Multimodal Impact Analysis of an Airside Catastrophic Event: A Case Study of the Asiana Crash

Aude Marzuoli, Emmanuel Boidot, Eric Feron, Paul B. C. van Erp, Alexis Ucko, Alexandre Bayen, and Mark Hansen

***Abstract*—Transportation networks constitute a critical infrastructure enabling the transfers of passengers and goods, with a significant impact on the economy at different scales. Transportation modes, whether air, road, or rail, are intrinsically coupled through passenger transfers and are interdependent. The frequent occurrence of perturbations on one or several modes disrupts passengers' entire journeys, directly and through ripple effects. This paper provides a case report of the Asiana crash in San Francisco International Airport (SFO) on July 6, 2013, and its repercussions on the multimodal transportation network. It studies the resulting propagation of disturbances on the transportation infrastructure in the USA, particularly on the U.S. air transport network and the ground transportation in the Bay Area. The perturbation takes different forms and varies in scale and time frame: cancelations and delays snowball in the airspace, with up to 86% of cancelations in the U.S. due to the SFO crash; highway traffic near the airport is impacted by congestion in previously not congested locations, with low speed and high delays on US 101; and transit passenger demand exhibits unusual traffic peaks in between airports in the Bay Area, with up to 180 passengers more per hour between SFO and Oakland International Airport Bay Area Rapid Transit stations. This paper also investigated the effect of the crash on the social media Twitter. This paper, through a case study, aims at stressing the importance of further data-driven research on interdependent infrastructure networks. The end goal is to form the basis for optimization models behind providing more reliable passenger door-to-door journeys and improved transport network resilience.**

***Index Terms*—Aircraft crash, multimodal transportation, network coupling, disturbance propagation, passenger-centric analysis.**

I. Introduction

In 2012, 2.9 billion passengers boarded an airplane, whether for business or leisure, across the world [1]. Yet, air transport is only a portion of the passenger door-to-door journey, which also relies on other modes of transportation, such as rail, road and water. Transportation modes are usually studied separately as if not interacting, although they are intrinsically coupled through passenger transfers. The failure of one mode disrupts the entire passenger journey. Over the past few years, many disruptions have highlighted the rigid structure of transport infrastructures and the potential for perturbations to snowball across multimodal infrastructures. In particular, the failures and inefficiencies of the air transportation system not only have a significant economic impact but they also stress the importance of adopting a passenger-centric perspective [2]–[5]. In 2010, the Icelandic volcano eruption resulted in the cancelation of more than 100,000 flights, with stranded passengers and their luggage across Europe, scrambling to reach their destination using other modes [6]. Every year in the US, hurricanes, snow storms or pop-up thunderstorms cause massive cancelations and delays in the entire transportation system [7]. As the number of passenger keeps growing [1], congestion and snowball effects threaten the resilience of the whole multimodal transport infrastructure. The Department of Transportation aims at reducing congestion on the whole transportation network [8]. A report for Congress [9], following 9/11, tackled the identification of critical infrastructures, in particular transportation systems.

The present paper undertakes a study of the Asiana crash in San Francisco airport on July 6th, 2013 and the resulting large-scale multimodal perturbation that propagated on the airside and the landside. The objective is to provide the first case study investigating the effect of a single disturbance on a specific transport network on the multimodal transportation system on different time frames and scales. The study also covers the effect of the crash on the communication network Twitter. The higher-level goal is to foster a better understanding of multimodal transportation to increase its resilience and facilitate the passenger door-to-door journey. This case study can provide the first experimental basis upon which several system engineering methods could be applied to improve the entire passenger journey. These methods encompass network science approaches, classical control and optimization techniques for infrastructure networks and queueing systems for traffic management [10], to name a few.

From a network science perspective, much research has focused on examining the structure of each transportation mode [11]–[14] and the associated patterns of delay propagation [15]–[17]. To the authors' knowledge, there is little

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A. Marzuoli, E. Boidot, and E. Feron are with the School of Aerospace Engineering, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: amarzuoli3@gatech.edu).

P. B. C. van Erp, A. Ucko, A. Bayen, and M. Hansen are with the Department of Civil and Environmental Engineering, University of California at Berkeley, Berkeley, CA 94720 USA.

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work on network coupling or interdependencies and hardly any on transportation infrastructures. One of the most documented examples to date is the electrical blackout in Italy in September 2003: the shutdown of power stations directly led to the failure of nodes in the Internet communication network, which in turn caused further breakdown of power stations [18]. At the theoretical level, the robustness of interdependent random networks is beginning to be understood [19] but research on real-world applications is lacking. Interdependent infrastructure networks are complex cyberphysical systems, and may also be seen as highly optimized tolerant systems [20]. Understanding the observability and controllability of complex networks [21] is critical to ensure their robustness under perturbations.

On the transportation side, there has been extensive research on disturbance propagation in the airspace [22]–[25], the impact of airline scheduling of aircraft and crew [26] and the best recovery optimization schemes [27], [28]. Recently, a shift towards passenger-centric metrics in air transportation, as opposed to flight-centric, has been promoted, highlighting the disproportionate impact of airside disruptions on passenger door-to-door journeys [29]–[31]. Indeed, disrupted passengers, whose journey was interrupted, only account for 3% of the total passengers, but suffer 39% of the total passenger delay [32].

The paper is organized as follows. Section II provides a brief description of the ASIANA crash and the subsequent events at San Francisco airport. Section III evaluates the direct impact of the crash on the airside. Section IV presents the effect of the crash on the ground transportation network, the railway system BART and the social network Twitter. Section V investigates future research paths. Section VI draws the conclusions of this paper.

II. Crash Description

This section summarizes the events leading to the Asiana crash at San Francisco airport. The layout of San Francisco International Airport (SFO) is displayed in Fig. 1. It is the seventh busiest airport in the United States [33], with about 400,000 movements and 45 million passengers per year.

On July 6th, 2013, the weather was clear, the winds were light. The instrument landing system vertical guidance (glide slope) on runway 28L was, as scheduled, out of service. At 11:28 a.m. PDT, Asiana Airlines Flight 214, a Boeing 777-200 ER aircraft, crashed just short of runway 28L's threshold at San Francisco International Airport. The accident investigation submission by the National Transportation Safety Board [34] states that "the probable cause of this accident was the flight crew's failure to monitor and maintain a minimum airspeed during a final approach, resulting in a deviation below the intended glide path and an impact with terrain." Of the 307 people aboard, 3 died, 181 others were injured. The crash resulted in a five hour total closure (and cancelation/redirection of all fights) of the runways at the airport. By 3:30 p.m. PDT, runways 19L/1R and 19R/1L were reopened; runway 10L/28R (parallel to the runway of the accident) remained closed for more than 24 hours. The accident runway, 10R/28L, reopened on July 12.

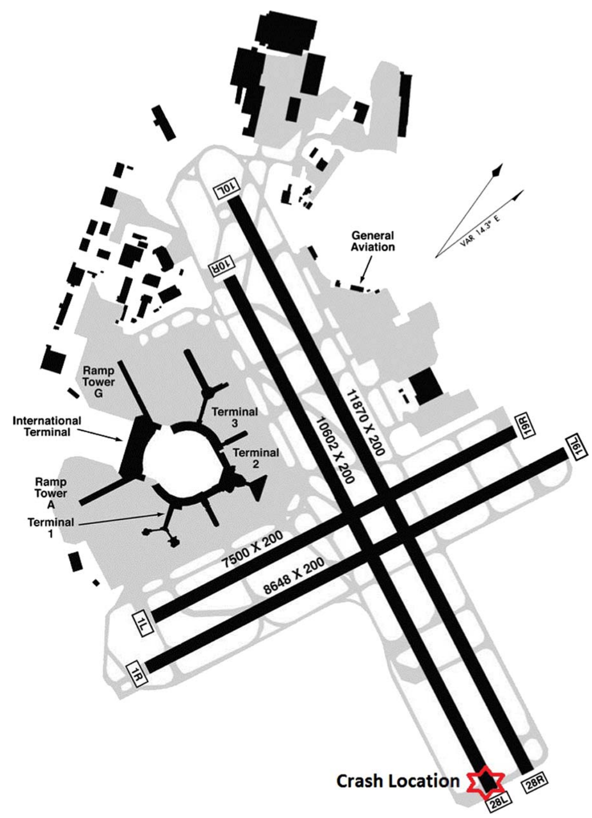


Fig. 1. San Francisco Airport Layout.

III. Airside Analysis

The crash led to the closure of SFO and, even after the airport reopened, its capacity was reduced by more than 50%. The crash led to cancelations, diversions and delays at SFO, and impacted the rest of the airspace with ripple effects. The work presented is based upon publicly available data from the Bureau of Transportation Statistics (BTS) that are primarily used to evaluate airline on-time performance.

A. Impact of the Crash in San Francisco

1) Departures, Arrivals, Cancelations and Diversions at SFO: Fig. 2 represents the difference between scheduled and actual operations at SFO from Saturday, July 6th 2013 to Tuesday, July 8th 2013. The divergence between scheduled and actual departures, as well as scheduled and actual departures begins immediately after the crash. The airport is closed until the two shorter runways, perpendicular to the crash runway, reopen in the afternoon. Departures and arrivals then resume at less than half the usual pace because of reduced runway capacity at the airport. The BTS data provides timing information on the scheduled flights that were neither diverted nor canceled. Fig. 2 shows that the traffic volume of the remaining schedule was much smaller than the following days. Summing the results over four days, more than 660 flights scheduled to land at SFO airport had either been canceled or diverted, and more than 580 flights had been canceled or diverted at departure from SFO.

Fig. 3 displays the temporal evolution of diversions and cancelations to or from SFO airport from Saturday July 6th 2013

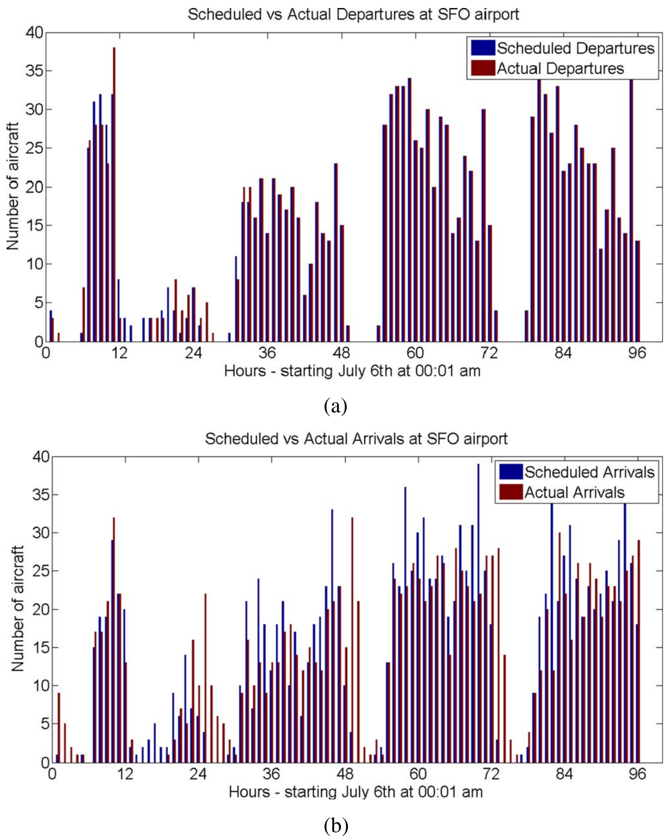


Fig. 2. Scheduled vs Actual Arrivals and Departures at SFO airport, July 6th-9th 2013, from BTS data. The crash occurred at 11:28 am, the two perpendicular runways to 28L reopened at 3:30 pm.

