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The uneven geography of US air traffic delays: Quantifying the impact of connecting passengers on delay propagation

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ABSTRACT

Sustained airport congestion periods translate into delays, especially in hub-and-spoke networks in which delay propagation is more evident.

We examine the impact of connecting passenger arrival delays on network delay propagation by using passenger level data combined with flight delay data that allow us to analyse the correlation between delayed incoming flights and departure delays at the 21 U.S. airports with most delays, in July 2018.

Results show that correlation between daily arrival delays and daily carrier induced departure delays are statistically significant only for flights carrying high proportions of connecting passengers. Correlation values are also higher for short-to-moderate arrival delays. In addition, a Neural Network model was trained for six major airports to build a delay prediction model and map the potential delay propagation. The results of the propagation scenarios suggest that the presence of a unique dominant carrier at an airport translates into a stronger correlation between arrival and carrier delays than that at airports where different carriers compete for connecting passengers. Furthermore, airline hubs located near the areas of the network with more traffic density, independently of the hub's volume of traffic, are more likely to propagate the delay than hubs located in the periphery. The results of this study can be relevant for airline, airport, and traffic control policies aimed at mitigating airport and network congestion.

1. Introduction

Transport and economic geography have demonstrated quite a long time ago that airliner space-time convergence is uneven and more intense in hubs (e.g., Knowles, 2006; Bowen, 2010). It is also known that unevenness and high concentration of services can lead to congestion problems (e.g., Oliveira et al., 2016). Although the COVID-19 outbreak has temporarily decongested the national and international air transportation systems, demand for air traffic will eventually rebound and air traffic congestion will rise. Some consider that the post-COVID-19 aviation environment will bring more point-to-point traffic than growth at hub airports (Bauer et al., 2020). However, other assessments based on industry interviews point towards a concentration of activity in major airports, especially in the first phases of the recovery (Suau-Sanchez et al., 2020), which could potentially bring back congestion earlier than expected.

Sustained congestion periods usually translate into delays. In hub-and-spoke (HS) networks, delays easily build-up from earlier flights and generate what is known as delay propagation. This occurs because of connected resources forcing subsequent flights to wait for the aircraft, connecting passengers or crew (Lan et al., 2006; Yao et al., 2014). Indeed, recent research shows the need to study the airport delay dynamic from the perspective of propagation (Li et al., 2020).

While it is generally accepted that the concentration in space and time of flights by FSNCs (Suau-Sanchez et al., 2016) during peak times aggravates congestion and delays' propagation (Beatty et al., 1999; Mayer and Sinai, 2003; Flores-Fillol, 2010; Oliveira et al., 2016), the exact relationship and impact of delayed incoming connecting passengers on departure delays has been somehow neglected and the existing contributions are limited.

The U.S. Bureau of Transport and Statistics (BTS, 2019) reports on one single category of arrival delays, while it distinguishes among five different types of departure delays: Late Aircraft Delay, Carrier Delay (CD), National Aviation System Delay, Extreme Weather Delay, and

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Security Delay. Late Aircraft Delay is the departure delay of a flight using an aircraft that arrived later than scheduled. The Carrier Delay category includes departure delays that are within the control of the air carrier, such as re-fuelling or cargo loading, and all events related to waiting for connecting passengers and crew members. According to BTS, the first cause of total departure delays was late aircraft delay, which accounted for 40% of delays in the U.S. in July 2018. Carrier delay accounted for 31% of total departure delays and was the second major cause of departure delays during the same period. Late aircraft delay and carrier delay are the only ones that can be generated as a result of a delayed aircraft. The other three groups of departure delays are not a result of a preceding aircraft delay.

The existing literature on delay propagation and its measurement is centred on the first type of departure delay, i.e., the late aircraft delay. Carrier delay, the second most important departure delay, is acknowledged and mentioned but without an attempt to quantify it. Hence, as the second biggest contributor to total departure delays and potentially a top contributor to delay propagation to other airports, carrier delay deserves special attention, as even small enhancements in managing departure delays can lead to considerable improvements in delay propagation (Jacquillat and Odoni, 2015). This paper aims at filling this gap by examining the relationship between connecting passenger late arrivals and carrier delays.

The delay propagation due to late aircraft delay is easier to determine and measure because one late arriving carrier is the direct cause of the following departure delay. The carrier delay propagation, on the other hand, poses a research challenge due to the complexity of the propagation mechanism. In the case of delayed arrival times beyond the minimum connecting time, depending on the amount of delay and the network carrier's policy, connecting passengers with an imminent connecting flight will either miss their connection or be accommodated on their planned flight, in the latter case causing a carrier delay (Deshpande and Arikan, 2012).

One single arrival delay may propagate the delay to many other connecting flights. Similarly, one single departing flight can be delayed by late connecting passengers or crews from various delayed incoming flights, as is the case with carriers operating several flights arriving in banks (Baumgarten et al., 2014). Examining the relationship between connecting passenger arrival delays and carrier induced departure delays at a particular airport can contribute to the understanding of how connecting passengers affect carrier delay and further delay propagation.

In this study, firstly, we analyse the impact of arrival delay on carrier delay by measuring the level of correlation between the two for different levels of connecting passengers on the arriving flights, and for different arrival delay groups. We perform a correlation analysis for the 21 airports that reported most delays in the U.S. network during the examined period to test to what extent these two variables, i.e., "share of connecting passengers" and "arrival delay group" of incoming delayed flights, expressed in minutes of arrival delay, directly impact carrier delays. In order to shortlist these 21 airports we applied a threshold requirement of 'minimum 20% delayed flights' based on BTS statistics for July 2018.

Secondly, we propose a forecasting model of the arrival delays' impact on delay propagation across the US network. The complex nature of delay propagation, −not linear and not normal due to the mentioned multiple impact of one single delayed arrival on many flights and the corresponding multiple impact on a departure delay of multiple late arriving flights- has motivated the use of a machine learning regression, in particular Neural Networks (NN), to produce a prediction model for the delay propagation through the U.S. domestic network and quantify the impact of arrival delays depending on the airport location and the carrier dominance at the airport level.

Both objectives require the access to not only delay databases, but also passenger demand databases (i.e., Marketing Information Data Tapes-MIDT) to crosscheck the volumes of connecting passengers for each airline at each airport.

The contributions of this paper are threefold. First, the study fills the research gap of measuring and modelling the impact of connecting passenger arrival delays on departing flight delays and delay propagation. Second, methodologically, we advance by combining delay data from BTS with connecting passenger data from MIDT. We then use the combined data as input for a NN regression analysis and delay prediction model. Third, we provide empirical evidence that allows a better understanding of delay performance of the U.S. airports and the spatial dimensions of delay in relation to HS networks.

