SIMULATING THE IMPACTS OF AIRPORT CLOSURES ON AIRLINE ROUTE NETWORKS

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ABSTRACT
Air transport represents the fastest way of moving people and goods. For this reason, it is critical to the global economy and the welfare of society. The resilience of air traffic networks is, therefore, of great importance. In the past two decades, various events have shown that air transport is vulnerable to disruptive events, such as extreme weather, terrorist attacks, volcanic eruptions, earthquakes, and pandemic influenza. The severity of the impacts on passengers and economic activities, and overall losses to stakeholders and for society in general, would highly depend on the vulnerability and resilience of these networks. The current research seeks to develop an agent-based model to simulate and analyze the vulnerability and resilience of airline routes to airport disruptions.

Keywords: Agent-based modeling; airport disruption; air transport vulnerability; resilience

1. INTRODUCTION
Transport networks represent core resources and critical infrastructure and facilities that enable social and economic development around the globe. The transportation sector is growing globally over the next decade (Transport Canada 2015). Air transport is among the fastest growing in the transportation sector. Nevertheless, they may be vulnerable to natural, technological, and human made hazards. In order to improve supply chain reliability, transportation systems must become more agile and resilient to such threats (Transport Canada 2015). Despite the fact that some of these networks have built-in redundancies (i.e., alternative infrastructures) more sustainable and viable strategies call for effective management of existing infrastructure that is based on thorough understanding, modeling and optimization of the underlying complexity of network systems when disruptions occur (Chow, Szeto, Wang, and Waller 2015).
For example, Barnhart and Smith (2012) reported that ice and snowstorms in recent winters left passengers stranded in airplanes for up to 11 hours and caused havoc in the affected airlines' systems for several days, besides resulting in direct costs to airlines. They noted that such disruptions have visible and harmful impacts on passenger goodwill.
The current research seeks to develop an agent-based model to capture and analyze the emergent dynamics generated in airline networks, in order to better assess the vulnerability and resilience of these systems. Risk and business continuity managers of both airlines and airports could utilize such a model to better understand the impacts of disruptions and to develop strategies and policies that could reduce vulnerability and enhance the resilience of airlines and airports.
The model has been developed using AnyLogic simulation software 7.3 (AnyLogic 2016). We used AnyLogic's GIS environment, which enables agents' interactions in space and time. As a case study, the authors report on simulated disruption impacts on the most important hub within the simulated system, the Toronto Pearson International Airport.
The rest of this paper is organized as follows: Section 2 provides a brief review of the current research. Section 3 describes the agent-based modeling (ABM) approach. Section 4 describes the case study. Section 5 provides details of the simulation. Section 6 presents the key results of the simulation followed by conclusions in section 7.

2. STATE OF THE ART
The network modeling approach enables an intuitive representation of several structural elements of air transportation systems. The major portion of previous work in this area has considered models of traffic, either in terms of aircraft or passengers (Wei, Chen, and Sun 2014; Lordan, Sallan, Simo, and Gonzalez-Prieto 2014; Bratu and Barnhart 2005; Nicolaides, Cueto-Felgueroso, Gonzalez, and Juanes 2012).
Several aspects of the air traffic network have been studied. Initial works (Barrat, Barthelemy, Pastor-Satorras, and Vespignani 2004; Guimerà, Mossa, Turtschi, and Amaral 2005), were focused on structural description of the air transport system (i.e., a topological description of the network structure). However, delay propagation dynamics can be also studied using this approach (Fleurquin, Ramasco, and Eguiluz 2013a; Fleurquin, Ramasco, and Eguiluz 2014; Fleurquin, Campanelli, Eguiluz, and Ramasco 2014).

Due to interconnectivity, the air transportation network is vulnerable to propagations (i.e., domino effects). Since the airlines operate on this network, their operations are also subject to propagation effects. A disruption in one flight or airport can quickly spread and have a cascading impact affecting other parts of the air transport network (Beatty, Hsu, Berry, and Rome 1999; AhmadBeygi, Cohn, Guan, and Belobaba 2008).

Several mechanisms allow the propagation of delays through the air transportation network, such as aircraft rotations, passengers and crew connections, or airport congestion. These factors considered in the models developed to reproduce delay propagation. Understanding how delays propagate in the airport network starting from primary events is thus of high economic relevance (Campanelli, Fleurquin, Eguíluz, Ramasco, Arranz, Etxebarria, and Ciruelos 2014).

