The Disruption at Rastatt and its Effects on the Swiss Railway System

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Abstract

A railway track near Rastatt, Germany, lowered on 12 August 2017 and caused a complete blockage of a sector of a major rail corridor, which lasted until 1 October 2017. This track closure had severe effects on the railway freight and passenger transport. This work investigates the effects on the Swiss railroad network, using openly available realized operation data. The behavior of the delays before, during and after the disruption is investigated on three different levels. First, the delay of arriving trains to Basel SBB, as it can be seen as the input delay into the Swiss railway system. Secondly, it is investigated how the delay evolves on the Swiss intercity and interregional lines in short distance (i.e. first stop) and thirdly how this delay evolves over the course of the lines. The results display a consistent improvement of punctuality during the disruption period, which however decreases when considering stations farther away from Basel SBB. This can be explained by the fact that during the disruption period, trains arriving from Germany at Basel SBB exhibit, due to the shorter running distance, significantly lower delays than during other periods. The improved punctuality is therefore a result of a reduced delay propagation of the trains arriving from Germany. The effects of this severe and long lasting disruption can be quantified even in some spatial and temporal distance. It can be used as an example to test theoretical delay forecasting models, or examine train network complexity and interconnectivity.

Keywords

Rastatt disruption, delay analysis, open data, delay patterns

Type of Submission

Type A: Research paper.

1 Introduction

The goal of this work is to investigate potential effects of a major and long lasting disruption on a railway system, and as such to assess the interconnectivity and phenomena of delay propagation in the system under this exceptional circumstance. The disruption studied is the Rastatt disruption, taking place during one and a half month on an important freight and passenger transport bottleneck.

Railways have the challenge to operate under high capacity to achieve good economic performance, and on the other hand to reduce their vulnerability to unplanned situations. While relatively frequent, small delays can be countered by robust timetabling or traffic management systems. Large disruptions on the other side are very rare, and their impact can be much larger. Thus, they underline the vulnerability degree of networks. In this work, though, we do not study the effects of the disruption per se, but its secondary effects, in the sense that we are able to estimate at system level effects of changes to the circulation and

their effect on delay propagation phenomena.

The Swiss railway network is known for its high punctuality, reliability and robustness, and not least the capability to successfully cope with many extreme weather conditions. The actual delay of trains in the Swiss networks is typically one of the lowest worldwide, despite a very high occupation of resources. Figure 1 reports a global ranking of many countries in terms of punctuality and train km per track km, i.e. density of services on the network. This includes also the neighboring countries of Switzerland, namely Austria, Italy, and Germany. We put focus on delays originating in the latter.



Figure 1 Punctuality (percentage of trains within 5 minutes delay) in relation to network load (train km per track km) (NS, 2017)

We perform a detailed descriptive analytics on train runs in Switzerland, where we focus on delays as key variables to quantify these effects, since they are easily accessible. The investigations focus on daily, weekly and yearly patterns of delays during the pre-/postdisruption period, and during the interrupted period.

Differently from most works in the literature, we aim to study the effects of a disruption onto a network by looking at operational data. We focus on data that span multiple months before and after the disruption, to take into account for seasonality. We are unable to identify all processes related at this point, but we can identify macroscopic effects of punctuality change at network level, as function of the distance from the disrupted area. We find that this change is in good agreement with accepted delay propagation theories.

The rest of this paper is structured as follows. Chapter 2 presents the disruption considered. Chapter 3 reports on literature on delay propagation and delay analysis. Chapter 4 reports on our methodology to study the network wide influence of the disruption. Chapter 5 reports on the analysis and the results. The last two chapter 6 and 7 respectively discuss the main findings, and conclude the paper.

2 The 2017 Disruption at Rastatt

On 12 August 2017, a track settlement occurred between Baden-Baden and Rastatt (Germany) due to the construction of a new tunnel. The affected section is part of the Rhine-Alpine Corridor (or Rhine Valley corridor) stretching from the north sea ports (Rotterdam) to Italy (Genoa), two of the most important harbors in Europe. The Deutsche Bahn (DB) had to take out of service a track section of around 20 kilometers. The normal operations resumed on 2 October 2017.