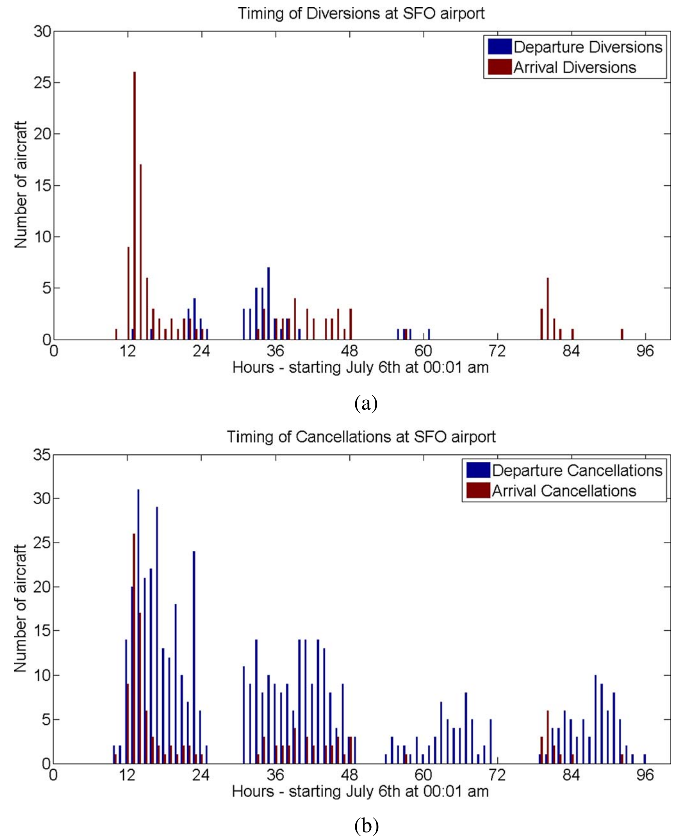


Fig. 3. Temporal evolution of Cancelations and Diversions at SFO airport, July 6th-9th, from BTS data. The crash occurred at 11:28 am, the two perpendicular runways to 28L reopened at 3:30 pm. The cancelations start immediately after the crash whereas diversions start arriving at other airports after 12:00 pm.

to Tuesday July 9th. First, Fig. 3 shows that diversions mostly occurred on Saturday as well as on Sunday. There are several departure diversions, meaning that flights that departed from SFO made a stop before reaching their final destination, mostly on Saturday evening and Sunday morning, when there are fewer arrival disruptions. The proportion of diversions is high: 17% of arrival flights to SFO were diverted on Saturday. Diversions are rare events, they represent less than 2% of operations in the US. After Sunday, the number of diversions goes back to normal, while cancelations remained considerable, impacting one third of the flights to and from SFO. Cancelations span the four days without any noticeable pattern regarding their timing. A closer look at the spread of cancelations and diversions over the crash week-end in Table I highlights the impact of the crash. More than half of the scheduled departures and almost half the scheduled arrivals were canceled on Saturday; these figures slowly decreased until Tuesday.

Operations were worse on Tuesday, July 9th than on Monday, July 8th, with more cancelations and new diversions. Moreover, due to the closure of the crash runway, runway capacity was still significantly reduced, leading to many cancelations. There are very few diversions after Sunday. This is to be expected since diversions are usually tactical operations. Upon further investigation of the departure diversions on Saturday evening and Sunday morning, these diversions impacted medium-haul flights only, with a short stop in SLC airport; they reached their final destination with little delay. The most likely explanation is that these flights were performed by fairly heavy aircraft. Because only the two shorter runways were opened until Sunday afternoon, they probably had to depart with less fuel than needed for their entire trip and their planned refueling at another airport appears in the data as a diversion.

The major carrier flights were diverted to a number of airports (see Table II). The other Bay Area airports, Oakland (OAK) and San Jose (SJC) accommodated most flights, from Saturday to Tuesday. Nevertheless, several other airports, as far

TABLE I
NUMBER OF COMPLETE, CANCELED AND DIVERTED FLIGHTS TO AND FROM SFO DURING THE ENTIRE CRASH WEEK-END, FROM BTS DATA

Day	Complete	Cancelled	Diverted
Sat	185	180	74
Sun	310	155	30
Mon	476	43	1
Tue	433	70	14

(a)

Day	Complete	Cancelled	Diverted
Sat	198	231	11
Sun	293	174	30
Mon	456	62	2
Tue	439	74	1

(b)

TABLE II
NUMBER OF FLIGHTS SUPPOSED TO LAND AT SFO AIRPORT AND DIVERTED TO OTHER AIRPORTS

Day	July 6	July 7	July 8	July 9
DEN	4	0	0	0
LAS	7	0	0	0
LAX	8	0	0	0
MSP	1	0	0	0
OAK	15	19	1	4
PHX	3	0	0	0
RNO	3	0	0	0
SJC	22	11	0	7
SLC	1	0	0	1
SMF	10	0	0	2
Total	74	30	1	14

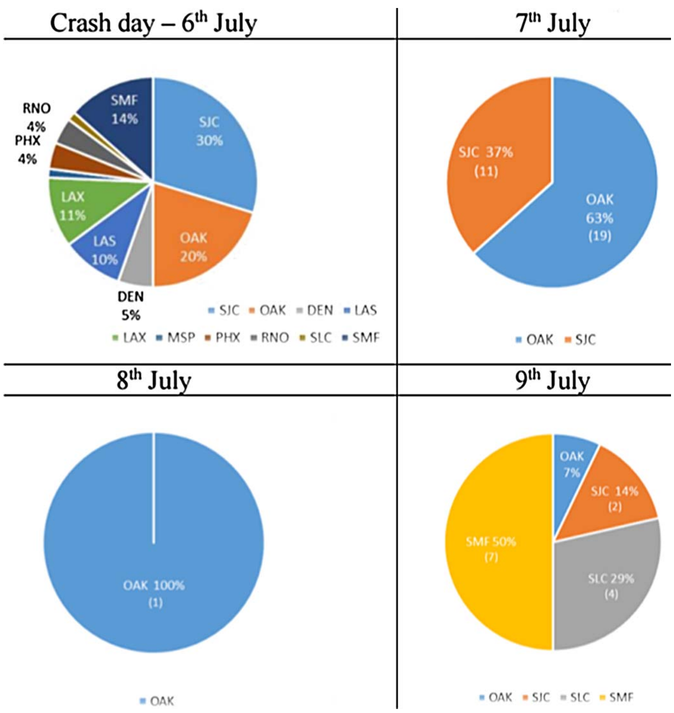


Fig. 4. Proportion of passengers diverted to different airports from July 6th to July 9th 2013.

as Denver, Los Angeles and Las Vegas, received many diverted flights on the crash day. Fig. 4 displays the estimated number of passengers who were diverted to different airports than SFO from July 6th to July 9th, based on the load factor reported by each airline for July 2013 to the BTS. Fig. 4 where passengers were diverted to other airports from July 6th to July 9th. More than 15,000 domestic passengers were diverted over four days. The BTS data does not provide indications regarding diversions of international flights but news reports [35] that several international flights were diverted to Seattle Tacoma (SEA) on Saturday, July 6th, coming from London, Dubai, Frankfurt, Paris and Zurich.

Many more issues arose when flights were diverted to airports in which their carrier does not operate. For instance, a SFO-bound United Airlines flight from Seattle was diverted to Oakland. Local news reporters [36] interviewed the 6th of July 2013 some of the flight passengers, who reported "United has no support here. They sent a dislocation team, but basically what they keep saying is: "You're dislocated." " The officials said they had to bring extra staff to accommodate passengers who were landing at the same time. Moreover, many passengers were diverted to airports where their airline operates at low frequency.

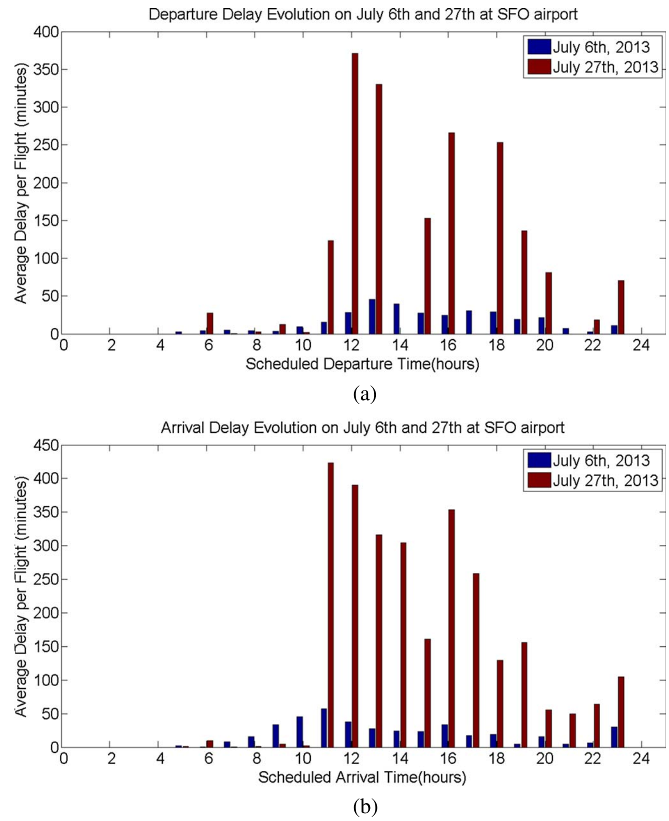


Fig. 5. Delay comparison between the crash day and a normal Saturday at SFO. The crash occurred at 11:28 am, the two perpendicular runways to 28L reopened at 3:30 pm.

2) Delays at SFO Airport: When it comes to operations at the airport itself, Fig. 5 displays the delay minutes for each departing and arrival flight against their scheduled departure or arrival time at SFO airport during (i) the crash day and (ii) Saturday July 27th, which is used as a reference day. There were 879 scheduled flights at SFO on July 6th and 901 on July 27th, corresponding to domestic US carriers. On July 6th, there were a total of 411 cancelations and 85 diversions, whereas on July 27th, 8 flights were canceled and none diverted. Immediately after the crash, departure and arrival delays rise significantly and are much higher than on July 27th, although the number of operations is considerably smaller. The delays go back to almost normal levels after 10 pm. Contrary to departure and arrival delays, the taxi-out times were normal through the day. This means that the departure delay observed is primarily due to delay incurred at the gate. Taxi-in times were normal except around the crash time. Because of the number of emergency vehicles going to the crash runway, arrival flights on the ground may have been held to let them through.

B. Impact of the Crash on the Air Transportation Network

Cancelations and delays due to the crash at SFO propagated through the airspace and the ripple effect lasted several days.

