ρ).

$$\hat{t}_F = t_F(1 + \mu_F + k\sigma_F) \rightarrow \hat{t}_F = t_F(1 + \varphi) \quad (1)$$

$$\hat{t}_G = t_G(1 + \mu_G + k\sigma_G) \rightarrow \hat{t}_G = t_G(1 + \rho) \quad (2)$$

Airports and airlines have the possibility to reduce a certain amount of delays due to some operational actors. However, this work does not consider this aspect, so the propagation is considered inelastic through the same route.

Furthermore, if the airport is congested, it can transfer delays. This transferability is modeled with a parameter that depends on level of utilization of the airport and hubbing practices of the airline. Airline network configuration is a key aspect to understand delays propagation.

A flight scheduling is considered (FS), which is planning taking the flight time between two scheduled airports and the turnaround time into account. When delays appear, this FS is degenerated to FS', which is the timetable after the perturbation. Airline has the option to design a flight schedule FS* with padding to be reliable in front delay propagation.

Figure 4 shows this concept, where a continuous line (SDT_i, SAT_i) is original FS. The series of the discontinuous line (SDT'_i, SAT'_i) represents FS'. Finally, airline plans FS* that is represented by a line of dots (SDT*_i, SAT*_i).

FS* can be the same flight schedule with departure and arrival time adjusted to new conditions or it can be designed *ad hoc*. This work considers the adjusted version that consists on introducing extra time for flight time and turnaround time to absorb mean values of delays and one or more times the standard deviation. Then, these rules are characterized by Equations 1 and 2, where parameter K decides the level of coverage that airline wants to have and it results in different values of φ and ρ . It is not allowed any value of K because fleet is constrained.

Second, a set of routes $R = \{r_j\}$ are considered and it is related to first assignment done for a flight schedule, where each route r_j contains a sequence of flights that are served by the same plane.

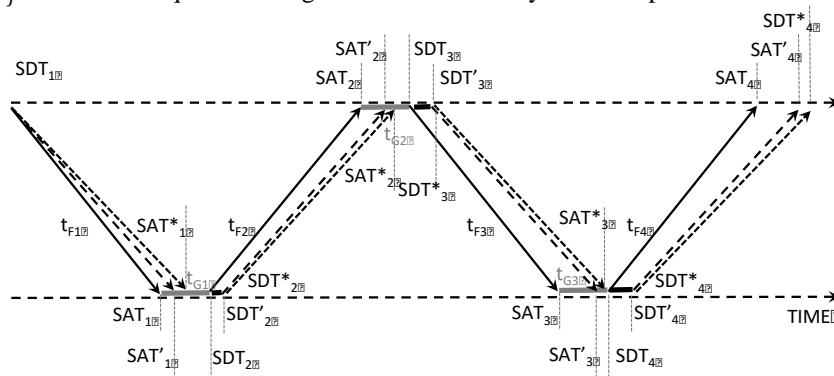


Fig. 4. Flight schedule with propagation of delays.

4.2. Cost of operation considering delays

First, operating costs increase with delays and padding, but in a different way. For unplanned delays, the cost for airline is evaluated in terms of variable costs (because fixed costs not vary in this scenario) and them can be estimated with expressions proposed by Trapote-Barreira (2015). However, a coefficient of penalization is considered because the perturbation enforces to reassign resources and extend duty time for crew (considering the equation $\Delta C_o = \nu \cdot C_o(\Delta t)$ and a standard value of $\nu = 1.0$ for this work).

Second, passengers are penalized in their travel time because extra time not expected is necessary. Then, passenger costs are estimated as proportion of value of time related to this increment of time ($\Delta C_p = \omega \theta \Delta t$, considering a standard value of $\omega = 1.0$ for this work).

If padding is considered, then more resources are going to be needed during planning phase (or not) but these costs are going to be balanced by savings on penalization. Furthermore, passengers are going to be benefited with more reliability.

4.3. Backup of resources for reliability

Airlines usually take the need into consideration of having backup resources in main bases to recover the planned service or mitigate perturbations in flight scheduling. When flight schedule is delayed and these delays exceed a threshold, airline can make the decision of breaking a route into two sub-routes and the second one departs on time

with the backup. In this kind of operation, eventually, a ferry flight can be necessary to send it to the airport where this is necessary.

These kinds of flights are not desirable by companies because of the expected costs. However, if penalization increases, then this strategy can be interesting to solve operational problems. Furthermore, costs of delays are variable costs, but backup resources are fixed and variable costs. Therefore, this extra cost (and padding strategy) decreases margins in profit and loss account. These are costs of reliability and it can make the difference between having negative or positive balance of accounts at the end of the year.

4.4. Algorithm of control

Assume a given flight schedule and quantification of time for flights and turnarounds. An algorithm of control is in charge to monitor the development of operation. Considering a delayed flight is, the following flight that is operated by the same plane it is very likely that is flight is being delayed due to low buffer times and transferability of delays. Except that padding strategy can absorb this delay or additional buffer is incorporated. Furthermore, in case of hubs, transferability of delays between different airplanes is possible because there is the coordination of connections (transfer passengers -usually LCC do not have connections-).