The remainder of the paper is structured as follows: in Section 2 we highlight the existing literature on the broader subject matter and explain the gap filled in by our study; Section 3 details the data and methods used for the analysis and presents the exploratory analysis to confirm the inclusion of different variables in the analysis; Section 4 presents the results and validates the model and methodology by applying them to six major U.S. hubs; finally, Section 5 summarises and discusses the findings of this paper.

2. Research background and literature review

Research on air traffic congestion and delay propagation stretches back to the 1990s and three broad fields of study can be identified.

First, several researchers approach air traffic congestion from a financial and economic perspective. Considering that generally congested airports are dominated mostly by an oligopoly of major airlines, economic studies advocated the introduction of pricing mechanisms to balance capacity and demand to reach an optimal welfare position (Basso, 2008; Brueckner and Van Dender, 2008; Flores-Fillol, 2010; Lin, 2013; Pels and Verhoef, 2004; Yang and Zhang, 2011). The discussion on controlling the demand side of the equation further involved research on slot allocation mechanisms (; Gillen et al., 2016). In addition, considering congestion externalities and an optimal congestion-based pricing scheme, economists dealt with the internalisation of flight congestion costs by network carriers. Several studies argue that if dominant carriers internalise such costs, congestion pricing for Full Service Network Carriers (FSNC) should be adapted to account for internalised costs (Bendinelli et al., 2016; Brueckner and Van Dender, 2008; Miranda and Oliveira, 2018; Pels and Verhoef, 2004; Rupp, 2009).

A second area of research focuses on airport and carrier operational improvements to relieve congestion. Among different studies with an operational improvement focus we highlight here the research of Castaing et al. (2016) who formulated an optimisation model to minimise the impact of gate blockage by earlier delayed flights on further delays, Simaiakis et al. (2014) who suggested how to meter push backs from the gate to prevent congestion, and Maharjan and Matis (2011) who developed a binary integer tool to optimise the reassignment of planes to gates in response to flight delays.

A third string of research studies the causes of congestion and includes models to measure and predict delays. Several scholars have exposed the dynamics of delay propagation within a hub-and-spoke network (Baspinar et al., 2017; Du et al., 2018; Wu and Law, 2019). Recent studies on delay propagation highlight the complexity of the delay origin and the importance of analysing its nature and impact on downstream delays in the system. This is particularly true for the contribution of arrival delay on intra-airport carrier delay due to awaiting connecting passengers. Indicatively, Laskey et al. (2012) found that most arrival delay in a system is caused by departure delays at previous airports, indicating the importance of arrival delay on delay propagation. However, Wu and Law (2019) expressed the need to include intra-airport transits as a significant variable impacting the whole network. More recently, Li et al. (2020) develop an epidemic model to simulate delay propagation in airport networks and apply it to China. Mazzarisi et al. (2020) propose new metrics of the propagations of events along the network using centrality and causality measures. Similarly to our study, Mazzarisi et al. also focus on the U.S. market and

Table 1
List of airports included in the study and their flight delays in July 2018. Source: BTS Statistics.

Airport Code	City	State	Flights	On-time %	Delayed % (+15 m)	Avg. Delay (minutes)
MDW	Chicago	IL	8663	65%	35%	50.5
MIA	Miami	FL	13,969	66%	34%	72.6
MCO	Orlando	FL	14,000	68%	32%	80.6
EWR	Newark	NJ	19,108	69%	31%	81.2
BWI	Baltimore	MD	10,834	69%	31%	62.0
FLL	Fort Lauderdale	FL	11,873	72%	28%	68.5
DFW	Dallas	TX	28,874	73%	27%	66.2
LAS	Las Vegas	NV	15,526	73%	27%	62.3
CLT	Charlotte	NC	22,511	74%	26%	65.7
JFK	New York	NY	20,240	74%	26%	72.4
PHL	Philadelphia	PA	15,782	74%	26%	71.3
DEN	Denver	CO	26,304	76%	24%	67.9
BOS	Boston	MA	18,057	76%	24%	69.5
LGA	New York	NY	16,048	76%	24%	80.5
ORD	Chicago	IL	39,820	77%	23%	66.2
DCA	Washington	DC	12,572	77%	23%	73.5
ATL	Atlanta	GA	38,700	78%	22%	62.4
PHX	Phoenix	AZ	15,889	78%	22%	62.5
IAD	Dulles	VA	10,538	78%	22%	80.9
SFO	San Francisco	CA	19,657	79%	21%	57.6
LAX	Los Angeles	CA	29,161	80%	20%	58.0

use BTS data, but they do not include information on real passenger itineraries (i.e., MIDT dataset), as we do.

Regarding delay propagation, scholars (e.g. Pyrgiotis et al., 2013; Kafle and Zou, 2016; Li et al., 2020) base their research on total aircraft arrival and departure delay data. But so far, the analysis is not focused on the impact of carrier induced departure delay and subsequently, the impact of connecting passengers as such. While flight delay data provides a good proxy for the impact of connecting passengers, true connecting passenger numbers can improve existing prediction models (Bratu and Barnhart, 2005), an approach encouraged by Barnhart et al. (2014). We fill this gap in our study, by combining true origin-destination (TOD) connecting passenger data with historical U.S. FAA statistics on flight delays to provide a new proxy for measuring the connecting passengers' impact on intra-airport carrier delays.

3. Data and methods

This section presents the three methodological steps that lead to the model construction. First, we collect data on flight delays and passenger connection information for the 21 U.S. airports in the study from two databases and merge them into a combined set, blending daily flight arrival and departure data with the proportion of connecting passengers for each airline at each airport. Second, we perform a correlation analysis for each airline and airport to determine the proportions of connecting passengers in each arrival delay group that establish the strength of statistically significant correlations between intraday accumulated minutes of arrival delay and recorded carrier delay. Third, we train machine learning regression models with real data for the main airports and use the results to simulate the impact of delay propagation on some selected airlines and sections of the U.S. network.