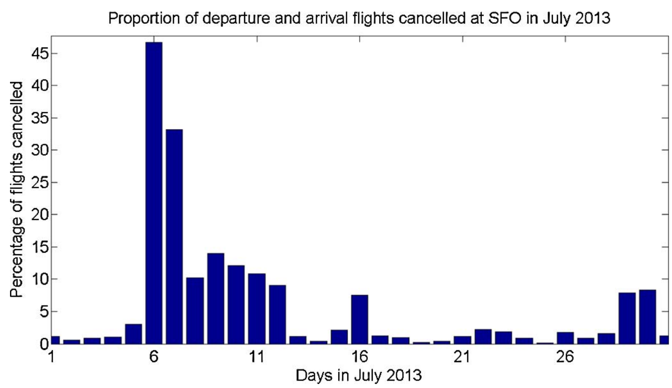
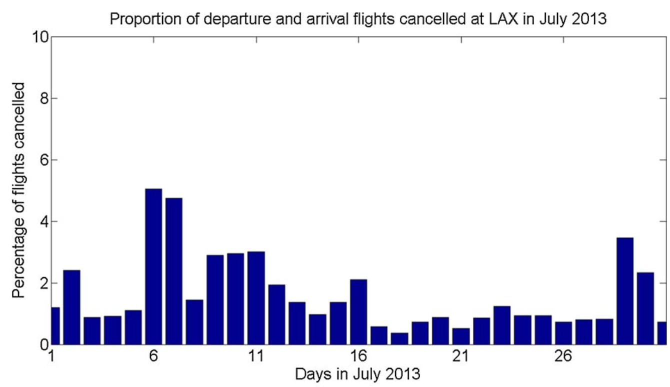


Fig. 6. Proportion of canceled flights among the total scheduled traffic departing or arriving at SFO airport for July 2013.



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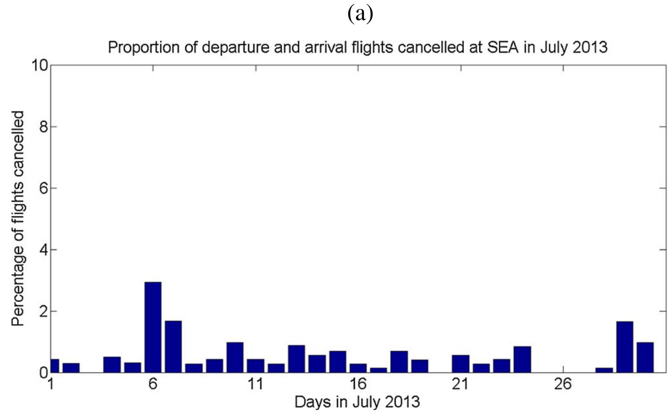


(b)

Fig. 7. Proportion of canceled flights among the total scheduled traffic departing or arriving at Los Angeles (LAX) and Seattle (SEA) airports for July 2013.

1) Cancelations and Their Propagation: Fig. 6 shows the number of departure and arrival cancelations at SFO for the entire month of July. The day of the crash, Saturday, is the worst in terms of cancelations, with more than 45% of the scheduled flights canceled. Sunday July 7th is the second worst. The recovery takes more than a week after the crash, with the week from July 8th to July 12th witnessing cancelations of more than 10% of the number of scheduled flights each day.

Fig. 7 shows the number of departure and arrival cancelations are Los Angeles International Airport (LAX) and Seattle-Tacoma International Airport (SEA). Among the other top 30 airports in the US, LAX and SEA were most affected by cancelations due to the crash. On July 6th and 7th, the proportion of canceled flights at LAX and SEA was highest for the month of July, with more than 5% of canceled flights at LAX and 3% at SEA.

Cancelations can propagate through schedules. Indeed, a given aircraft is scheduled to fly several legs through a given day. Once one of these legs has been canceled, the airline tries

TABLE III
FLIGHT CANCELATIONS PROPAGATION DUE TO SFO AIRPORT

Day	July 6	July 7	July 8	July 9
Missing aircraft id	144	62	17	11
Available aircraft id	137	119	48	59
Flights scheduled for the available aircraft id	707	708	338	452
Flights cancelled for the available aircraft id	279	269	92	139

TABLE IV
CANCELATIONS IN THE AIRSPACE ATTRIBUTABLE TO PERTURBATIONS AT SFO AIRPORT

Day	July 6	July 7	July 8	July 9
Number of flights cancelled at departure or arrival at top 35 airports in the US	488	609	456	510
Number of cancellations due to SFO crash	423	331	109	150
Percentage due to SFO crash	86%	54%	24%	30%

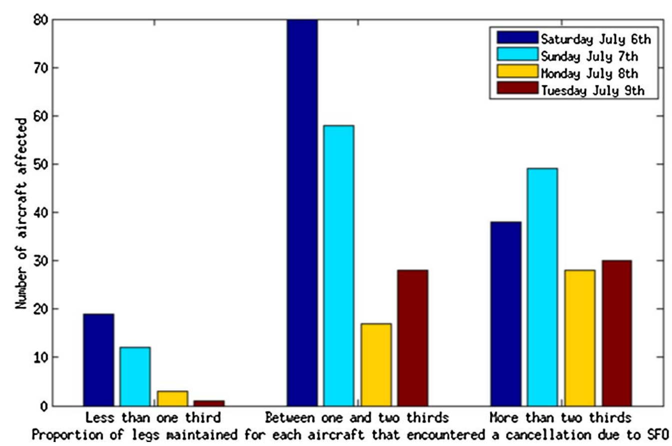


Fig. 8. Number of flights maintained per aircraft encountering a cancelation due to SFO airport from Saturday July 6th to Tuesday July 9th.

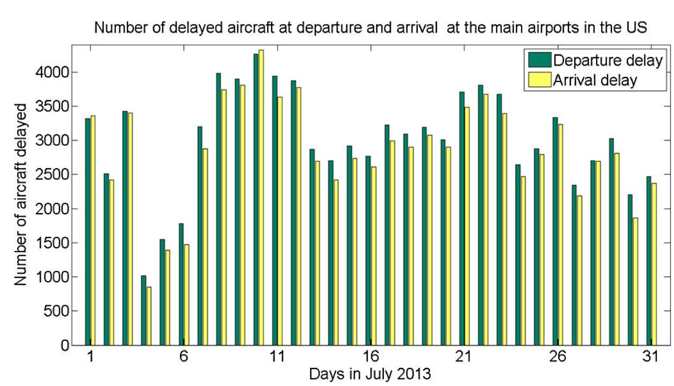


Fig. 9. Delays at the top 35 airports for July 2013.

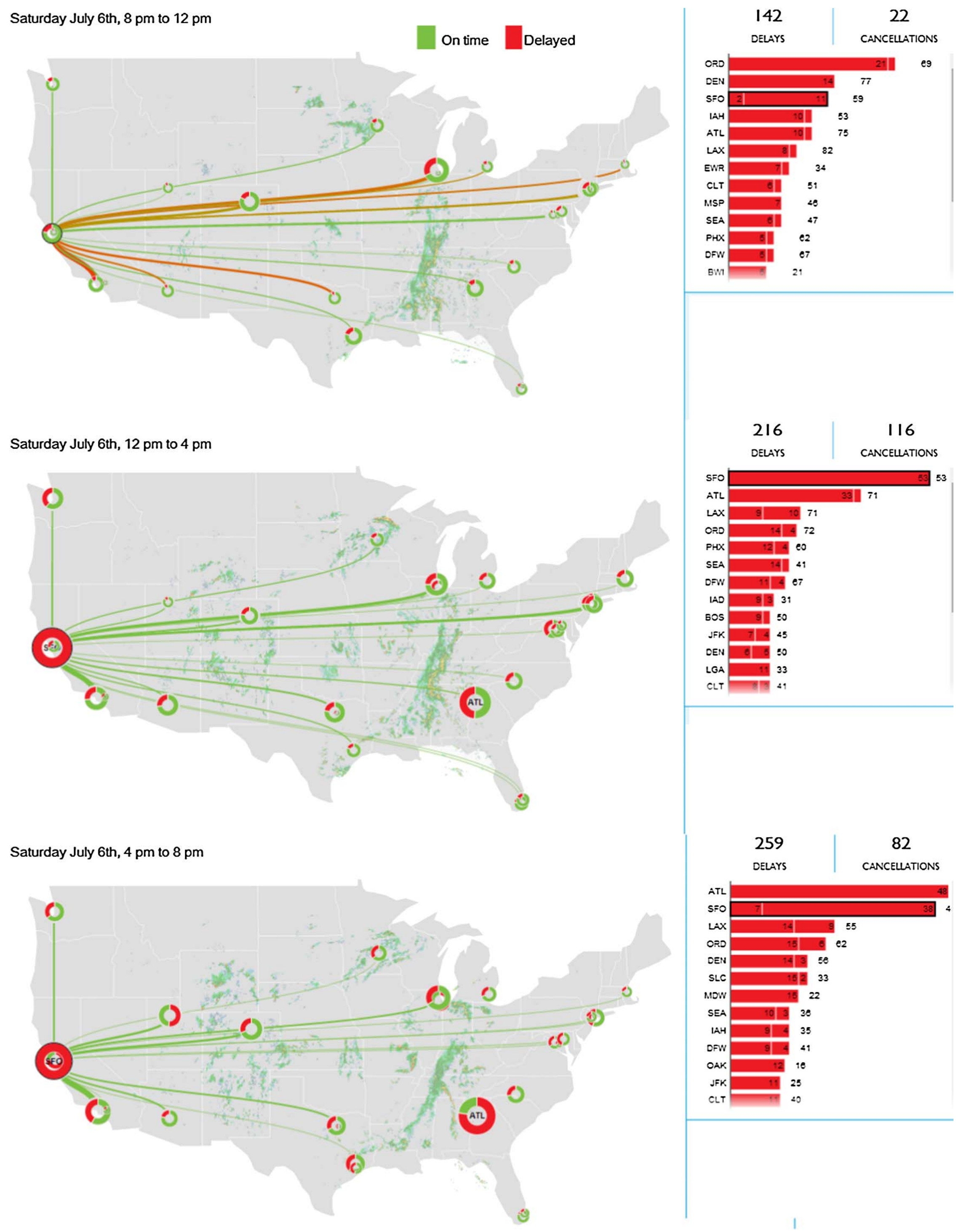


Fig. 10. Proportion of delayed flights and number of cancelations at the top airports on July 6 2013.

to get back on schedule, but this schedule recovery is airline- and aircraft-specific. To analyze this propagation phenomenon, the tail numbers of all aircraft involved with flights canceled at departure or arrival to SFO airport from July 6th to July 9th were tracked. In the BTS data, some tail numbers are missing, making these aircraft impossible to track. Such flights are counted in Table III under ‘missing aircraft id’ and only one cancelation is computed. For the aircraft with available tail numbers, each aircraft’s individual schedule is recovered. The number of legs each aircraft was supposed to fly is computed. Among these scheduled legs, the total number of cancelations is recorded. In Table IV, the number of cancelations encountered by any aircraft with available or missing tail numbers are summed. This Table provides the total number of cancelations directly attributable to the SFO crash over the crash week-end. The total number of cancelations regarding flights departing or arriving at one of the top 35 airports in the US is also computed for the crash week-end. The ratio between cancelations