The algorithm considers each flight of FS (Figure 5 shows a conceptual scheme). However, it starts computing all delays according with distributions (section 4.1) and it applies a mechanism of propagation (described above) and control. This mechanism opens a channel to operators to introduce actions to recover the plan or mitigate delays. For each arrival, the algorithm evaluates the prevision of delays and it can decide:

1. To mobilize a backup. If predicted delay in a route exceeds a threshold (τ), one backup is mobilized, recovering the original SDT for the following flight. Only if airline has this resource in the base, else the airline can send it where is necessary with an extra cost.
2. To reorganize routes. If another route accumulates less delays and the swap is allowed (coincidence of flights at the same airport at the same time). Changing the routes may increase the cost due to reallocating crew and flights at the end of the cycle with ferry flights or recover the original end of routes if it is possible (very improbable because this option propagates delays). This selection is done applying Tabu Search principles.
3. To permit the delay propagation. If other alternatives are not possible, then it is necessary to accept the delay propagation. This alternative would give the option to work at level of flight plan and turnaround operations to absorb a certain amount of the delay (which is not the goal of this work).

The total cost of operation with compensations (or penalizations) is evaluated and it defines the criteria to make the final decision.

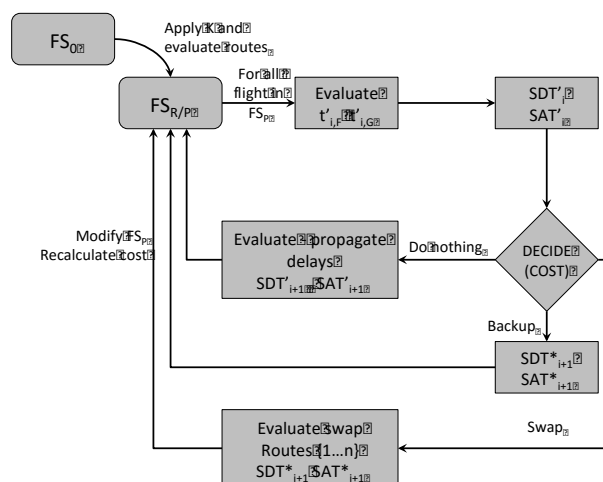


Fig. 5. Basic flow of algorithm of delay control.

The algorithm runs a simulation based on probability distributions (Eq. 1, 2). At the beginning all flights are included in a future event list. All of them are considered as events not conditioned. The schedule departure creates an evaluation of time flight and turnaround time, which is a conditioned event, and this evaluation modifies flight schedule for this flight arrival. Then, this arrival time fires a conditioned event, which is in charge to decide which of the three described options should be chosen, therefore the flight schedule is perturbed FS_p.

Finally, for each pair of variables K and number of aircrafts in the backup, the operator finds a trade-off to improve reliability of their flight scheduling.

4.5. Numerical experimentation

Given a flight scheduling FS₀ and distributions for flight delays $N(\mu_F, \sigma_F) = N(1.78, 3.30)$ and turnaround delays $N(\mu_G, \sigma_G) = N(2.32, 3.43)$, both in minutes per hour. The airline decides the padding and estimates FS_R for different scenarios (Table 2), which produces different routing strategies.

Table 2. Scenarios for delay propagation.

Numb. Flight	Airports		Scenario 1. No delays considered		Scenario 2. Delays considered with k=0.		Scenario 2. Delays considered with k=1.		Scenario 2. Delays considered with k=2.		Scenario 2. Delays considered with k=3.	
	Departure	Arrival	SDT	SAT	SDT*	SAT*	SDT*	SAT*	SDT*	SAT*	SDT*	SAT*
1	1	2	8.0	10.0	8.00	10.06	8.00	10.17	8.00	10.28	8.00	10.39
2	2	1	10.5	12.5	10.58	12.64	10.72	12.89	10.86	13.14	10.99	13.38
3	1	3	9.0	12.0	9.00	12.09	9.00	12.25	9.00	12.42	9.00	12.58
4	3	1	12.5	15.5	12.61	15.70	12.80	16.06	13.00	16.41	13.19	16.77
5	1	4	10.0	15.0	10.00	15.15	10.00	15.42	10.00	15.70	10.00	15.97
6	1	2	14.0	16.0	13.16	15.22	13.43	15.60	13.71	15.99	13.99	16.38
7	2	1	16.5	18.5	15.74	17.80	16.15	18.32	16.57	18.85	16.98	19.37
8	4	1	16.0	21.0	16.19	21.34	16.52	21.94	16.85	22.55	17.18	23.16
9	1	2	16.5	18.0	16.22	18.28	16.60	18.77	16.99	19.27	17.38	19.77
10	2	1	18.5	20.0	18.80	20.85	19.32	21.49	19.85	22.13	20.37	22.76

A preliminary evaluation of cost of delays is carried out without applying the algorithm of delay propagation (without mechanisms of active control, Table 3). The costs are related to the level of the network reliability.