3.1. Data collection and merger of datasets

The first dataset used consists of MIDT sourced, detailed true origin-destination passenger information on connecting flights for each itinerary. Each record contains information on the ticketing airline and indicates the points of origin and destination, the connecting airports, and the number of passengers. The original sources of information for the MIDT dataset are Global Distributions Systems (GDSs) such as Galileo, Sabre, and Amadeus, among others. The MIDT raw data is initially processed by our data provider, OAG (OAG Analyser, 2018), to combine all carriers' data into complete, marketable datasets. Several studies have used these datasets for the analysis of airport connectivity (e.g. Voltes-Dorta et al., 2017). MIDT allow us to determine the volume and proportion of connecting passengers per airline for flights to or from each of the 21 airports analysed in our study. The monthly data show passenger details for the itinerary and connections at each airport monthly, but do not indicate whether the flights were delayed, connections were missed, or passengers were affected by delays and re-allocated on other flights. To provide this information, we utilise the BTS Transtats databases. The Transtats set includes an airline on-time performance database with granular data for on-time performance of all domestic flights in the U.S. market. This second dataset employed in our analysis totals more than 700,000 arrivals and departures, including flight delay type and magnitude in minutes. In both cases, we collect data for July 2018 and concentrate our study on the 21 airports in the U.S. airport network with most delays during the analysed period. Table 1 lists the airports included in our study.

Next, we combine the BTS dataset with the connecting passenger data from MIDT, expressed as a proportion of connected passengers for a specific itinerary by a specific air carrier for July 2018.

BTS measures both arrival and departure delays in minutes of delay. Arrival delay is measured in minutes of delay for each individual flight and expresses the difference in minutes between scheduled and actual flight arrival time. Carrier delay for each flight is measured in minutes of delay and expresses the difference in minutes between the flight's scheduled and actual departure time. For each arriving flight, we re-allocate arrival delays into the five arrival delay groups. This re-allocation permits differentiating between short and long arrival delays when measuring the potential impact on intra-airport carrier delay. Flights beyond the 2.5 h delay threshold are discarded since it is unlikely a connection on the same day could still be made at this time. Table 2 illustrates the parameters included in the combined dataset.[1]

3.2. Correlation analysis

An initial exploratory analysis suggests that the link between arrival delay and carrier delay is only significant for airlines that provide many connections at a specific airport. The exploratory analysis also highlights that there seems to exist significantly different impacts on the link between arrival delay and carrier delay depending on the arrival delay time. Before selecting these two factors to include them in the regression model, further statistical evidence of their behaviour has been assembled.

Correlations are computed by arrival delay group. Each airport is tested to determine if there is a statistically significant correlation between arrival delay and carrier delay for a particular airline within a day and, if so, to what extent the correlation is related to the number of connecting passengers or the numbers in each arrival delay group. The combination of airports, delay groups and airlines operating at each airport produces 678 correlation tests. The results of the correlation, which we show in the Results section, lead to the second stage of the research of this paper, where a regression model is built to predict and quantify the delay propagation.

The total minutes of arrival delay for each delay group, per airline and airport is computed. Then, the correlation with the total carrier delay per main airline and airport for July 2018 is measured. For the correlation results to be considered statistically significant, we set the minimum correlation factor $r > 0.6$ with a $p < 0.01$ (Cohen, 1988; Meyer

[1] A common practice among carriers is that in order to decide to delay a departure due to late arriving passengers, the waiting time must be limited to a maximum of 2 or 2.5 h. Very late connecting passengers are normally allocated to another flight, if possible on the same day and alternatively on the following day.

Table 2
List of variables in the merged BTS-MIDT database (including newly created variables).

Variable Description	Comments
Flight Date	The flight delays were analysed daily
Operating Carrier	Used to link arrival and departure flights at the airport
Flight Origin	Used to group flights by airport
Flight Destination	Used to group flights by airport
Scheduled Departure Time	Base for computing departure delays
Actual Departure Time	From gate. Base for computing departure delays
Departure Delay	Difference from the two parameters above, in minutes
Positive Departure Delay	Same as above, but only positive delays, 0 otherwise
Departure Delay Group	0 to 5 for the six delay blocks of 30′ (5 = equal or above 2.5 h)
Scheduled Arrival Time	Base for computing arrival delays
Actual Arrival Time	At gate. Base for computing departure delays
Arrival Delay	Difference between Scheduled and Actual Arrival Time
Total AD for an airline/day	In minutes. For a day, total arrival delays for an airline
Positive Arrival Delay	Same as above but only positive delays, 0 otherwise
Arrival Delay Group	0 to 5 for the six delay blocks of 30′. Used to split the minute delays by group
Accumulated Delays in group 0	In minutes. For a day, total arrival delays for group 0 for an airline
Accumulated Delays in group 1	In minutes. For a day, total arrival delays for group 1 for an airline
Accumulated Delays in group 2	In minutes. For a day, total arrival delays for group 2 for an airline
Accumulated Delays in group 3	In minutes. For a day, total arrival delays for group 3 for an airline
Accumulated Delays in group 4	In minutes. For a day, total arrival delays for group 4 for an airline
Cancelled Flight	Used to study only non-cancelled flights
Scheduled Elapsed Time	In minutes. Not part of the study
Actual Elapsed Time	In minutes. Not part of the study
Group for flight Distance	Not part of the study
Carrier Delay per flight	In minutes. Base for computing the daily Total Carrier Delay
Total CD for an airline/day	In minutes. For a day, total carrier delays for an airline
Weather Delay	In minutes. Not part of the study
NAS Delay	In minutes. Not part of the study
Security Delay	In minutes. Not part of the study
Late Aircraft Delay	In minutes. Not part of the study
% of Connecting Passengers	For each airline and airport, monthly average % of connecting passengers (July 2018)
Number of Connecting Passengers	Average daily connecting passengers of the airline at each airport (July 2018)

et al., 2001; Hemphill, 2003).

3.3. Regression methods

Regression models for air traffic congestion can present limitations. One of them, the lack of data normality, represents a challenge when building regression models for delays. For example, the impact of the variables such as extreme weather, technical issues, a sudden cascade of propagation delays during peak hours or on particularly congested days, produce distribution of delays that follow patterns far apart from a normal distribution. Additionally, existence of collinearity among the model variables brings about an additional issue. Some examples of non-normal and highly collinear variable behaviour include the percentage of connecting passengers and the arrival delay groups. Therefore, Ordinary Least Square Regression (OLS) is not advisable in this case (Yeniay and Göktas, 2002).

Recent studies, aimed at understanding air traffic congestion using statistical modelling, take advantage of machine learning and deep learning approaches to analyse and predict air traffic delays (Gui et al., 2020; Lambelho et al., 2020; Yu et al., 2019). These techniques allow complex computations of parameters beyond simple regression models and advance on the usage of statistical models in explaining and predicting air traffic delay and its propagation.

In our study we considered using one of three robust alternative regression models: Partial Least Square Regression (PLSR); Random Forests (RF); and Neural Networks (NN). Each were tested with the same set of data.