Although airlines deal consistently with operational disturbances (e.g., deviations in departures and arrivals due to traffic congestion at the airports or in the airspace sectors), they also face disruptions (i.e., high impact disturbances) that impact their pre-planned operations. For example, severe weather conditions, such as icing on a runway, can close an airport for several hours (Rosenberger, Johnson, and Nemhauser 2003). The influence of schedule adherence of aircraft rotation becomes more significant when the consequences of flight delays are investigated on a network scale (Wu and Caves 2002). Vulnerability and resilience of transport networks have been typically addressed by means of graph theory, primarily through topological studies. Since these studies consider static information only, they cannot include the dynamic behaviour of the network (travel demand, aircraft rotation, passenger and crew connections, and others), so they miss the emergent effects (e.g., delay propagation) that appear due to the influence of a failure on the rest of the elements within the system. Airlines could improve their performance in operations by considering the possibility of disruptions during the planning phase (Rosenberger, Johnson, and Nemhauser 2004).

Various works concerning vulnerability of transport networks have been carried out. A very extensive survey of these publications is provided in (Mattsson and Jenelius 2015). However, very few of the reported studies are related to air transport. A recent study of resilience analysis for air traffic networks reported in (Dunn and Wilkinson 2016), reveals that only static analysis of the networks (topological approach) has been applied. In the present work, the aim is to apply a systemic approach to cover the gap in the current literature, developing a dynamic model through ABM.

In recent years, two agent-based models to study and forecast delay propagation in the USA and European networks were introduced (Fleurquin, Ramasco, and Eguiluz 2013a; Ciruelos, Arranz, Etxebarria, Peces Campanelli, Fleurquin, Eguiluz, and Ramasco 2015). However, both investigations focus only on operational delay effects (i.e. low impact disturbances).

3. AGENT-BASED MODELING APPROACH

ABM is chosen because the more widely used approaches (topological, based on graph networks) impose unrealistic restrictions and assumptions on the system being modeled under aggregate data considerations. In contrast, ABM can be used to conduct policy experiments to investigate the vulnerability and the resilience of airline routes, including the emergent effects due to dynamic behaviour on the system under analysis (Crooks and Wise 2013). In particular, ABM simulation allows:

- virtual simulation of the consequences of decisions,
- integration of multiple theories regarding the phenomenon under investigation,
- representation of agents with multiple decision strategies, and
- modeling of heterogeneous actors who can modify their behavior over time.

In the last decade, ABM has been successfully applied to a variety of domains. Several research projects have demonstrated the potential of this technique to advance science, engineering, and policy analysis (Anderson, Chartuvedi and Cibulskis 2007; Collier and North 2012; Asakaura, Aoyama, and Watanabe 2011), which expands its applicability with the integration of geographical information systems (GIS) (Crooks and Wise 2013).

4. CASE STUDY

This simulation was applied to a selection of Air Canada flights. Air Canada has major hubs in four Canadian cities (Toronto, Montreal, Vancouver and Calgary). Air Canada's network currently provides service directly to 63 Canadian destinations, 56 destinations in the United States, and 86 in Europe and other continents. Air Canada operates on average 1,500 scheduled flights each day (Figure 1) and, in 2015, carried more than 41 million passengers (AirCanada 2016). Air Canada is among the 20 largest airlines in the world. Air Canada's Airbus aircraft that were incorporated into the present model are:

- A320 family (37),
- A321 family (14),
- A319 family (12), and
- A319 Air Canada Rouge family (7).

Figure 1: Air Canada Routes Network (OpenFlights 2016)

5. SIMULATION MODEL

The simulation model is composed of four major components:

- Map and visual interface,
- Agents,
- Input interface, and
- Output interface.

The map and visual interface shows the evolution of the simulations considering different traffic introduced in the input interface and simulation set up. The map and visual interface dynamically visualizes the real routes (obtained from Flight Radar 24 website) that are used by the aircrafts. It also allows the users to see the variations of the routes, when there is one or more airports disrupted. Besides, the map and visual interface shows the location of different airports in the model, considering an accurate geo-positioning of the airports.
Figure 2 shows the map and visual interface that includes airports (for the route network under analysis) and aircrafts on their routes at a specific time.