Table 3. Results of scenarios for delay propagation without active control.

Indicator	Scenario 1. No delays considered	Scenario 2. Delays considered with k=0.	Scenario 3. Delays considered with k=1.	Scenario 4. Delays considered with k=2.	Scenario 5. Delays considered with k=3.
Fleet	3	3	3	3	3
Original cost planned (EUR)	1.3689·10 ⁵	1.4066·10 ⁵	1.4754·10 ⁵	1.5443·10 ⁵	1.6131·10 ⁵
Real cost (EUR)	1.4094·10 ⁵	1.4117·10 ⁵	1.4235·10 ⁵	1.4407·10 ⁵	1.4579·10 ⁵
Accumulated delay for airline (h)	1.09	0.38	0	0	0
Extra cost of delays for airline (EUR)	4.9942·10 ³	1.7347·10 ³	0	0	0
Accumulated delay for passengers (h)	605.69	300.44	36.49	6.79	0
Cost of delays for passengers (EUR)	3.6342·10 ⁴	1.8026·10 ⁴	2.1897·10 ³	407.6793	0

Applying the algorithm of delay control with backup fleet, some disruptions are eliminated or mitigated. Table 4 shows results if different value of threshold time is considered to activate backup resource.

The results indicate that reliability has an extra cost for airline in terms of extra resources in backup to recover the service or mitigate delays or the cost of padding (allocating more time for each operation). However, this operating strategy has advantages for both airlines and passengers. Obviously, if an airline has not to pay penalizations, the strategy only generates costs. Passengers could be the part beneficiated of this strategy because they save a lot of time.

Table 4. Results of scenarios for delay propagation with active control.

Indicator	Scenario 1. No delays considered	Scenario 2. Delays considered with k=0.	Scenario 3. Delays considered with k=1.	Scenario 4. Delays considered with k=2.	Scenario 5. Delays considered with k=3.
Fleet	3	3	3	3	3
Original cost planned (EUR)	$1.3689 \cdot 10^5$	$1.4066 \cdot 10^5$	$1.4754 \cdot 10^5$	$1.5443 \cdot 10^5$	$1.6131 \cdot 10^5$
Real cost (EUR)	$1.4094 \cdot 10^5$	$1.4117 \cdot 10^5$	$1.4235 \cdot 10^5$	$1.4407 \cdot 10^5$	$1.4579 \cdot 10^5$
Accumulated delay for airline (h)	1.09	0.38	0	0	0
Extra cost of delays for airline (EUR)	$4.9942 \cdot 10^3$	$1.7347 \cdot 10^3$	0	0	0
Accumulated delay for passengers (h)	605.69	300.44	36.49	6.79	0
Cost of delays for passengers (EUR)	$3.6342 \cdot 10^4$	$1.8026 \cdot 10^4$	$2.1897 \cdot 10^3$	407.6793	0

5. Conclusions

The present section summarizes the quintessence of the described research. First, indices of complexity, airline networks are fascinating examples of emerging complex and interacting structures, which may evolve in a competitive environment under liberalized market conditions. They may exhibit different configurations, especially if a given carrier has developed alliances and has extended its service network. However, this work has analyzed two simple networks of low cost carriers. One of them is a new entrant in the market and the other is a big carrier.

The presented network is characterized by an important concentration of the activity. The most important reason is the need to consolidate strong bases and give financial support to airport or airline development plans. This fact is consistent with the ways of early entrants that manage large networks today. Furthermore, network carriers considered in the present study exhibit a hierarchical structure despite the service point to point.

Indices of complexity and performance of cost of reliability for networks are linked together. LCC airlines present concentration but not much as hub-and-spoke. Their level of propagation of delays is low in practice and analytical model confirms this fact with theoretical approach. Furthermore, it is consistent with indices of complexity.

The results obtained are interesting and invite to further developments to understand in parallel aspects related to customers and demand. Furthermore, a weighted network analysis with flow of passengers could be interesting to understand how topology of links is related to demand patterns.

Second, related to propagation of delays, the model developed to improve reliability shows that airlines have to assume higher costs due reactionary delays. These could be very important at the end of each route if there are no mechanisms to mitigate or eliminate delay propagation. This delay generates costs for airlines and for passengers. Airlines assume more costs because they have to react against perturbations of flight schedule. However, introducing padding, backup resources or re-scheduling improves reliability resulting in extra costs. Backup mechanisms obligate to assume more fixed costs, but increasing the quality of service. Re-scheduling is difficult if there are not coincidences of planes at the airport. Padding is one option, but costs have to be considered. This strategy runs fine for point-to-point networks if ferry flights are not allowed, while hub-and-spoke could take profit of back-up resources in hubs.

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