Although the three candidate models provide good prediction power with low levels of RSME, NN produces the lowest RMSE after cross validation and therefore is the technique chosen for the regression. The appendix provides a more technical explanation of Neural Networks and its application to regression models.

4. Results

4.1. Correlation analysis results

Out of the 678 correlation tests performed, only arrival delays of airlines carrying substantial percentages of connecting passengers appear to have a significant impact on daily carrier delays for the same carrier, at the same airport. Setting thresholds for correlations values higher than 0.6 and $p < 0.01$, results in 31 cases of statistically significant correlations for flights with more than 40% of connecting passengers at the corresponding airports. Seven cases are for flights within the range of 20–40% of connecting passengers, and only two cases for other connecting passenger share values. Less demanding significance constraints continue to produce larger numbers of correlated cases with similar relevant and meaningful results. As expected, airlines with low percentages of connecting passengers exhibit no significant correlation between daily accumulated arrival delay and total carrier delay. Hence it is the airlines with the stronger hub focus (i.e., requiring more connections) that are prone to the delay issue. Fig. 1 illustrates four examples of correlation charts between daily total arrival delay and daily total carrier delay for Delta Airlines (DL) and American Airlines (AA), with different percentages of connecting passengers at Atlanta Airport (ATL) and Charlotte Douglas Airport (CLT). Clear correlations appear only when the percentage of connecting passengers is significant. In the two charts marked with a trend line, correlations are both higher than 0.6 and the correlation value is statistically significant with a $p < 0.01$. The other two cases have either a correlation value below the 0.6 threshold or the correlation is not statistically significant. While causality cannot be confirmed by said analysis, the results seem to confirm that connecting passengers are a factor in linking the gap between arrival and departure delay.

Fig. 2 summarises the correlation values before factoring in the statistical significance of each test. The correlation values between arrival delay and carrier delay are, on average, in the range of 0.5 and 0.7 for airlines carrying more than 70% of connecting passengers and well below 0.6 for the remaining airlines. Airlines with low-end percentages of connecting passengers show virtually no significant correlation values. The results from the correlation analysis are debated below in the discussion section.

The above aggregate results are further analysed by considering three additional parameters. The first is the geographic location within the U.S. traffic network grid. Airports are labelled as "Central Airports" (when they have access to other major hubs in all the geographic directions and are located near the gravity centre of the traffic density in the U.S. network), as "Semi-Central" (if they are located near the East or West Coasts but still in a central position to connect with other major national hubs North or South), and "Periphery" (if the airport is near one of the corners of the traffic density grid). The second parameter considers two groups: one group containing airports with only one dominant carrier and a second group, containing airports where two or more carriers operate large volumes of flights. Finally, as a third parameter, we distinguish the three airports in the U.S. that are Level 3 slot regulated.[2]

[2] IATA categorises airports as either Level 1 (Non-Coordinated), Level 2 (Schedule Monitored), or Level 3 (Coordinated).

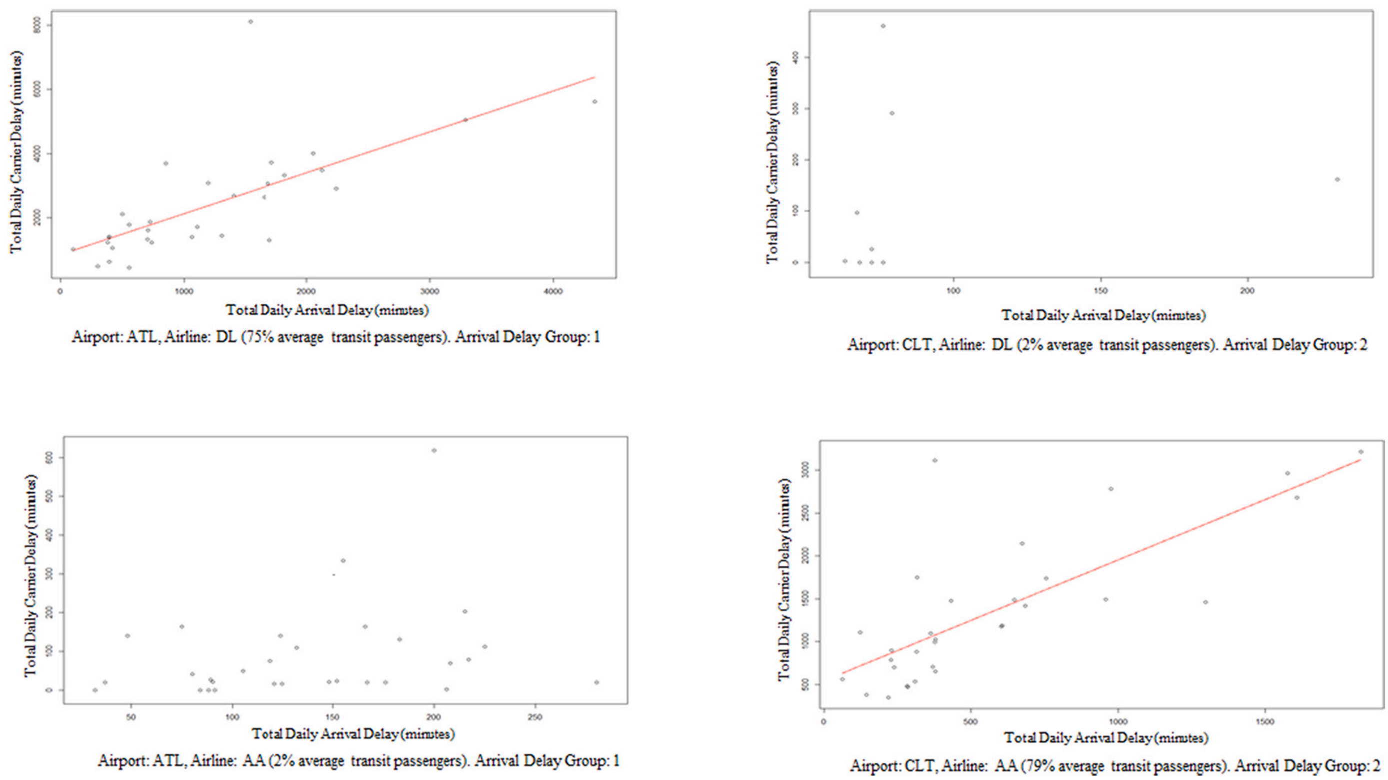


Fig. 1. Examples of daily AD impact on CD for two airlines and two airports. Each data point corresponds to one single day and shows the total minutes of the airline's Carrier Delay (y-axis) plotted against the total minutes of Arrival Delay (x-axis). Delta Airlines flights arriving at ATL carried on average 75% of connecting passengers, whereas only 2% of DL passengers connected at CLT. American Airlines is an opposite case, with 79% connecting passengers at CLT but only 2% at ATL.