Figure 2: Simulation Model Map and Visual Interface

In the present model, two different agents were implemented:

- Destination (airport), and
- Airplane.

Figure 3 shows the state chart for the airplanes. The agent "Destination" represents the airports that are included in the model. These airports correspond to the origins and destinations for the aircraft (scheduled flights). Each airport contains different features and information such as the airport name, latitude and longitude, the length of the main runway, and one variable that represents the availability of the airport (if it is open or close due to some disruption). The current model has 29 airports already implemented: 12 Canadian airports, 6 USA airports, one Mexican airport, and 11 Caribbean airports.
The agent "Airplane" represents the aircraft fleet included in the flight schedules under simulation. It needs to consider each aircraft and its rotation. The aircraft rotation is considered as a set of legs for this aircraft in a specified time period.

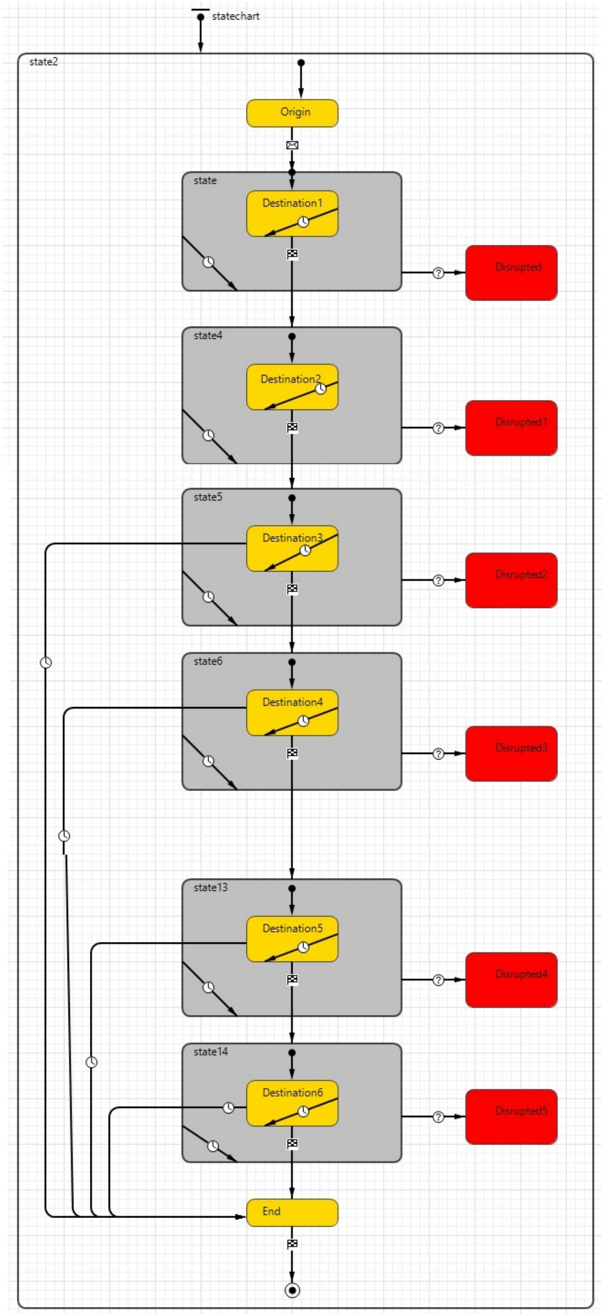

Figure 3: Airplane State Chart

Each aircraft has to respect certain conditions before taking off from an airport of origin to its destination. The first condition is the take-off time. An aircraft can take off only at a specific time and that aircraft has to stay at least for a specified time in an airport (in the current model this time is 45 minutes, which represents the time to complete the turnaround process in the airport before taking off again). The second condition is the availability of the destination airport. If this condition is not satisfied, the aircraft cannot take off. In the simulation, this state is highlighted in the map and visual interface, where this aircraft turns yellow. This color change means that either the origin or the destination airport is not available before taking off. On the other hand, if one aircraft is able to take off but during the flight the destination airport is not available (because of an internal or external disruption) the aircraft has to change its destination and the simulation shows the aircraft in red. This color signifies that the aircraft has been disrupted. In this case, the aircraft needs to go to another airport as follows:

- Aircraft tries to reach the nearest destination from the current position.
- Aircraft selects the nearest airport that has the minimum runway length needed for that aircraft.