Such a disruption has been one of the economically most relevant disruption in the last years. Most severely affected was the freight transport. The quantifiable costs in industrial and manufacturing terms amount to more than 2 billions euro. From those, about 12 million euros per week are related to freight companies' losses, according to the European Railways Network (ERFA, 2018; BLS cargo, 2018).

Diversions had to be put in place for the 200 freight trains, from different operators, that travel every day on the Rhine valley corridor. A DB Cargo usually schedules about 80 trains on the Rhine valley corridor every day. In order that as many trains as possible could use the diversion route, DB Cargo deployed additional diesel and electric locomotives and 70 train drivers; Special agreements were put in place to allow operations from vehicles and drivers, which would not normally be involved in the freight transport on the Rhine corridor (Deutsche Bahn Group, 2017).

Overall, it has been estimated that most freight trains were able to run, via a set of very complex diversion routes, as the most direct ones were affect by maintenance works, or with different power systems. The monitoring of freight at the alpine crossing (Gotthard and Lötschberg tunnels) estimates about 1500 trains being cancelled, and 400 being rerouted. Other statistics would suggest that two thirds of the expected volume of freight traffic was actually running on the alpine crossing (UVEK, 2018). The precise estimation is of course difficult as freight trains took diversions; and some freight trains were not directed towards the other side of the Alps (HTC, 2018).



Figure 2 The Rhine valley corridor between the north sea ports and Italy (Source: https://www.corridor-rhine-alpine.eu/downloads.html, adapted)

Also the passenger transport was affected. In fact, it is very difficult if not impossible to quantify now the compensation costs for passengers, modal shift, time lost for passengers, and extra money required for extra work to restore services as soon as possible. Some trains were unable to reach their maintenance workshop, which was on the other side of the disruption (Deutsche Bahn Group, 2017). Passengers travelling from Switzerland to Germany faced travel time increases from one to two hours, possible transfers, and extra bus services. To organize the replacement services for about 30.00 passengers, 450 shuttle buses runs have been organized per day, across the main stations (Deutsche Bahn Inside, 2017).

3 Related Scientific Work

The study of disruptions in transport networks and their vulnerability has been described by many researchers in the last years. Most studies refer to real-life situations, but are able to perform quantitative studies only under hypothetical situations, which are simulated in a calibrated environment, where some of the variables can be controlled.

Key concepts are and the reaction in terms of resilience, reliability, robustness, friability. While there is not complete agreement on those terms, the most common interpretations, which are also considered in this paper, are as follow (see Corman et al, 2018; Janic, 2015; Jenelius, 2007). Robustness is considered the ability of a transport system to perform its functions when it is under perturbed conditions. Reliability is related to a transport service, which deviates in a limited manner from a prescribed time plan. Resilience is the ability to recover to a normal state after having been disturbed, i.e. to neutralize the impacts of disruptive events, after their occurrence. Friability is related a reduction on a network resilience due to removing particular nodes or links, and consequently cancelling some services. Vulnerability might be related to the susceptibility to extreme strains on a dynamic system (Reggiani et al, 2015).

Resilience has been studied for road networks and more recently for public transport networks, based on simulated conditions, and with a direct filter by the demand, i.e. the users of the system, which are exposed to a different abnormal situation (see for instance, Malandri et al, 2018). When dealing with case-studies, real (quantitative and qualitative) data are used, and the focus is on understanding probability and impact of shocks and sudden change in states. Differently from all studies reviewed in (Reggiani et al, 2015) and (Mattson and Jenelius, 2015), we focus on railway system, and on the analysis of a real-life situation.

The connectivity of the network either in a purely topological sense, or in a more service oriented manner, has been identified often to play a major role. Different connectivity structures would enable different exposure and impacts of the same disruption (such an approach has been for instance studied in Malandri et al, 2018). A disruption in a heavily connected part of the network has larger impacts than a disruption in a less-connected part of the network. Moreover, a connected network enables a higher resilience to disruptions, i.e. mitigating its exposure or impact, if focusing on users or operations, respectively.