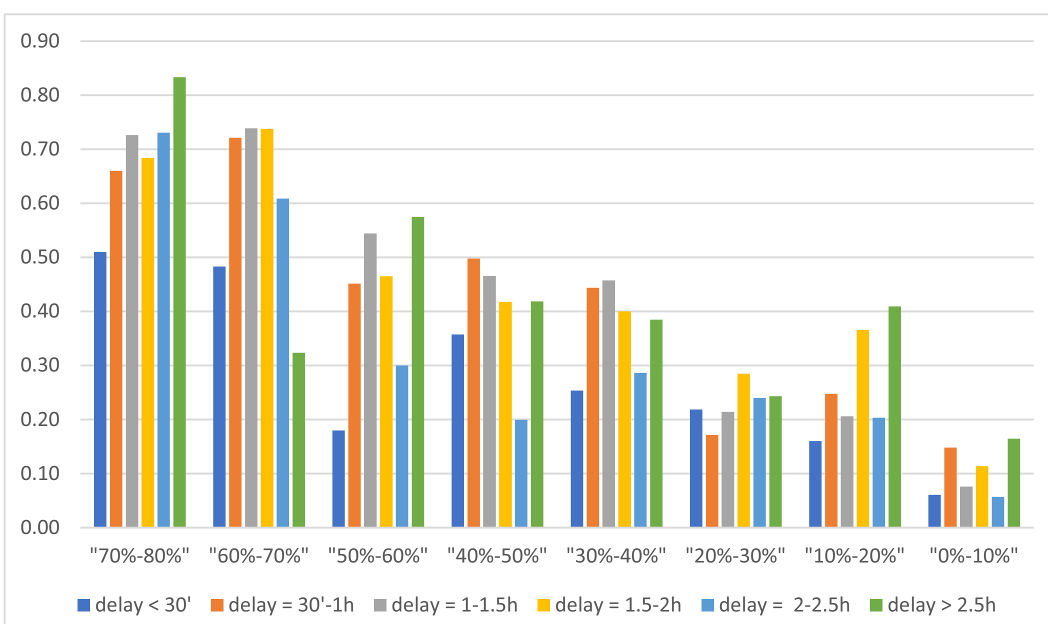
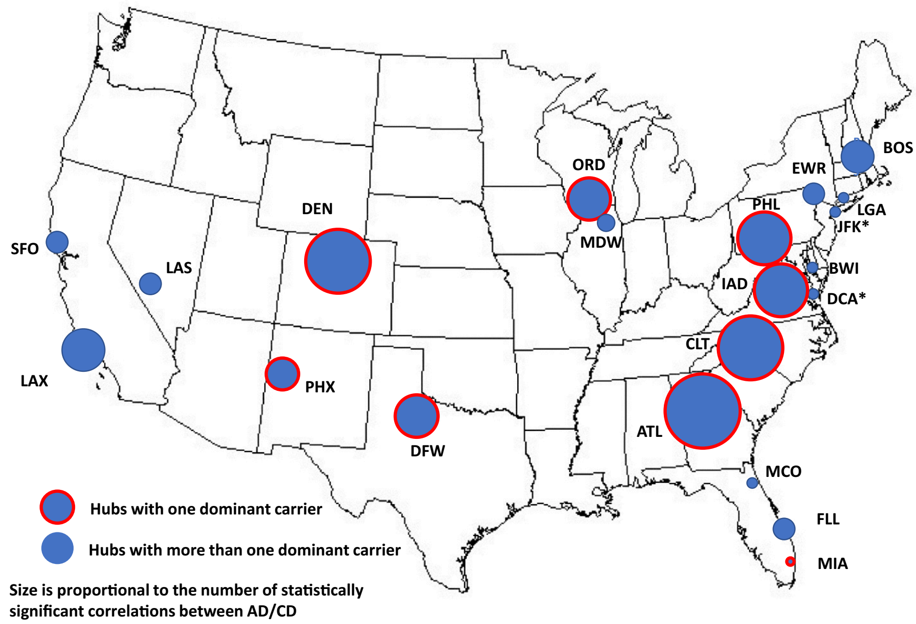


Fig. 2. Average correlation values between AD and CD for the carriers arriving at or departing from the 21 analysed airports. Correlation values appear to be more significant for airlines with high proportions of connecting passengers and for arrival delay groups 1, 2 and 3.

Fig. 3 shows some salient results. First, airports that are geographically located in central positions have significantly more cases with a statistically significant delay correlation. Airports located in the corners of the network, like Miami, regardless of the airport traffic volume, tend to have only few cases of clear correlation or no cases at all. Semi-central airports have altogether more correlation cases than the periphery airports, apart from Charlotte Douglas Airport (CLT), with results similar to those of central airports. It is interesting to note that the



Airport Grouping		Significant Correlation Cases
Central Airports	ATL	7
	DEN	6
	DFW	4
	IAD	5
	MDW	1
	ORD	4
	PHX	3
	Total	**30**
Semi-Central Airports	CLT	6
	DCA*	1
	EWR	2
	JFK*	1
	LAS	2
	LGA*	1
	MCO	1
	PHL	5
	Total	**19**
Periphery Airports	BOS	3
	BWI	1
	FLL	2
	LAX	4
	MIA	0
	SFO	2
	Total	**12**

Fig. 3. Geographical representation of the results of the correlation analysis. Circles are proportional to the number of cases were significant correlation between AD and CD has been found. The red circles indicate that at least one carrier connected 50% or more of its passengers within the airport in the study period, indicating a hub dominance at the airport level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

correlation in New York-JFK Airport, New York-LGA Airport and Ronald Reagan Washington Airport (DCA) is minimal. These last three airports are the only three facilities in the US network that are Level 3 slot regulated[3].[4] Second, we observe more cases of statistically significant correlations in delays in airports with one dominant carrier than in airports where hub facilities are shared by two or more carriers.

We discuss further the results shown in Fig. 3 in the Discussion and Conclusion section.

4.2. Regression model results

To illustrate and validate the potential of the proposed models, six trained NN networks are applied to the top six airports in terms of passenger numbers. The models are trained with real data of arrival delay in minutes of delay as described in the previous sections. Two scenarios are simulated: (1) a day with a low total arrival delay of 200 min, and (2) a day with a moderate total arrival delay of 500 min. In groups '1' and '2' corresponding to an individual arrival delay between 30 min and 1.5 h, 67% of delay minutes are placed in the simulation. The reason is because according to the regression model results, these two time intervals have most influence on carrier delay in downstream connection flights. The remaining 33% of daily delay minutes are distributed evenly among the remaining delay groups. The simulation forecast is run for four virtual airlines, each carrying different proportions of connecting passengers on arrival flights.