In selecting each of the above options, the Extended Twin Operations (ETOPS) conditions should be met. ETOPS describes the operation of twin engined aircraft over a route that contains a point further than one hour's flying time from an adequate airport at the approved one-engine inoperative cruise speed (Martins, Nerosky, Fernandez, and Senna 2007; Ballal and Zelina 2004). The purpose of the ETOPS conditions is to provide very high levels of safety while facilitating the use of twinjets on routes which were previously restricted to three- and four-engined aircraft.
It is possible to set the ETOPS certification value as an additional parameter for each aircraft. In the current model, only three different ETOPS certifications are considered:

- ETOPS 90 (this means that an aircraft can follow one route that is not far from the nearest airport more than 90 minutes),
- ETOPS 120 (this means that an aircraft can follow one route that is not far from the nearest airport more than 120 minutes), and
- ETOPS 180 (this means that an aircraft can follow one route that is not far from the nearest airport more than 180 minutes).

Therefore, when an aircraft changes its destination because of an airport disruption, this aircraft has to check not only if the nearest airport has an adequate length of runway but also if the time to reach this new airport is compliant with the aircraft's ETOPS certification.
There are different variables that represent the attributes of each aircraft. It is possible to check the *state* of each flight. The various states are:

- *departed* when the aircraft takes off,
- *arrived* when the aircraft lands,
- *diverted* if the aircrafts is diverted to a new destination because of airport disruption,
- *cancelled* if this flight is cancelled because the aircraft cannot take off from the originally scheduled airport because of airport disruption.

Other attributes of aircraft are the *origin* and *destination* for all the aircraft rotation, the *scheduled departure time* and the *scheduled arrival time* (taken from Flight Radar 24 website) for each flight, the *real arrival time* for each flight, the *delay* for each flight, the *total delay* for one aircraft (calculated as the sum of flight delays). There is also a *scheduled flight time* for each flight. In addition, there are specific information about each aircraft such as *aircraftID* (serial number), *FlightCode*, type of *Airbus* and number of *seats*.
The input interface allows the user to set up different parameters. For instance, the user can decide the closure of an airport by writing the name of the airport in the edit box. The user can also decide to change the time frame for the disruption through a slider created in this part of the model. Moreover, the user is able to set a disruption area by drawing a circle or polygon (this is more useful in case of certain hazards that impact large areas such as hurricanes, volcanic eruptions, etc.).
It is also possible to add different new aircraft in the model through an external database file. In this database, it is possible to add different schedules and aircraft attributes such as *departure time*, *arrival time*, *flight time*, *origin* and *destination names*, *aircraftID*, *flight code*, *number of seats*, type of *airbus*, minimum *length of runway for landing*, and *ETOPS certification*.
Figure 4 shows the interface for the Input Section where the users can set up different parameters.

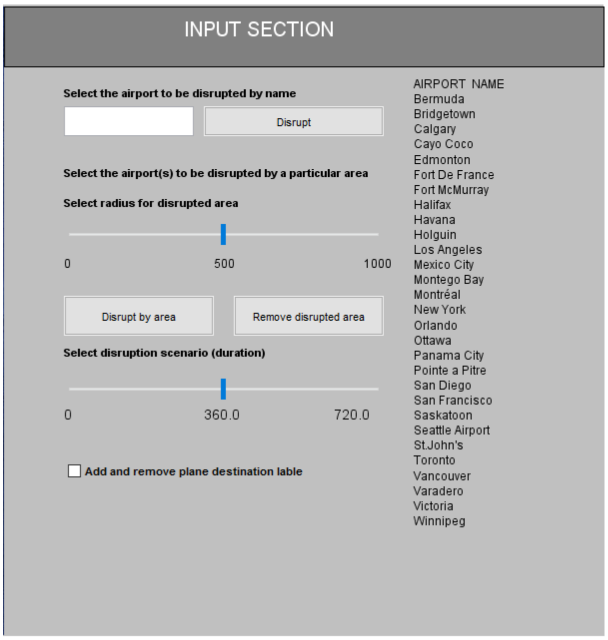

Figure 4: Interface for the Input Section

The interface for Output Section shows the results that can be obtained after running the simulation. As default, the model provides the following indicators:

- *Planes Chart* is a Time Plot with the number of airplanes in a network before completing their rotation.