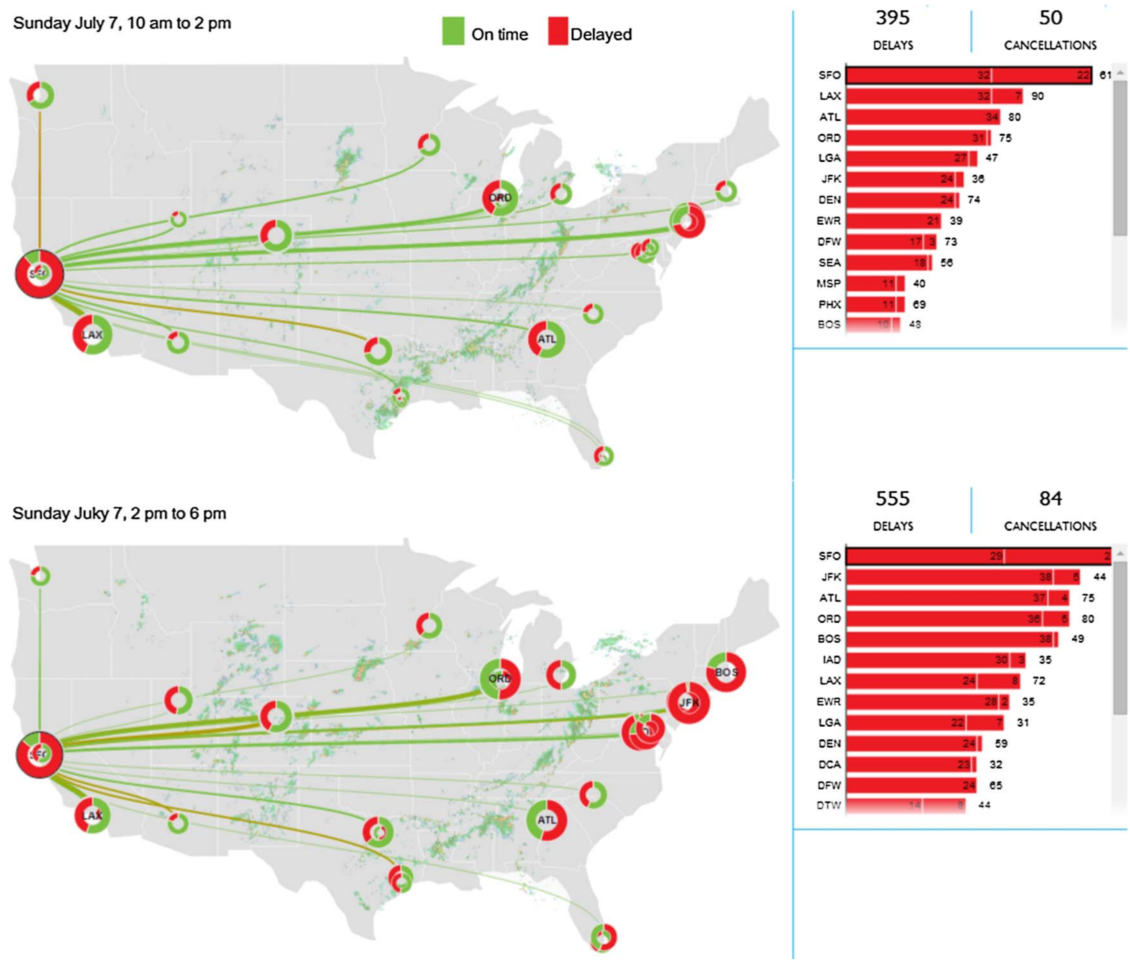


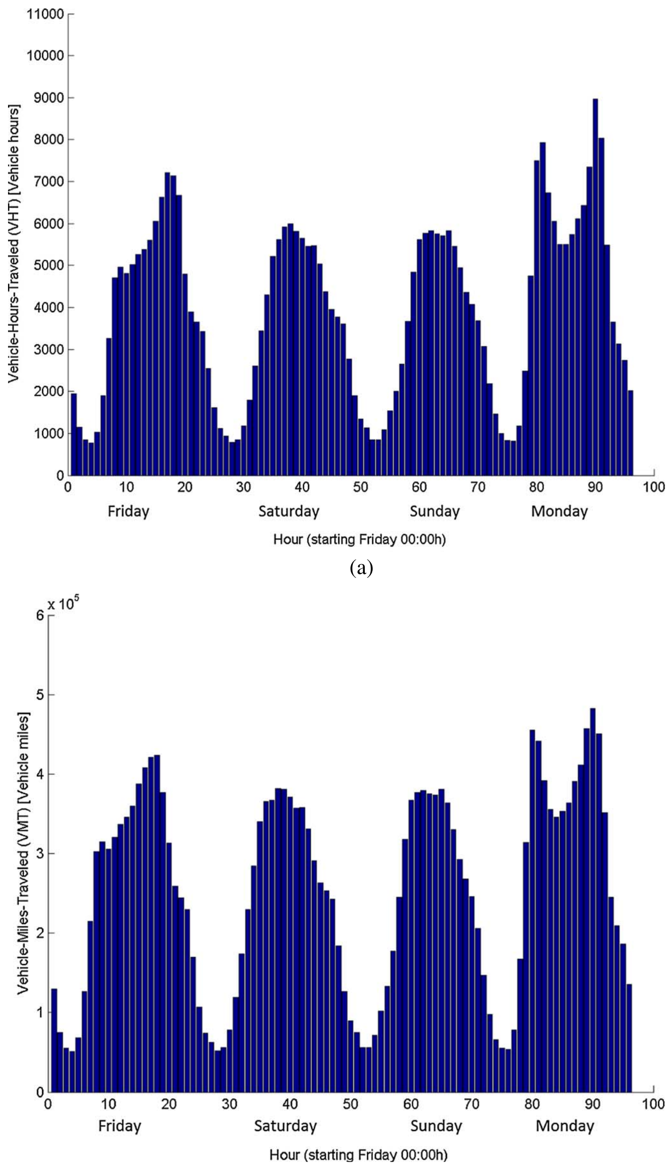
Fig. 11. Proportion of delayed flights and number of cancelations at the top airports on July 7 2013.

attributable to the crash and cancelations in the entire airspace is underestimated, because of the missing tail numbers. On the day of the crash, the propagation of cancelations due to the Asiana crash accounts for more than 85% of all cancelations in the airspace, more than 50% on Sunday and more than 25% on Monday and Tuesday. Over the four days, the Asiana crash led to more than 49% of all cancelations in the US.

Fig. 8 shows, for each aircraft with a tail number that encountered a cancelation to or from SFO airport, how much of its schedule was disrupted. Some aircraft were supposed to operate up to eight legs on the crash day. Some aircraft had a first flight canceled early in their schedule and could not perform any of the remaining legs through the day, whereas others encountered cancelations but could still complete most of their scheduled legs. On Saturday July 6th and Sunday July 7th, most aircraft completed between one and two thirds of their scheduled legs. On Monday July 8th and Tuesday July 9th, more than 50% of the aircraft that encountered a cancelation were then able to complete more than two thirds of their scheduled legs.

2) Delays and Their Propagation: To evaluate the impact of the crash on delays throughout the national airspace, the number of delayed aircraft at the top 35 passenger airports in the US is computed for July 2013. The results are displayed in Fig. 9. Saturday, July 6th and Sunday, July 7th have some of the lowest total delay in the entire month because canceled flights are not accounted for in the delays. Since a large proportion of flights were canceled, even if many of the maintained flights were delayed, the effect of lower flight volume made the overall delay lower.

A visualization tool, inspired from the publicly available "misery map" from Flight Aware [37] was developed to display the proportion of delayed and on-time flights at the top passenger airports in the US over 4-hour periods. The tool also ranks these airports by number of cancelations. Figs. 10 and 11 are screen shots of the visualization tool through July 6th and 7th. The time indicated is Pacific time. First, on July 6th, before the crash, Chicago O'Hare was the airport with the most cancelations and the highest proportion of delayed flights, because of a weather perturbation. Right after the crash, the number of cancelations at SFO increases significantly, leading to cancelations at LAX, PHX, SEA in particular. ATL cancelations increase too, but it is also due to the weather pattern observed that day. The proportion of delayed flights also increases throughout the entire airspace. On July 7th, the proportion of delayed flights is much higher than on the previous day at most of the busiest airports, particularly in the afternoon. This could also be an effect of the end of a holiday week-end. For instance, the number of cancelations is much



(a)

(b)

Fig. 12. Road traffic performance data for the long weekend in which the ASIANA crash occurred.

higher in the New York Area airports and Boston than on the previous day.

IV. Impact of the Crash on Other Transportation Modes

A. Ground Transportation: Highway Traffic

The major data source for the road network in California is PeMS, which stands for Freeway Performance Measurement System [38]. Measurements from loop detectors on the major roads in California are recorded and stored in PeMS. The loop detectors measure the number of vehicles passing per time period (flow) and the fraction of time that the loop is occupied (occupancy). From these measurements, a number of traffic properties are estimated, for example the average speed of vehicles on a given road. However, the PeMS data presents two main limitations. First the traffic conditions on a road stretch between two detectors are not observed. Second, many loop detectors are out of order for periods of time. The second limitation has an compounding effect on the first limitation.

TABLE V
Performance Variables for Three One-Mile Road Stretches With Uniform Traffic Conditions During One Hour (the Reference Speed for Delays is 65 mph)

State	Flow[veh/h]	Speed[mph]	Delay[veh/h]	VMT[veh/mi]	VHT[veh/h]
1	6000	65	0	6000	92.31
2	7900	64	1.90	7900	123.44
3	7180	50	33.14	7180	143.60

TABLE VI
Performance Variables for Six Road Stretches Consisting of Two One-Mile Road Stretches With Uniform Traffic Conditions During One Hour (the Delay Reference Speed is 65 mph)

States	Speed_{avg} [mph]	Delay [veh h]	VMT [veh mi]	VHT [veh h]
11	65	0	12000	184.62
22	64	3.80	15800	246.88
33	50	66.28	14360	287.20
12	64.43	1.90	13900	215.75
13	55.87	33.14	13180	235.91
23	56.47	35.04	15080	267.04

Choe [39] proposes a method to analyze road traffic conditions using PeMS. PeMS has been used in several studies to study congestion growth [40]. For the present study, the hourly Vehicle-Hours-Traveled (VHT) and Vehicle-Miles-Traveled (VMT) in an eight-mile radius[1] around SFO airport are studied from Friday, July 5th to Monday, July 8th, as displayed in Fig. 12.

The variables used to understand road traffic are defined as follows. q is the flow in [veh/h], T is the time period in [h], L_s is the length of the considered road stretch in [mi], and v and v_r are the observed and reference speeds in [mph], respectively

$$\text{Delay} = qTL_s\left(\frac{1}{v} - \frac{1}{v_r}\right) \tag{1}$$

$$\text{VMT} = qTL_s \tag{2}$$

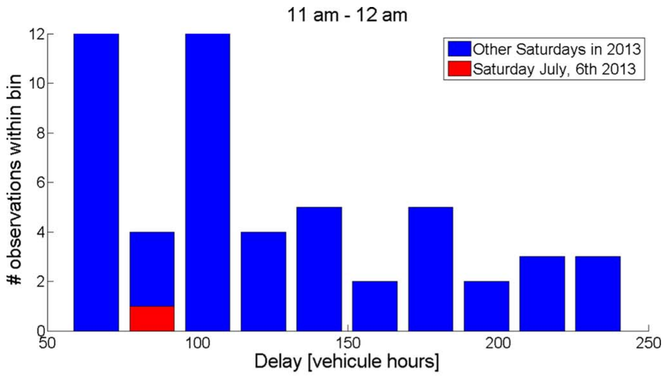
$$\text{VHT} = qT\frac{L_s}{v} = kTL_s \tag{3}$$

$$\text{Speed}_{avg} = \frac{\text{VMT}}{\text{VHT}}. \tag{4}$$

To better understand performance data based on certain traffic conditions, consider an hypothetical road stretch of one mile during a period of one hour. For this space and time, assume uniform traffic conditions. Table V shows the resulting performance variables. This example only works for uniform traffic conditions, but gives a good indication of the contribution of traffic conditions types.

A traffic state is defined for a given flow rate and speed, for a specified time period and road stretch. State 3 in Table V is the only congested state. In the road stretches where this state is observed, the average speeds are lower and the delays higher than in the other road stretches. From this example, congestion leads

[1]This data does not correspond to a direct output of PeMS. The VHT and VMT for the different PeMS roads stretches within this area are summed.