The results from Table 3 confirm the influence of hub operations and location effects discussed earlier. Consistent with the correlation analysis, the delay simulations point to an impact of arrival delay on carrier delay for all airports tending to increase with higher proportions of connecting passengers on arriving flights. This impact is exacerbated for flights carrying more than 50% of connecting passengers. Adding to the findings from the correlation analysis, the models suggest that the incremental propagation delay produced by a late arriving flight can be three to four times higher for a carrier with high proportions of connecting passengers than for carriers with moderate proportions of connecting passengers.

4.3. Validation and application example

As an example of the potential use of the model, we now show propagation examples centred on the connections of United Airlines (UA) at three main hub airports: Denver Airport (DEN), Los Angeles Airport (LAX), and Chicago O'Hare Airport (ORD). We also show the impact on delay propagation from each airport to the other two. Table 4 displays how an arrival delay increases of 500 min per day propagates across the other two selected airports in the United Airlines network. For example, according to the NN prediction model, a 500-min increase in total arrival delay at Denver Airport (DEN) would generate a carrier delay increase of 495 min at the same airport. This outcome may imply that airline operations could absorb some arrival delays, hence reducing departure delays. Taking into account that during the study period, 6.16% of all United Airlines flights departing from Denver Airport (DEN) had Chicago O'Hare Airport (ORD) as their direct destination, the generated delay results in a 30-min additional arrival delay at Chicago O'Hare Airport (ORD), due entirely to the impact of the carrier delay at the origin airport. This additional arrival delay at Chicago O'Hare Airport (ORD) would result, according to the model, in a 118-min carrier delay increase at the airport, which would further propagate to other airports in the network. These results are mapped in Fig. 4.

Another factor identified in the previous sections as relevant in the link between arrival delay and carrier delay, is the relative dominance of the competing carriers at an airport. As can be observed in the second

[3] Previous research has highlighted how airfreight companies sometimes use hubs in the interior of the country as gateways to avoid some of the congestion associated with peripheral gateways (Lasserre, 2004).

[4] Our results are influenced by the limitation of using the BTS data limiting the analysis to the domestic network. However, the majority of traffic operations are domestic. As examples of top international airports, data for JFK, EWR, and ORD show that the total domestic traffic operations in 2018 were 75%, 88% and 89% respectively (ATR, 2018).

Table 3
Total estimated departure carrier delay in a single day (minutes) at six selected airports using the NNs trained with the real data. Percentage of connecting passengers on arriving flights: Airline 1 (<10%), Airline 2 (10–25%), Airline 3 (25–50%), Airline 4 (>50%).

	Total Arrival Delay/Airline = 200 min				Total Arrival Delay/Airline = 500 min			
	Airline 1	Airline 2	Airline 3	Airline 4	Airline1	Airline 2	Airline 3	Airline 4
ATL	167	283	329	373	581	624	706	891
LAX	40	55	78	159	65	94	141	182
ORD	83	80	110	636	462	489	893	1012
DFW	83	109	159	521	237	292	388	754
DEN	97	153	252	378	380	419	530	495
JFK	90	92	97	168	199	219	240	381

column of Table 4, a 500-min arrival delay of United Airlines flights had a higher impact on carrier delay at the airports where United Airlines has higher relative dominance, e.g., Denver Airport (DEN) and Chicago O'Hare Airport (ORD).[5]

With these examples we are showing how one single airport spreads the delay over other airports. On top of the 118 min of carrier delay at Chicago O'Hare Airport (ORD) resulting from the delays at Denver Airport (DEN), flights departing from Chicago O'Hare Airport (ORD) will also be impacted by the delays originated at other airports also connecting at Chicago O'Hare Airport (ORD).

5. Discussion and conclusion

In this study we have quantified the relationship between arrival delay and carrier delay for the domestic network of the 21 U.S. airports with the highest percentage of delayed flights. The results of the correlation analysis and the NN regression performed in our study, contribute to several areas.

At the carrier level, the results strongly suggest that late arriving flights for airlines with a high proportion of connecting passengers are correlated with increased carrier delays on departure delays. This contrasts with the outcome for incoming flights of carriers with a low proportion of connecting passengers. Furthermore, our analysis suggests that different arrival delay times have different effects on departure delays.

Arrival delay for incoming flights delayed between 30 and 60 min have a higher downstream impact on overall daily carrier delay. This result suggests that longer connecting times in hubs could potentially reduce the delay propagation and improve the overall operational efficiency and resilience. This can be actively promoted by airlines with flight scheduling and revenue management techniques, or with policies, not always easy to implement, by the airport and regulators that could include gate rental pricing to reflect the connecting time allowed in time-tabling or airport investments.

The importance of the time interval between arrival and departure delay highlighted in our study is compatible with previous findings by Fageda and Flores-Fillol (2015) who found that, in congested airports, point-to-point carriers reduce frequencies in response to delays, while carriers operating hub-and-spoke networks increase frequencies. Indeed, the market dominance usually associated to a hub represents a deterrent to de-peak the hub operation or release slots. The planning solution of scheduling flights with longer connecting times can contribute to reducing associated delays, while maintaining high frequencies and slot control. However, it can lead to a weak position in the connecting markets (Suau-Sanchez et al., 2015) and lower perceived quality of service (Sismanidou et al., 2013). Hence, there is no easy solution to delay control.

At the airport level, the results illustrate that while all airports studied exhibit a statistically significant positive correlation between arrival delay and carrier delay, for airports with high proportions of connecting passengers, both the correlation analysis and the subsequent NN prediction model show some significant differences.

First, the study results suggest that airports located near the spatial centre of the domestic network exhibit more cases of airlines experiencing statistically significant correlation between arrival delay and carrier delay. Furthermore, the arrival delay for these airports seem to have a stronger impact on subsequent carrier delay. These findings suggest that when carriers use hubs located in the centre of a network's traffic corridors, they are inclined to wait for connecting passengers, favouring carrier delay over punctuality. Indeed, previous research has shown the benefits of waiting-for-passenger rules in terms of reducing operating costs (Delgado et al., 2016). Waiting-for-passengers measures then become a way of counteracting the negative impacts of congestion associated with operating a hub-and-spoke operation at a large airport. This is consistent with the idea that dominance at the airport level is more relevant than dominance at the route level to achieve market power (Evans and Kessides, 1993), influence airport's decision making (Berry, 1990) and capacity to increase fares (Bilokach and Lakew, 2014).