- *Planes Disrupted* is an indicator showing the number of the aircraft disrupted at any given time; according to the current model, an aircraft is considered disrupted if it has at least one flight delay of more than 15 minutes.
- *Flights Disrupted* shows the number of flights disrupted based on the time; in particular a flight is considered disrupted if its delay is more than 15 minutes because of an airport's clouser.
- *Flights Diverted* shows the number of flights diverted at any given time; a flight is diverted if it cannot reach its scheduled destination but it's already on flight; for these reasons this aircraft has to change its destination.
- *Flights Cancelled* shows the number of flights cancelled at any given time; a flight is cancelled if a previews leg is diverted and it is impossible for this aircraft take off from the scheduled airport.
- *Passengers Disrupted* shows the number of passengers disrupted at any given time; a passenger is disrupted if his/her flight is disrupted or diverted. We consider an average of 80% occupancy for each flight.
- *Total Delay* shows the amount of delays resulting from an airport closure after one day of simulation.

Figure 5 shows the indicators of the model in terms of number of aircrafts in one specific time frame, Plane Disrupted, Passenger chart, number of flights disrupted, diverted and cancelled, and Total Delay.

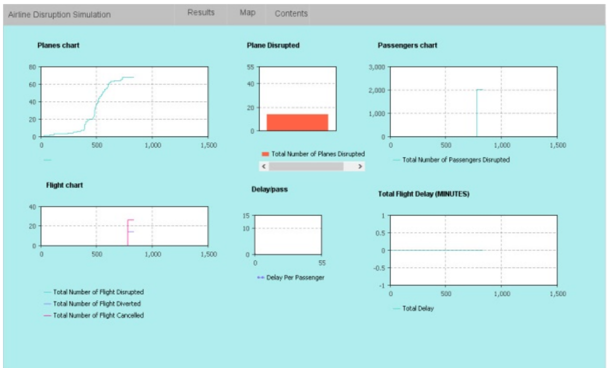

Figure 5: Interface for the Output Section

The presented model has been validated in two steps. First by means for an exhaustive *Structured walkthrough* and secondly by several *Data relationship correctness* revisions. Both techniques are commonly used in model verification and validation (Sargent 2013).

6. SIMULATION RESULTS

The capability of the model to simulate the impacts of a disruption on a predefined network allows one to compare Airline Disruption in different airports at the same time. It is useful to identify the most and the least vulnerable routes, aircrafts or even airports.
Table 1 reports the results of various disruption scenarios (based on the duration of disruptions) for the Toronto airport. It shows total number of aircrafts, flights, and passengers disrupted in each scenario, as well as the total amount of delay. Figure 6 and 7 show the number of aircrafts and the number of flights disrupted for each disruption scenario.

Table 1: Aircraft, Flights and Passengers Disrupted and Total Delay based on Different Simulation Experiments

Toronto (start at 00:00)				
Duration of closure (hours)	# of Aircraft Disrupted	# of Flights Disrupted	# of Passengers Disrupted	Total Delay [hours]
3 h	3	3	416	5.25
6 h	5	13	1808	27.80
9 h	31	92	12746	181.43
12 h	41	143	20004	550.38
15 h	48	164	23300	1030.50
18 h	51	172	24548	1541.80
21 h	55	179	25540	2074.80
24 h	56	181	25828	2613.30

Figures 6 and 7 exhibit behaviours of vulnerability indicators. In particular, it is possible to notice how the simulated network is time sensitive, due to workload variation among the flight schedules (Figures 8 and 9).