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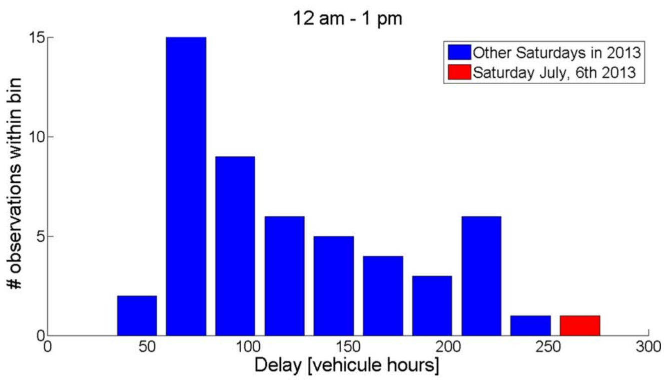

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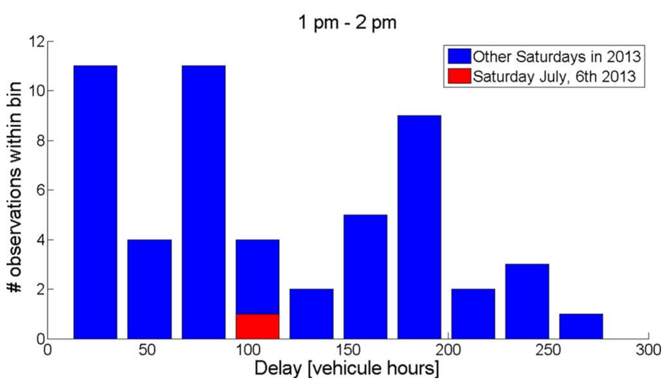
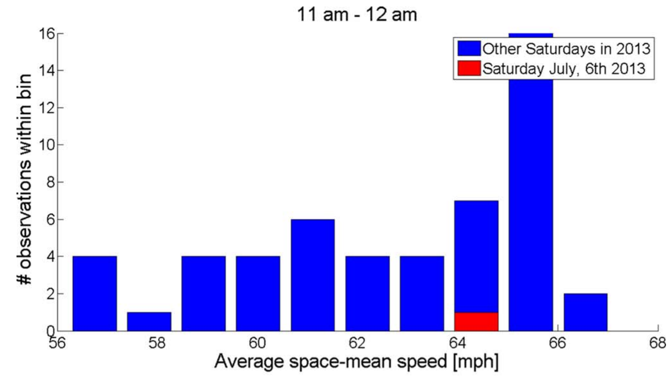


(c)

Fig. 13. Histograms of the delay on the US101-N PM 415-425 for the 26 Saturdays between April and September 2013.



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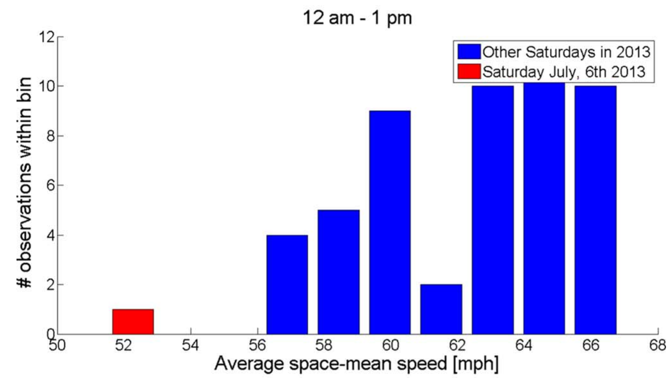

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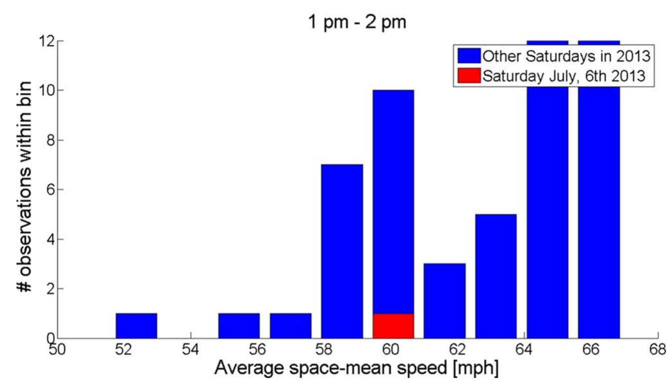

(c)

Fig. 14. Histograms of the speed on the US101-N PM 415-425 for the 26 Saturdays between April and September 2013.

to a large delay and low speed. Near capacity (synchronized) flow contributes mostly to an increase in VMT.

Now consider the example of a two mile road stretch during a one-hour period, with two equal length uniform traffic conditions. The corresponding performance data is depicted in Table VI. The VMT and VHT are both larger in state 22 than in state 13. It is not always the case when there is a combination of free-flow and congestion, yet it indicates that it is possible. It corresponds to light congestion and free-flow that is not close to capacity.

The traffic performance data around SFO displayed on Fig. 12 do not indicate any clear effect of the crash on the aggregated traffic conditions for Saturday, July 6th. However, a more detailed analysis can be performed using the space-time contour plots described in [39]. We define "abnormal congestion" as congestion that does not occur on reference days and thus is not caused by regularly occurring bottlenecks. The road traffic conditions are compared with reference days, namely with the 26 Saturdays between April and September 2013. Using the method in described in [39], the congestion on US101, I80 and I880 near SFO is recorded for each of the Saturdays. The congestion on the US101N near SFO stands out as abnormal. At all other locations and times where congestion was observed, congestion had also occurred at least once during the reference Saturdays. Therefore, the rest of this subsection focuses on the US101N to observe the traffic jam reported in the news [41]. When it comes to freeway traffic, under nominal conditions, week days exhibit morning and evening peaks, but weekends do not. Fig. 12 shows that only the congestion pattern on Friday, July 5th is different. This is expected for a normal

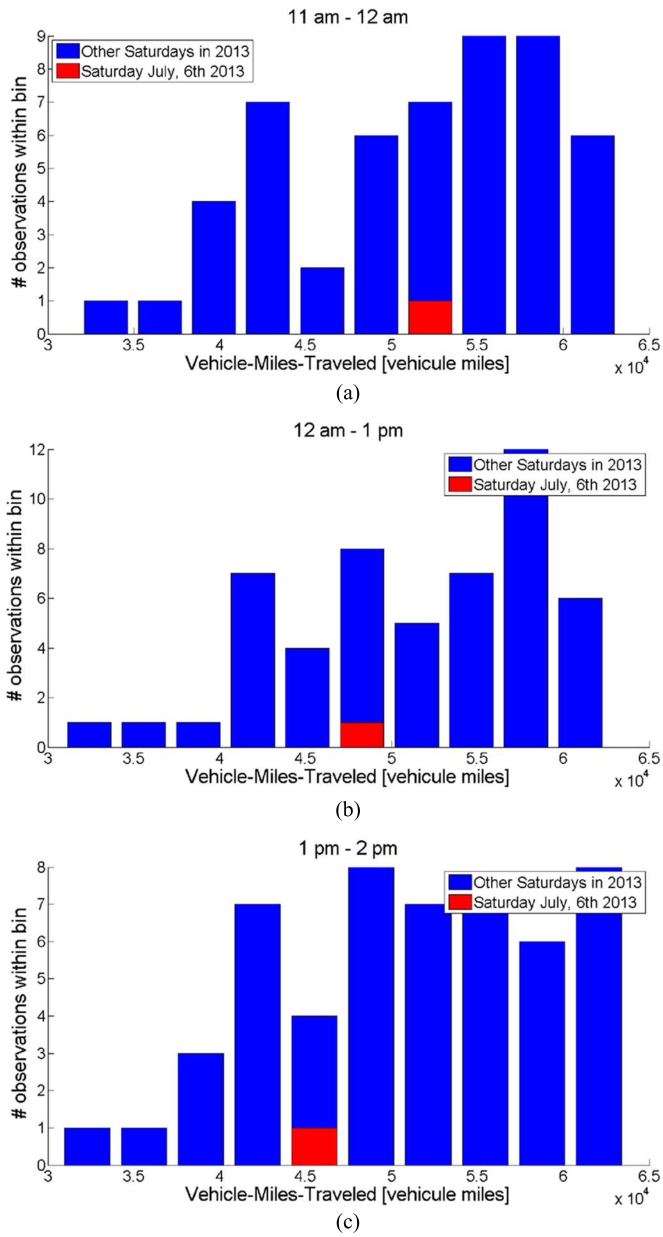

Fig. 15. Histograms of the VMT on the US101-N PM 415-425 for the 26 Saturdays between April and September 2013.

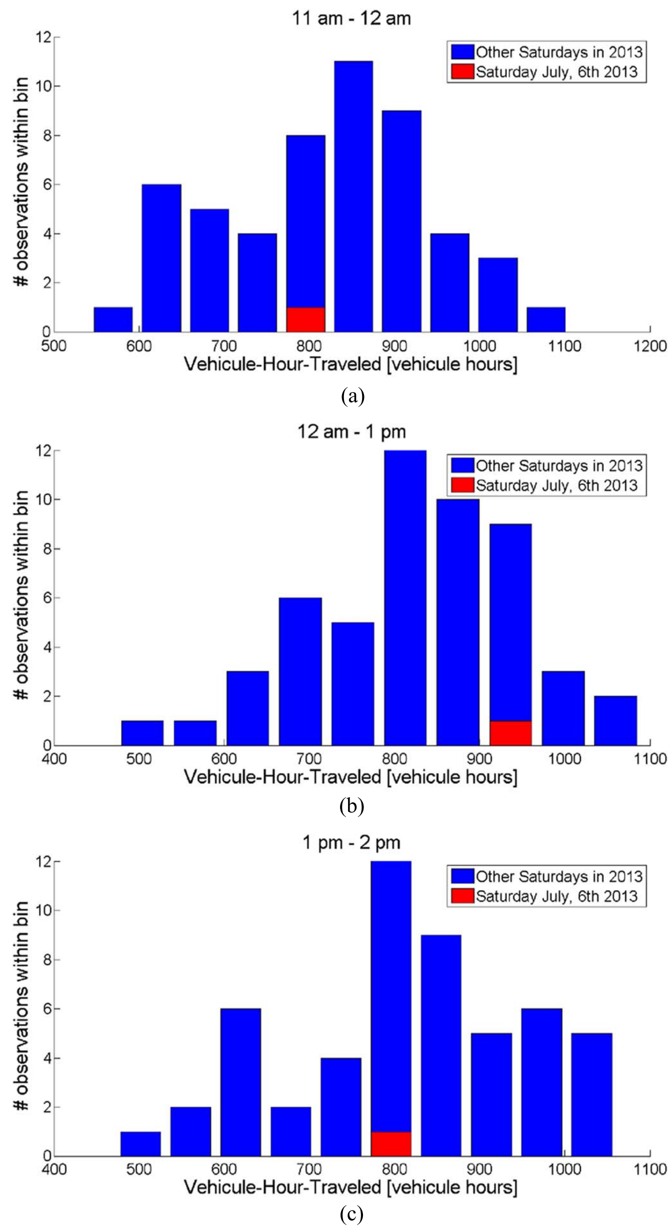

Fig. 16. Histograms of the VHT on the US101-N PM 415-425 for the 26 Saturdays between April and September 2013.

long weekend, with no morning peak because of July 4th on Thursday. A pattern change on Saturday due to the ASIANA crash is not clear from these figures because the data is too aggregated.