Similar regional differences have also been identified by Fuellhart et al. (2016) who map the aggregate trends in the US airport network using common measures of airline and airport activity by monitoring the growth or decline in departures, seats and passengers during the critical decade between 2003 and 2013. Their findings indicate that the top performing regions seem to be located in the northern plains, Florida's vacation oriented areas in the southeast coast and the urbanized area between Washington, DC and Boston, MA. On the other hand, the areas neighbouring the Rust Belt, Appalachia, the Mississippi Valley, and parts of the northern Intermountain West perform poorly. The superior performance of the plains and the big cities could be attributed to their position in the urban hierarchy combined with their important national and international connections, as opposed to the Rust Belt and Appalachia areas that, suffer from industrial decline and stagnation and a weak local market.

Similarly to Fuellhart et al. (2016), our findings also suggest that

Table 4
Example of the potential impact of a 500 min total daily AD at a main hub on other network hubs due to the generated carrier delays at the origin hub. In this example the simulated carrier is UA. The percentages of flights to destinations correspond to the real figures for UA in July 2018.

Origin Hub			Destination Hub		
Airport Code	Increase in CD (min)	% of flights to destination	Airport Code	Increase in AD (min)	Increase in CD (min)
DEN	495	6.16%	ORD	30	118
DEN	495	4.04%	LAX	20	7
LAX	94	12.98%	ORD	12	48
LAX	94	8.36%	DEN	8	19
ORD	1012	5.00%	DEN	51	118
ORD	1012	4.97%	LAX	50	16

[5] In July 2018, UA flights operating at LAX connected 23% of the carrier's passengers, while at DEN and ORD, the airline connected 54% and 57% of its passengers respectively.

Fig. 4. Selection of three main airports originating UA flights. At each airport, arrival delays (AD) of flights with connecting passengers (blue incoming arrows) will cause carrier delays (CD) in outcoming flights (red arrows) which in turn, will propagate the delay at the destination airports. The arrival delays at the destination airports will generate an impact on their carrier delays (blue outcoming arrows) for the UA connecting flights to other destinations. The figures show the modelled propagation in minutes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

airport size does not seem to be an important factor of explaining the differences between the airports. Other explanations should be sought. In our study, New York (JFK), San Francisco (SFO) or Miami (MIA) exhibit low correlation cases, whereas the central airports of Chicago (ORD) and Atlanta (ATL) are on the top of the list. Further individual airport case study analyses are required in order to understand the reasons behind regional patterns. This may include exploring the operations of dominant LCC carriers in specific US airports, examining how airlines manage their hubbing operation at each airport, and understanding hub airlines' relative route strategies, their choice of frequencies and size of aircrafts (O'Connor and Fuellhart, 2012). Additional findings from future case studies will allow to illuminate better the regional differences identified in this paper.

Second, and in line with the previous point, our prediction model shows that airports with one dominant airline have stronger correlations between arrival delay and carrier delay, suggesting that dominant airlines could be more inclined to internalise the cost of allowing carrier delay due to late arrival connecting passengers than airlines with lower dominance. This is also consistent with the intuition that airports with higher concentrations of a single airline will tend to have correlations in their delays because these hubs have more connecting passengers between the same airline's flights.

Third, the marginally lower correlation scores, when compared to other major airports, for the three U.S. airports with Level 3 slot control exercised by FAA (i.e. JFK, LGA and DCA), suggest that slot regulation could, directly or indirectly, have a material impact on the delay propagation due to carrier delays. This result is also consistent with previous research that has shown that slot controls can potentially reduce delays in US airports (Swaroop et al., 2012) and there are shorter delays for European slot constrained airports (Santos and Robin, 2010). Apart from the unique slot allocation policy aspect, the different correlation scores in our study could be explained by other parameters, including the airports' design, its operational efficiencies, or the impact of international connections. These differences offer an opportunity for further research to determine optimisation factors at the airport level that could be replicated throughout the U.S. airport system.

Further to these conclusions, our study provides empirical evidence and a methodological framework to support policies and interventions aimed at enhancing connecting passenger turnaround or at mitigating delays through operational improvements of airline, airport, and Air Traffic Flow Management (ATFM) procedures. The outcome of these policies can be predicted, measured, and monitored using the techniques employed here.

Delay predictability is particularly crucial for airlines when building their schedules and incorporating time-buffers (also known as firewalls). Enhanced predictability can improve resource allocation and increase punctuality and customer satisfaction. Furthermore, the framework of this study, in terms of data gathering and merging as well as the machine learning models proposed, can help generate efficiency metrics for current and future improvement initiatives at the network, airport, or carrier level. The connecting passenger variable could be included in airline scheduling decisions and in ATFM, airport landing procedures and policies prioritizing queued flights with high volumes of connecting passengers. This is particularly true for congested airports and, as a matter of fact, two industry initiatives right before the Covid-19 pandemic are examples of the nascent efforts to isolate and control the connecting passenger delay parameter. For example, Zürich Airport would test the feasibility of introducing ad-hoc, priority landing protocols on arrival flights with a significant proportion of connecting passengers, and United Airlines had announced a dynamic decision-making tool based on the number of connecting passengers arriving at the hub to alleviate the problem of ATFM's lack of information about possible passenger misconnections.

This study is not free of limitations. One limitation is that the aviation environment is highly dynamic, making it difficult to forecast air traffic congestion behaviour from historical data. Another limitation is the lack of complete, granular data of flight operations in combination with passenger data. Delay prediction and mitigation could benefit from a wider choice of data collection in the form of big data, combining detailed air traffic control, flight and passenger information, and the application of machine learning algorithms to create more complete, personalised, and reliable delay prediction models. Furthermore, this study focuses on the carrier delay impact in isolation to other departure delay causes, such as late aircraft delay, or those originated by air traffic control problems or weather conditions. Another potential limitation of this study is that the airport sample contains most of the largest airports in terms of passenger traffic and air operations. In terms of customer welfare, it may turn out that the impact of arrival delay on carrier delay is more important at smaller airports, where there are fewer or no later flights to accommodate the passengers. Future studies could enlarge the scope of the analysis to include all different delay parameters in one single model as well as determining the proportion of delays caused by connecting passengers versus the other causes of carrier delay. Finally, replicating this study for the European or Asian air networks can provide additional explanations of the results.