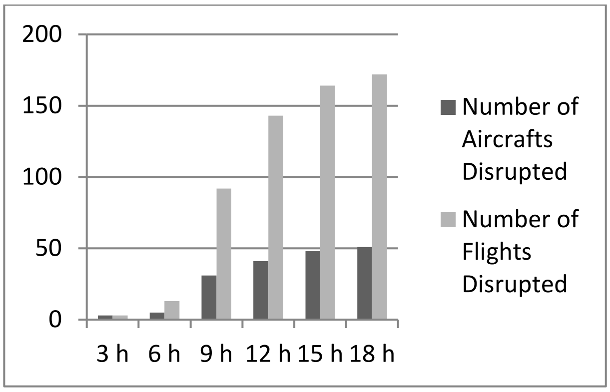

Figure 6: Numbers of Aircraft and Flights Disrupted under each Disruption Scenario

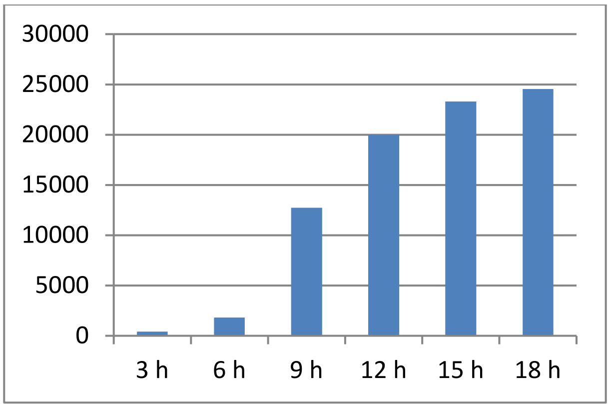

Figure 7: Number of Disrupted Passengers under each Disruption Scenario

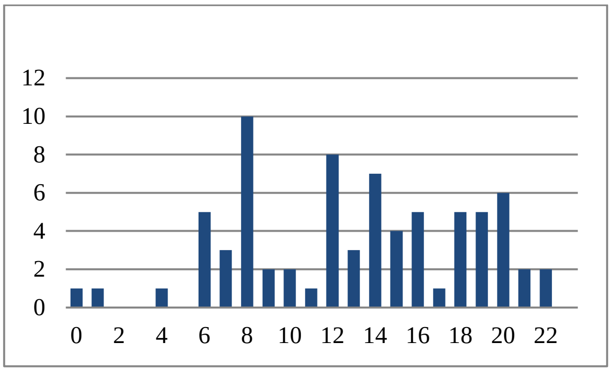

Figure 8: Number of Simulated Air Canada Scheduled Departures per Hour from Toronto Pearson Airport

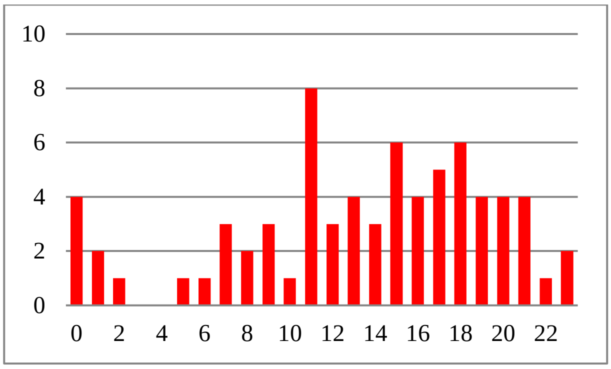

Figure 9: Number of Simulated Air Canada Scheduled Arrivals per Hour from Toronto Pearson Airport

7. CONCLUSIONS

The main goal of this study was to apply ABM to develop a support tool for the analysis of airport disruptions on airline route networks. In this paper, a specific airline network has been analyzed. The network includes 29 airports in Canada, USA, Mexico and the Caribbean and 70 aircraft which are categorized into four Air Canada Airbus families (A321, A320, A319, A319 Air Canada Rouge). Each aircraft has a specified number of legs and the current model includes 255 legs considering non-bidirectional routes. Based on these data and information, the authors have developed a simulation model that is able to generate relevant indicators about the impacts of an airport disruption on the network.

The simulation model allows a comprehensive and dynamic visualization of the main elements during the simulation (by means of the animation interface), with an easy to use input section (for parameters variation) and with an output section to show the simulation results. The model provides important information about Aircraft Disrupted, Flights Disrupted, Flights Diverted, Flights Cancelled, Passengers Disrupted, and Total Delay.

The present work provides a useful tool to assess the impacts of disruptive events on air traffic networks, providing insights about the most vulnerable areas and elements within the network under a systemic approach. Resilience measures could be estimated and verification of the possible improvements on the network's performance could be tested due to new configurations or new contingency strategies.

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