Different connectivity in network structure would also put different strain on the network components and may lead to different disruption probability and or resilience. This concept is related to friability, as a change in resilience after removing some of the network links/nodes. In fact, network with different levels of interconnections can exhibit different dynamics when exposed to abnormal conditions (see for instance Corman and D'Ariano, 2012). In the light of the friability analysis performed in (Janic, 2015), railway systems face similar corrective actions under disruptions, namely cancelling and rerouting services. Similarly to the analysis in (Janic, 2015), we aim to quantify how the resilience (or more

properly, the performance) of the network reached a higher value in some parts of the network, during the disruption thanks to the mitigating actions implemented. From a different perspective, our analysis aims to understand the "unknown connectivity" (Reggiani et al, 2015) which is underlying a large scale railway network. In particular, we target to identify some implications on network reliability based on a disruption, which has no direct physical connections by means of services or links, but only to indirect effects of service quality.

Railway systems are typically built with very small reserve capacity, and the effect of traffic to service quality is relatively strong (see Figure 1 above). In fact, delays and irregularities in operations, which can be related to disruption or many other events, propagate in heavily used networks as knock on delays. Many works studied formulas to either simulate delay propagation from a deterministic perspective or from a stochastic perspective, or to recognize delay propagation phenomena in operations (see for instance Goverde, 2010). The study of network operations, pertaining stability, reliability and robustness, and also their interconnection is typically addressed from a theoretical point of view, simplified networks, ideal conditions, or simulation studies. Instead, we refer to only operational data, where multiple factors have been recorded and aggregated and the precise root cause of all phenomena cannot be clearly separated. Delay propagation or delay prediction approaches using those models are often used in small perturbations, while little evidence is used that similar prediction models can perform good in presence of very serious changes to operations, such as disruptions (Corman and Kecman, 2018).

How to react to a disruption typically involves a series of actions, like cancelling trains, rerouting them at a global network scale, or introducing additional stops or turnaround points, depending on the severity of the disruption and the expected length (Ghaemi, 2018). The effect of short turning, and shuttling during disruptions has been also investigated in Corman and D'Ariano, (2012), who evaluated it from a large amount of possible performance indicators. Nevertheless, both of those approaches refer to academic situations, and not recorded operations. In those cases, simulation, optimization models and what-if scenarios might deliver useful data, as far as they are fed with correct data. This is typically a challenge in the frenetic aftermath of disruptions and during the strong efforts to bring situation to normality.

Summarizing, with regards to the literature, we focus on realized operations during a real-life disruption, which include a large amount of uncontrollable and unmeasurable phenomena; we tackle railway networks of particularly limited available capacity; we study the impact of disruption and mitigating actions over a large network, where mostly indirect effects of delay propagation can be seen.

4 Data and Methodology

4.1 Data

An effort that started some years ago is the publishing of open data about realized operations. This has been established since a few years in many countries, including Norway, Netherlands, UK, and also Switzerland. In particular, the Swiss Federal Railways (SBB) publishes actual arrival and departure data of train, bus, tram and boat rides in Switzerland since December 2016 on their Open Data Platform. This paper bases on the timetable years 2017 and 2018, which start and end in mid-December respectively. The recorded and published data in this time window result in a size of 120 GB, which were used as raw material for this investigation. For graphical representations, the data of the full available period was used. For statistical analysis, however, we focus on the timetable year 2017, starting on 11 December 2016 and ending on 12 December 2017, to avoid any

systematic effect.

4.2 Methodology

We consider delays of the higher product level of train service. Therefore, we consider the international passenger trains running through Basel SBB, namely EuroCity (EC), Intercity-Express (ICE), and TGV. Furthermore, we consider national services namely InterCity (IC) service, which connect major cities within Switzerland, and InterRegio (IR) service, which connect regions within Switzerland and typically stop in cities and mid-size towns only.