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Appendix A. Regression models based on neural networks

NNs constitute a group of deep learning techniques from the domain of Artificial Intelligence (AI). They imitate the structure of brain neurons and take advantage of the computing power of current processors to predict results based on a learning process of real patterns present in the sample data. NNs create robust prediction models in situations where collinearity among the variables and lack of normality of the data advise against the use of linear models such as OLS. The training of a NN produces connections between neurons, also called nodes, where each connection has different weights.

The simplest Neural Network, called perceptron (Fig. 5), consists of a single layer with input nodes (x1, x2, x3….xn) corresponding to the input variables and a single output node corresponding to the result. The input nodes are directly connected to the output node. With the training process, similar to the Least Square process to determine the variable parameters that optimise the prediction power of the model, each input node will have a weight corresponding to the importance of that variable in the final prediction. In NN, a bias term b is added to the sum of the weights that multiply each variable. The bias b allows to build linear models for one node that is not fixed at the origin.

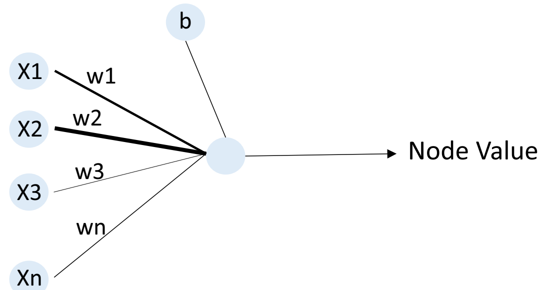

Fig. 5. Schematic representation of a perceptron, the simplest form of NNs, with one single node, the inputs *Xn*, the weights *w* -represented by the line width- and the bias *b*.

The corresponding estimation eq. (1) or (2) for a perceptron is similar to a classical linear regression, where the weights *Wn* that optimise the model can easily be interpreted as the importance of each input factor on the estimated output:

$$Node\ \ Value = f(x) = b + w1{\cdot}x1 + w2{\cdot}x2 + w3{\cdot}x3 + \ldots + wn{\cdot}xn \tag{1}$$

Or in general.

$$Node\ \ Value = f(x) = b + \sum_{i=1}^{n} wi{\cdot}xi \tag{2}$$

The robustness and prediction power of a NN structure, however, arise when one or more additional hidden layers of nodes are added between the input and output layers. As shown in Fig. 6, each node in the hidden layers receives inputs from all the nodes in the previous layer with different weights (depicted in the chart by the thickness of the connections between nodes). The node is activated according to an activation function *g()* –for example a sigmoid or logistic function, a ReLU function, etc.- and sends its output to each and every one of the nodes in the next hidden layer. Both the bias values and the weight values are trained during an optimization process that, starting with random numbers, readjusts step-by-step each value in the network until reaching a minimum RMSE (Root Mean Squared Error).

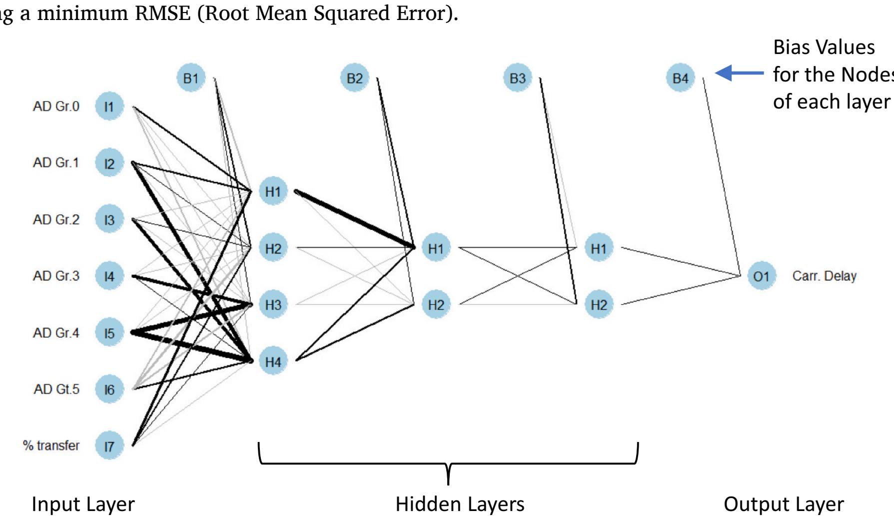

Fig. 6. Trained NN after learning from the data corresponding to ORD. The variables ADs by group and % of connecting passengers were fed into the model for each day and airline. I = input nodes; H = hidden layers; O = output; and B = bias applied to each node after the learning process. Solid black lines indicate positive values, and grey lines indicate negative values. For most airports, the percentage of connecting passengers and delay groups in the 30–120 min range impact the prediction.

While the training of the NN with the data is automatic, the available statistical packages, like R, require that the shape of the NN is build prior to the training, in other words, the number of hidden layers and the number of nodes in each one of the hidden layers have to be defined before training. An optimal shape of the NN ultimately translates into achieving the maximal reduction in RMSE through cross validation. Adding more hidden layers tends to improve the prediction accuracy of the NN at a cost of increased computational requirements. In this study we tried various potential shapes and the cross validation showed that NN structures with three hidden layers containing four, two, and two nodes, respectively (Fig. 3) provided the best results. Other configurations with additional hidden layers or additional nodes did not improve the RSME values for any of the airports modelled.

The inputs are scaled by their corresponding weight, *wi*, and added together along with the bias term, *b*. While the weights indicate the importance of the value of each precedent node on the next layers node, the bias determines whether or not, or by how much, a node will meaningfully fire the value to the next node. Adding the bias to the equation increases the flexibility of the computing process to train the network.

When one or more hidden layers are added, however, deriving a single estimation equation is not feasible. The essential difference with linear equations is that NN are not linear due the presence of an activation function. For just one single node located in the hidden layers, the output can be expressed with the following eq. (3):

$$Node\ \ Value = f(x) = g\left(\mathrm{b} + \sum_{i=1}^{n} wi{\cdot}xi\right) \tag{3}$$

Due to the complex interaction between all the nodes from one layer and the nodes of the next layers, the parameters no longer act independently from each other in influencing the shape of the optimised NN. Despite NNs' flexibility in modelling arbitrary functions and their excellent predicting power, the convenience of having a visual linear estimation equation with separate weights for each parameter is lost, and there are challenges to even generating values that explain the power of the model variables. Different methods to visualise the NN learning outcome have been proposed (Garson, 1991; Goh, 1995). However, the nature of the NN learning process, with iterations that include combinations of all variables to converge an optimal output, is a source of confusion when interpreting each variable's prediction potency. Other authors proposed improvements to original visualization methods (Olden et al., 2004; Beck, 2018) but they are still not ideal, as they remain based on the use of the connection weights between layers of a neural network for determining variable importance.

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