The performance data (speed, delay, VMT, VHT) at a US101N road stretch near SFO are shown in Figs. 13–16. From the speed and delay histograms in the 12 am - 1 pm period, the speed and delay on the crash day stand out as outliers. On the 26 reference Saturdays in 2013, the delay was never as large and the speed never as low as on the ASIANA crash day. From the VMT and VHT plots in Figs. 15 and 16, no clear effect of the ASIANA crash is observed after 1 pm on the crash day. The breakdown occurred shortly after the ASIANA crash and directly next to SFO. Our focus is on understanding the congestion behavior and, if possible, the causality between the crash and congestion. Therefore, an in-depth analysis is performed into this congestion to examine if it is caused by the crash. As a starting point, the following hypotheses about the potential causes of the congestion are formulated:

- Increase in demand caused by vehicles leaving the airport.
- Rubbernecking, a traffic breakdown is caused by users watching the crash and thereby changing their behavior.
- Effect caused by emergency vehicles trying to reach the airport.
- Accident on the highway.
- Lane or ramp closure.

In order to investigate whether external events other than the ASIANA crash, such as an accident, caused the congestion, we consider the California Highway Patrol (CHP) incidents feed

TABLE VII
CHP INCIDENTS FEED ON THE US101N BETWEEN PM 400–430 ON JULY 6TH, 2013 BETWEEN 8AM AND 10PM. NONE OF THESE CHP NOTATIONS ARE RELATED TO THE BREAKDOWN NEAR SFO AIRPORT

Time	15:26	12:18	12:41	19:25
Dur. (min)	18	27	19	6
Location	San Fran. US101 N/ US101 N Sierra Point Pkwy	Redwood City US101 N/ Willow	Redwood City US101 N/ US101 N Kehoe Ave Ofr	Redwood City US101N/ US101 N Broadway Ofr
Event	Traffic Hazard	Hit and Run no injuries	Traffic Collision	Traffic Hazard

TABLE VIII
LANE CLOSURES ON THE US101N BETWEEN PM 400–430 ON JULY 6TH, 2013 BETWEEN 8 AM AND 10 PM. THE ABS PM CORRESPOND TO THE FIRST OFF-RAMPS UPSTREAM AND DOWNSTREAM OF SFO

Begin	End	Abs PM	Facility	Closure Lanes
12:30	16:30	420,134	Off Ramp	2
12:30	16:30	422,572	Off Ramp	2

on the US101N near SFO on the crash day. The CHP incidents feed provide the incidents reported on that specific road stretch and time period. The Abs PM correspond to the first off-ramps upstream and downstream of SFO, it indicates the location of the road stretch studied. Here all reported types, namely accident, hazard, breakdown, police, congestion, weather and other are included. Table VII shows the CHP incidents reported on July 6th, 2013 on the US101N near SFO. The CHP incidents feed provides no indication for the cause behind the observed aberrant congestion. All reported incidents occurred either after the aberrant congestion and/or on different locations. PeMS also has a lane closure system, in which the historical lane closures are reported. On the ASIANA crash day, two lane closures were reported by the system, see Table VIII.[2] We assume that these combined indicate that the off-ramp to SFO was closed at 12:30pm.

To study the congestion over time, the animation function available in PeMS [38] is edited to highlight the important moments. In Fig. 17, screen shots of the animation tool are displayed to highlight the main events on the highway. At 11:28am, the ASIANA aircraft crashed just short of one of the SFO runways, see Fig. 17(a). At 11:53am, the first breakdown occurred at the on-ramp from Millbrae (PM 420.5), see Fig. 17(c), just upstream of the off-ramp to SFO. At the same time, conditions (lower speed) are deteriorating at the second upstream on-ramp (PM 419). However, a further breakdown first occurs at PM 420.5. Later, around 12:06pm, a further breakdown happens at PM 419, see Fig. 17(c). This creates the heavy congestion between PM 417–419, as previously observed. Around 12:49 pm the largest road stretch of the US101N is congested, as seen in Fig. 17(d) with the red color. The congestion does not dissolve until 1:30pm, then the traffic conditions are restored to normal. In Fig. 17(e) some lower speeds are spotted on the PM 419 on-ramp.

These observations suggest that the congestion was not likely to be caused by a large number of road vehicle departures from SFO (or inflow on the US101N) after the crash, because congestion occurs far upstream of the SFO to US101N on-ramp. The congestion observed on the US101N road stretches between PM 416.3 and 420.9. This range was selected such that the most upstream and downstream detectors show no sign of congestion. For further analysis, the road layout and individual loop detector stations on the mainline and ramps of the important road stretch are considered, as shown in Fig. 18.

For the considered road stretch, fifteen mainline stations were available. Their locations are shown in Table IX. Besides these stations, traffic information is available on the Anza Boulevard on- and off-ramp and one of the two Broadway on-ramps, namely about the vehicles using the fly-over.

For all stations, the occupancy and flow is decomposed in 5-minute time periods. For these time periods, the average space-mean speed is also available at the mainline stations. Following [39], the present focus is on the occupancy over time on the different station locations. The first station is located downstream and the last upstream of the congestion on US101-N. At this location no congestion occurs, see Fig. 19(a). The occupancy upstream of the congestion remains stable between 0.070 and 0.075 (fraction of time a detector is occupied), while it varies more at the downstream station. However, the occupancy there remains under 0.100, indicating that there is no or very limited congestion. Between 12:00 pm and 12:30 pm, a break occurs, causing the occupancy to drop and oscillate around 0.065. This indicates that after this period, fewer vehicles use the US101-N at this location. At that point in time, the congestion may have been known to users and shortly after the authorities asked people to use the I280 instead of the US101. The fact that congestion clear afterwards may suggest that people listened to the calls of the authorities.

A decomposition of the congestion pattern on US101 is provided in Fig. 17, showing that two breakdowns occur. The first breakdown happens close to the Millbrae connection. The occupancy measured at the three detectors in the affected road stretch is shown in Fig. 19(b). The first peak indicates the breakdown timed at 11:53 am with the video animation. Yet, this does not provide new insight regarding the potential causes of this breakdown.

The second, more severe, breakdown occurs at the Broadway connection, where the causes may be better understood: the congestion resulting from the second breakdown is clearly observed by the seven detector stations shown in Fig. 19(c). This

[2]This can either mean that the two off-ramps were closed or that the one in-between (the SFO off-ramp) was closed. With additional information from news reports and tweets, the most likely meaning is that the off-ramp to SFO was closed. However it is unclear whether the off-ramps were closed for the entire period. The last update was at 13:54, which could correspond to the reopening of the off-ramps. The timing could also match an announcement of the reopening of the two shorter runways at SFO. Because the congestion observed is mostly between noon and 1 pm, therefore before 13:54.

Fig. 17. Traffic situation on the US101N at different times on July 6th, 2013. Two breakdowns can be observed: the first at 11:53 am, the second at 12:10 pm.

Figure shows that the congestion starts at the most downstream stations, as the PM 419.237 and PM 418.827 station first show a higher occupancy. A jump is observed during the 12:10–12:15 time period. Although a decrease in speed is noted just before that in the video animation, the breakdown in this period is displayed in 19(c).

One probable explanation is that the congestion corresponds to "extra" emergency vehicles dispatched to assist with the Asiana crash. From the Asiana crash investigation report, a transcript states that: "By 11:33, (...) all seven airport firefighting companies and paramedics were on scene. (...) One minute later, 56 ground ambulances arrived on scene. (...) At 13:01, the last patient was transported by ambulance." [42]. Additionally, a helicopter and two buses also helped transport patients to 12 area hospitals.

The ASIANA crash affected the ground traffic conditions. Although there were multiple breakdowns, we can only state that the congestion on the US101N near SFO was a direct consequence of the crash. The (visible) smoke, the disturbance due to emergency vehicles and the ramp closures are the most likely causes. However, further details about the coupling between the airside and the highway system remains difficult to quantify.

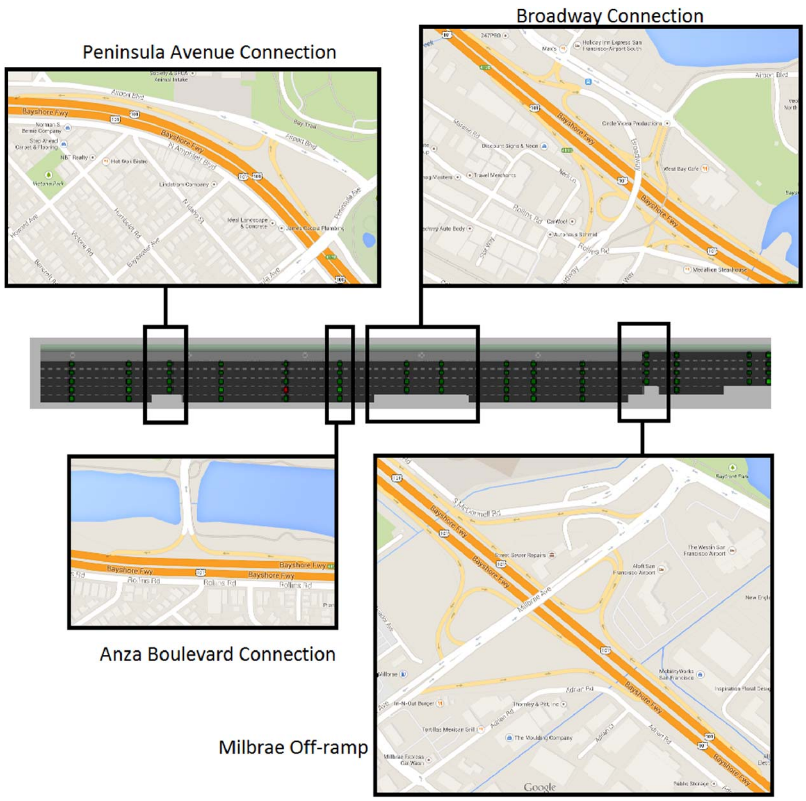

Fig. 18. Layout of the US101N road stretch where congestion occurs near SFO after the ASIANA crash. The three connections, namely Peninsula Avenue, Anza Boulevard and Broadway, consist of both off and on-ramps, while the traffic coming from the Millbrae off-ramp stays on a secondary road until after the considered road stretch.

TABLE IX
THE FIFTEEN CONSIDERED DETECTOR STATIONS ON MAINLINE US101N. THE ABS PM CORRESPOND TO THE LOCATIONS OF FIRST OFF-RAMPS UPSTREAM AND DOWNSTREAM OF SFO

Detector station number	Abs PM	Detector station number	Abs PM
1	420.887	8	418.827
2	420.767	9	418.607
3	420.307	10	418.187
4	420.117	11	417.847
5	419.717	12	417.437
6	419.407	13	417.117
7	419.237	14	416.857

B. Ground Transportation: Public Transit With the BART

The BART, or Bay Area Rapid Transit, is one key element of the transit transport in the San Francisco Bay. It links SFO to OAK as well as SJC via the Caltrain connection, see Fig. 20. The BART data obtained provides the origin-destination matrix of passengers for 15 minutes periods on Saturday, June 29th and Saturday, July 6th.

The comparison between June 29th and July 6th for departing and arriving passengers at the SFO BART station, displayed in Fig. 21 shows that the total number of passengers using this transit station was smaller on the crash day, with up to 100 fewer passengers per hour at arrival after the crash at 11:28 am. Because the airport was closed for part of the day and many flights were canceled, we can hypothesize that simply fewer passengers used this transit station.

Next, passenger traffic at the OAK BART station is studied. The results are displayed in Fig. 22 for passenger traffic between SFO and OAK, between OAK airport and SFO airport. In both directions between the two airports, there is a significant increase of passengers soon after the crash. From SFO to OAK, there is very little traffic on both Saturday, June 29th and Saturday, July 6th, with fewer than 10 passengers per hour. On the crash day, between 2 pm and 3 pm, up to 180 passengers choose to travel from SFO to OAK. The reason behind this is still unclear: these passengers could be trying to reach air travelers diverted to OAK airport, or airline employees could be suddenly needed to accommodate the incoming air traffic at the airport. The Oakland to San Francisco passenger traffic is also an outlier on the crash day, but the number of additional passengers is not as high, up to 20 per hour after the crash. One hypothesis is that it might be due to passengers diverted to OAK who had to go back to SFO for subsequent travel. Both abnormal patterns persist throughout the day.

V. IMPACT OF THE ASIANA CRASH ON THE COMMUNICATION NETWORK

The social network Twitter constitutes another network coupled with the infrastructure network. This is the only social media analysis performed because it was entirely publicly available. This subsection aims at highlighting another dimension of disturbance propagation on infrastructure networks: the communication network that includes phone communications, any

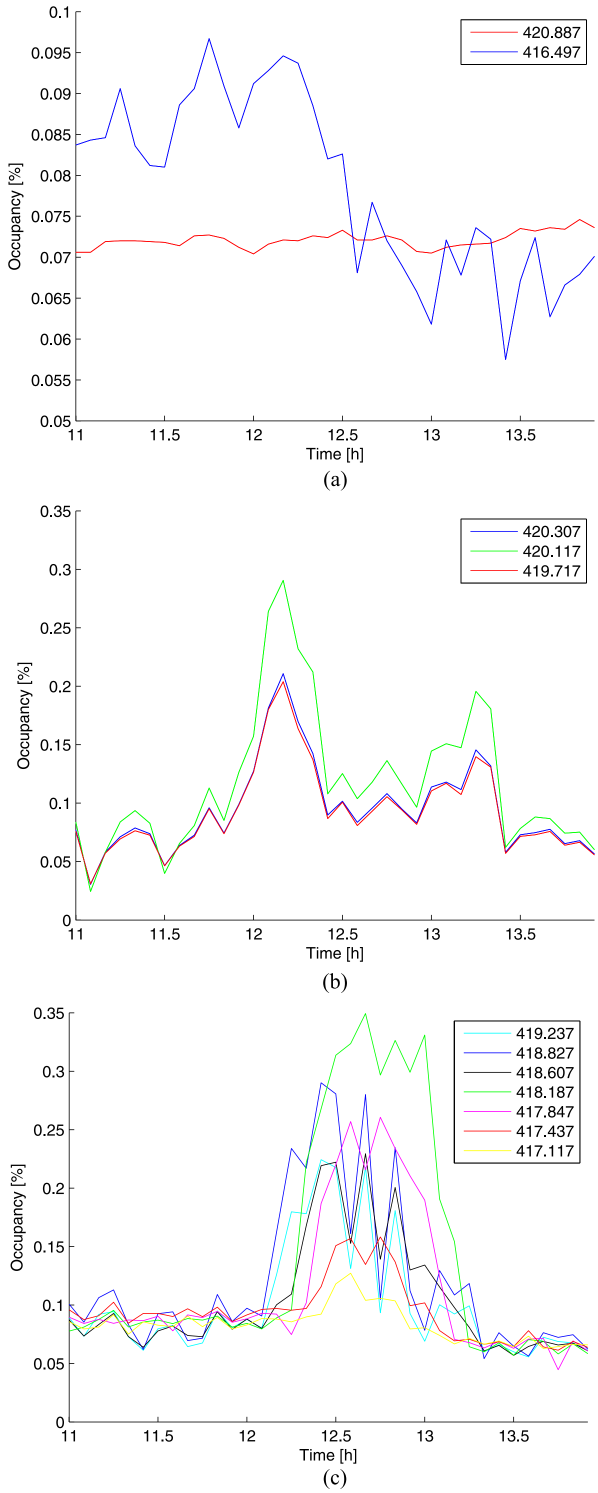

Fig. 19. Occupancy on US101 highlighting the two breakdowns after the crash.

Fig. 20. BART network.

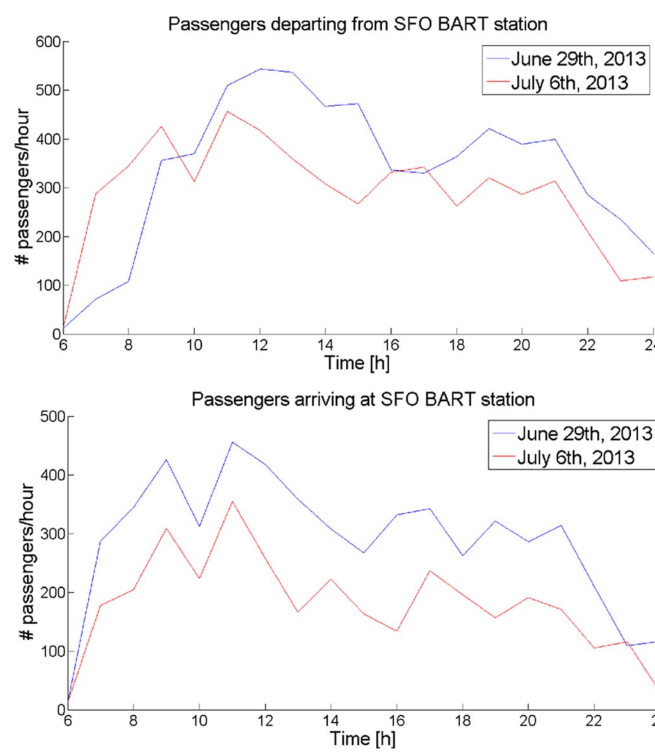

Fig. 21. Departing and arriving passengers at SFO via BART. The crash occurred at 11:28 am.

information available on the internet, e-mails exchanges, social media relays, etc. Indeed, infrastructure networks constitute cyber-physical systems and the communication channels are critical in crisis situations. From a network science perspective, this social media has been widely studied over the past few years. Such research aims at understanding how information propagates, via "infection" mechanisms, revealing that the vast majority of users passively access information but very few actually relay it [43], [44]. Authorities, airlines and airports often use it as a fast means of conveying time-sensitive information. Passengers also use it to access real-time information from other passengers when stakeholders might be dealing with crisis situations and delaying the provision of information to passengers. Twitter activity records can be accessed with an R interface for instance, but only up to 9 days back or 1500 tweets, which is not far back enough for this paper, whose analysis

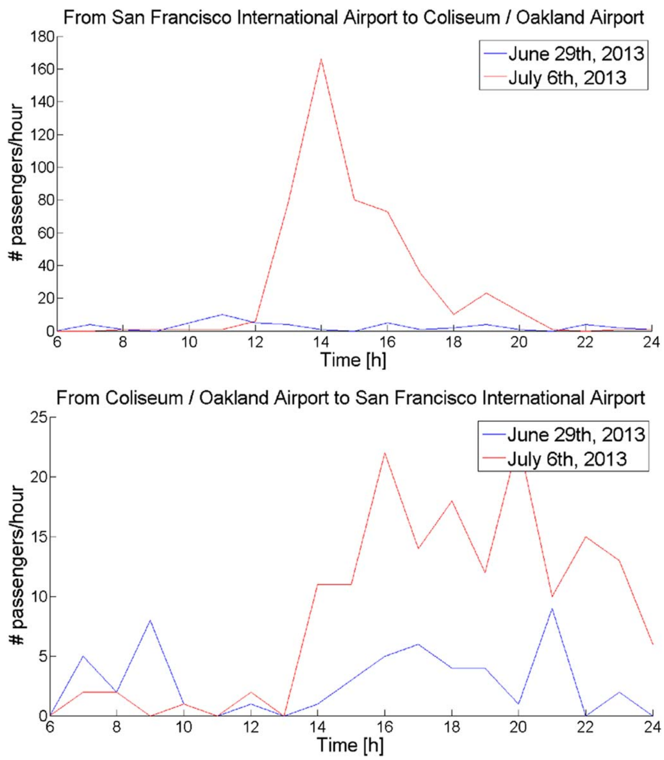

Fig. 22. Number of passengers on July 6th on between San Francisco and Oakland airports. The crash occurred at 11:28 am.

started in November 2013. Several websites provide different tools to access older data, but the amount of accessible data is limited and each website only provides a variety of aggregated information. However, a short analysis of several hashtags (keyword used in tweets) and account names, and their corresponding tweet frequency provides information about the timing of information provision, the reactivity of several stakeholders and the spreading of information on the communication network. Tweets and re-tweets, meaning relaying of tweets by other users, are illustrated in Fig. 24.

When it comes to timing, tweets provide a means to access the information available to passengers at specific time stamps. Such information was otherwise very unlikely to resurface with usual internet searches because the large news coverage flooded the internet with similar summaries of events but little precision on the timing of events. Regarding the response of emergency vehicles, the San Francisco Fire Department spokeswoman stated that: "Within 18 minutes of receiving word of the crash, five ambulances and more than a dozen other rescue vehicles were at the scene or en route, in addition to airport fire crews and crews from San Mateo County and other agencies already on the scene" [45]. Because of the congestion growth on the highway, the California Highway Patrol, at 12:39, was advising road users to avoid I-280 which was congested, as seen in Fig. 23. San Francisco airport informed passengers at 9:13 pm on the crash day that the restaurants in the airport would exceptionally remain open to accommodate passengers whose flights were disrupted or canceled and who were staying overnight in the airport.

Fig. 23. CHP tweet to avoid US101 and use I280.

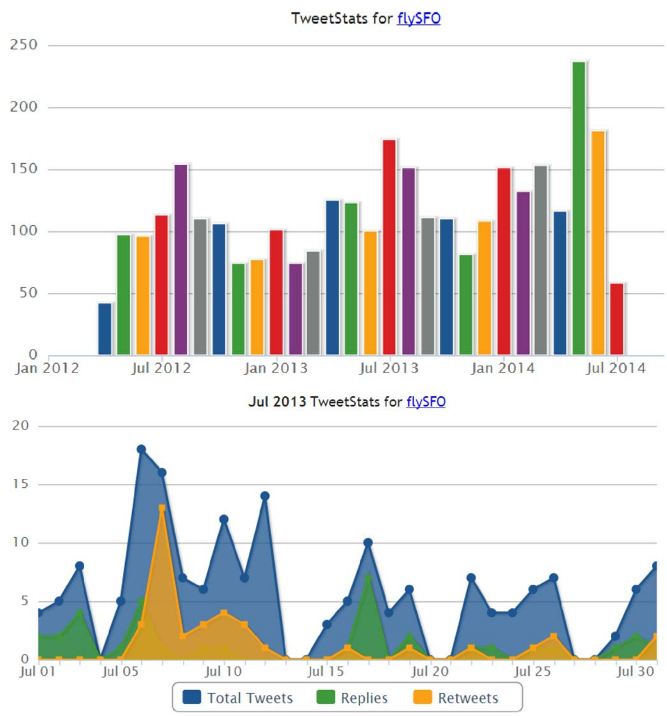

Fig. 24. Tweet frequency of the official San Francisco Airport account @FlySFO for the past two years, and for July 2013. (www.tweetstat.com).

To highlight how unusual the Twitter activity became in the Bay area, the frequency of tweets of several accounts or with specific hashtags is examined. The official Twitter account of San Francisco Airport, @FlySFO, tweeted more during July 2013 than on any other month in 2012 and 2013, see Fig. 24. Moreover, zooming in on July 2013, there is a peak of tweets, replies and retweets on the crash day and the following week.

The crash was such a widely covered event by the media, that a twitter account was opened by a journalist on the day following the crash, @SFOcrash. This account tweeted only July 2013, May and June 2014, as seen in Fig. 25. Zooming in on July 2013, the plot only starts on July 7th, and shows that the account tweets correspond mostly to the week following the crash. While the number of tweets shows that the crash constitutes an outlier in the behavior of certain accounts, it does not provide an estimate of the impact of these tweets. The number of retweets gives some idea of information spread on the social network, yet it does not indicate how many users accessed or read that information and how it was used. According to tweetreach.com, @FlySFO has an estimated reach of 106,388 people.

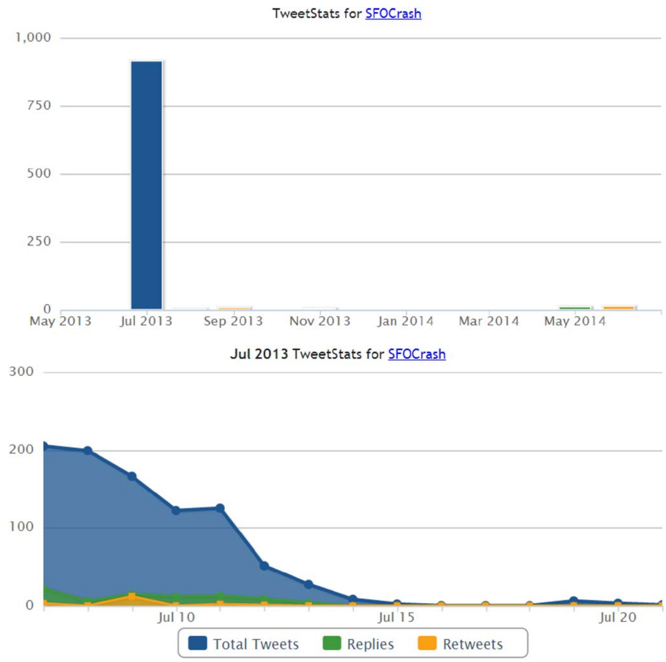

Fig. 25. Tweet frequency of the official San Francisco Airport account @FlySFO for the past two years, and for July 2013. (www.tweetstat.com).

As a conclusion, much information has been extracted from Tweets that would have otherwise been very unlikely to resurface with usual internet searches, because the large news coverage added to the internet with similar summaries of events contain little event timing resolution. Only Twitter was used for this analysis, because it is openly accessible and offers wide coverage. The authors are currently exploring the use of mobile phone data recordings to better understand passenger flow movements and provide a complementary view of the passenger side.

VI. Future Work

A. Network Coupling

Transportation networks are intrinsically tied or coupled. In the present study, we consider the air, road and rail transit networks, plus the internet through Twitter's information envelope and contents. It must be noted that these networks exhibit interdependencies with other networks, such as the power and communication networks for instance. Networks are usually studied separately. To the best of the authors' knowledge, this paper constitutes the first study of interdependencies between transportation networks.

When studied individually, networks may appear to have a fairly robust structure towards random failures. However, when their coupling with other networks is taken into account, their sensitivity is higher than when studied independently. However, the coupling between the air transportation network and the communication network, and between the highway network and the communication network, can allow authorities to suggest rerouting options to travelers, therefore mitigating the effect of the high-traffic density. The coupling between networks might therefore support increased resilience strategies.

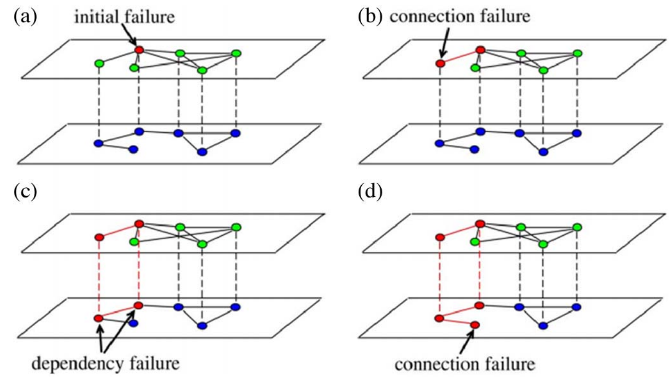

Fig. 26. Propagation of Disturbances in Coupled Networks. [46].

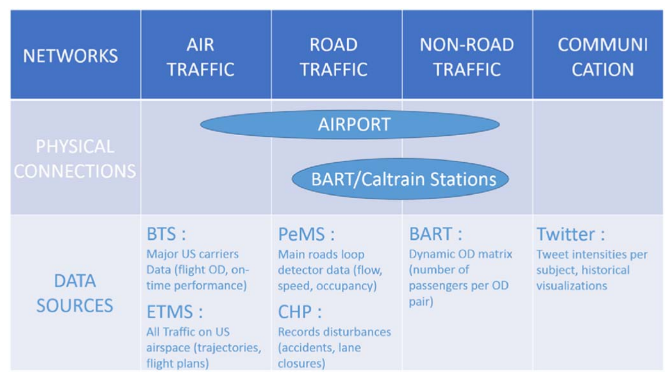

Fig. 27. Data sources available for each network studied.

Fig. 26 shows an example of such snowball effect on interdependent networks: the initial failure on the green network leads to the failure of another green node. Because these green nodes are themselves coupled with blue nodes, blue nodes begin to fail, triggering cascading failures on the blue network. Because the structure of each network is different and the dynamics on each do not have the same temporal and spatial characteristics, the propagation on each is studied separately.

The ASIANA crash is a powerful example of node failure leading to ripple effects on several networks. An airport is a node for the air transportation network, the road network because of easy highway access and the transit network, with a BART station in the Bay Area. Fig. 27 provides an overview of the data sources that supported the analysis. When it comes to interdependencies between transportation networks, the data analysis shows its existence but the underlying mechanism and its properties remain to be studied. Passengers constitute, of course, the transfer flows at the multimodal nodes between networks. A combination of data analytics and queuing models may provide more insight on such coupling mechanisms.

B. Crisis Management and Passenger Reaccommodation

Most stakeholders only have access to a partial view of the crisis situation and, in most cases, for only one mode of transport. Following the Asiana crash, if the main stakeholders had had access to real-time data feeds of reliable traffic data via collaborative decision making, it is likely that the recovery process could have been improved. Our future work will therefore focus on optimization of aircraft operations and diverted passenger reaccommodation. At the present stage, only hypotheses can be drawn when it comes to how diverted passengers who landed sometimes several hundred miles from their destination airport actually traveled there. Social Media provides pieces of information suggesting that the treatment of passengers varied greatly, depending on which airport they were diverted to, which airline they were traveling with, and whether they were domestic or international passengers.

VII. Conclusion

A case report of the Asiana crash in San Francisco International Airport on July 6th 2013 and its repercussions on the multimodal transportation network is proposed. The main contributions are as follows: First, this work appears to present the first analysis of a multimodal disturbance propagation on three transportation infrastructure networks, focusing on air, rail and highway traffic analyses. The disturbance takes different forms and varies in scale and time: cancelations and delays snowball in the airspace; highway traffic near the airport is impacted by congestion in locations not usually congested, and public transit passenger demand exhibit unusual traffic peaks in between airports in the Bay area. Second, this work provides a passenger-centric analysis of disruptions in multimodal transportation systems, and passenger usage of social media to access information on the crash. Third, this work shows that traffic data fusion can help quantify real-world examples of network inter dependencies. Last, this work motivates further research on interdependent infrastructure networks for increased resilience and more reliable passenger door-to-door journeys.

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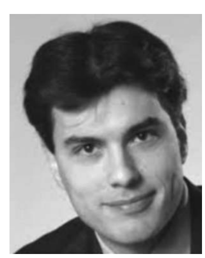
Aude Marzuoli received the Diploma of Engineering from the École Supérieure d’Électricité (Supélec), Gif-sur-Yvette, France, and the master’s and Ph.D. degrees in aerospace engineering from Georgia Institute of Technology, Atlanta, GA, USA, in 2012 and 2015, respectively, with focus on air traffic, optimization, control, and network management. Previously, she was with NASA Ames Research Center, SESAR Joint Undertaking in Brussels, and the French National School of Aviation. She is currently with the School of Aerospace Engineering, Georgia Institute of Technology.

Emmanuel Boidot received the master’s degree in electrical engineering and computer science, in 2011 from the École Supérieure d’Électricité (Supélec), Gif-sur-Yvette, France, and the master’s degree in computer science from Georgia Institute of Technology, Atlanta, GA, USA, where he is currently working the Ph.D. degree in aerospace engineering. His research interests focus on robotics, game theory, networks, and air transportation.

Eric Feron received the B.S. degree from the École Polytechnique, Palaiseau, France; the M.S. degree from the École Normale Supérieure, Paris, France; and the Ph.D. degree from Stanford University, Stanford, CA, USA, in 1989, 1990 and 1994, respectively. From 1993 to 2005, he was with the faculty of the Department of Aeronautics and Astronautics, Massachusetts Institute of Technology. Since 2005, he has been the Dutton-Ducoffe Professor of Aerospace Software Engineering with Georgia Institute of Technology, Atlanta, GA, USA. He has published two books and several research papers; his former research students are distributed throughout academia, government, and industry. His interests are to use fundamental concepts of control systems, optimization, and computer science to address important problems in aerospace engineering, including: aerobatic control of unmanned aerial vehicles and multiagent operations, including air traffic control systems and aerospace software system certification.

Paul B. C. van Erp received the bachelor’s degree in aerospace engineering and the master’s degree in civil engineering from Delft University of Technology, Delft, The Netherlands, and the master’s degree in econometrics and management science from Erasmus University Rotterdam, Rotterdam, The Netherlands, in 2014. He is currently with the Department of Civil and Environmental Engineering, University of California, Berkeley, CA, USA.

Alexis Ucko received the master’s degree in civil engineering from the École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland, in 2014. He is currently working toward the master’s degree in entrepreneurship from the École Centrale Paris, Châtenay-Malabry, France, and ESSEC Business School, Cergy-Pontoise, France. During the summer of 2014, he visited the Department of Civil and Environmental Engineering, University of California, Berkeley, CA, USA.



Alexandre Bayen received the Engineering degree in applied mathematics from the École Polytechnique, Palaiseau, France, in 1998 and the M.S. and Ph.D. degrees in aeronautics and astronautics from Stanford University, Stanford, CA, USA, in 1999 and 2003, respectively. From 2000 to 2003, he was a Visiting Researcher with NASA Ames Research Center. Between January 2004 and December 2004, he was the Research Director of the Autonomous Navigation Laboratory, Laboratoire de Recherches Balistiques et Aérodynamiques, Ministère de la Défense, Vernon, France, where he holds the rank of Major. He is currently an Associate Chancellor Professor with the University of California, Berkeley, CA, USA, where he has been also the Director of the Institute for Transportation Studies since 2014.

Mark Hansen received the Bachelor of Arts degree in physics and philosophy from Yale University, New Haven, CT, USA, in 1980 and the Master’s degree in city planning and the Ph.D. degree in transportation engineering from the University of California, Berkeley, CA, USA, in 1984 and 1988, respectively. He is currently the Codirector of the National Center for Excellence in Aviation Operations Research (NEXTOR) for the University of California, Berkeley. His research interests include transportation economics, policy and planning, air transportation, and public transportation.