To be able to do reasonable evaluations of change of delays, delays have to be aggregated. We aggregate delays in three spatial levels. Firstly, since Basel SBB is the first major entrance station in Switzerland for services of the Rhine Valley Railway, we investigate the arrival delays of trains coming from Germany to Basel SBB. This delay is considered as the initial delay in the Swiss Railway Network. In a second step, stations with direct (non-stop) connection to Basel SBB are considered. Finally, we also investigate the delays at all stops of direct lines running from Basel SBB. Always arrival delays of trains from Basel SBB are considered.

Stations with a direct connections to Basel SBB are Liestal, Rheinfelden, Olten and Zürich HB. For the analysis, delays in Liestal and Rheinfelden as well delays in Olten and Zürich HB are considered together (see Table 1). This, as Liestal and Rheinfelden are quite close to Basel and are subordinate stations, where also IR trains offer direct connections, whereas Olten and Zürich HB are further away and are superordinate stations of the Swiss railway network.

	superordinate st	ations	subordinate stations	
Stations	Zürich HB	Olten	Rheinfelden	Liestal
Direct connecting	TGV, ICE, IC	TGV, EC, IC	IR	ICE, EC, IC,
services				IR
Travel time from	53 min	24 min	12 min	9 min
Basel SBB				

Table 1: Considered Stations with direct connections from Basel SBB

To have a comparison, we also investigate delays at stations, which are most likely not or only very limited affected by the Rastatt disruption. The chosen stations are located in the south western part of Switzerland and have direct (non-stop) connections from Lausanne, and are not connected by a service to Basel SBB (see Table 2). Also considering these stations, we can distinguish between superordinate stations (Yverdon-les-Bains, and Fribourg / Freiburg) and subordinate stations (Morges, Palézieux, and Vevey). A geographical depiction of lines and considered station is reported in Figure 3.

Table 2: Considered Stations with direct connections from Lausanne

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	superordinate	e stations	subordinate stations			
Stations	Yverdon-	Fribourg /	Morges	Palézieux	Vevey	
	les-Bains	Freiburg	_		-	
Direct connecting	IC	IC	IR	IR	IR	
services						
Travel time from	24 min	43 min	10 min	15 min	13 min	
Lausanne						

We not only aggregate the delays on a spatial level, but also on a temporal level. Therefore, we consider percentile delays on a daily base. When considering e.g. the 20^{th} percentile, the percentile value is the delay value below which 20% of the daily delay observations may be found.



Figure 3: Map of the investigated stations. The black railway lines are routes that IC and IR trains take from Basel SBB (red). These lines stop first in Rheinfelden, Liestal, Olten or Zürich HB (green). The comparison stations in southwestern Switzerland (Yverdon-les-Bains, Fribourg / Freiburg, Morges, Palézieux, and Vevey (violet) are first stops from Lausanne (blue).

The characteristics of the time series of arrival delays were analysed during preliminary tests. The time series are highly variable; there is no clear trend nor seasonality. However, the series show significant auto correlation for lags 1, and 7. This means that the delay at a given day and at the next day, as well as the delay of the same day a week later, are correlated. There is no distinct weekly pattern throughout the year, as can be seen in Figure 4, where exemplary the median daily arrival delay to Basel SBB is shown split into days and weeks. Therefore, we do not investigate the weekdays separately.



Figure 4 Median daily arrival delay to Basel SBB over the course of the year 2017. During the blue marked period, the disruption took place.

Given the highly variable daily pattern of delays, it is difficult to prove a distinct difference in the time series of daily delays during the disruption period in comparison with daily delays of the period before and after the disruption. Furthermore, we don't have a baseline time series of the disrupted period for comparison. Therefore, a difference cannot be proven but only indicated. To do so we perform three different tests.

First, we define an indicator that addresses the fact that the disruption might lead to a remarkable change in a short term to the time series (i.e. a shock). Therefore, we calculate the difference of the mean value of the percentile delays of the seven days before the disruption and the respective value of the first seven days in the disrupted period (d_b). Analogously, we calculate the difference of the mean value of the percentile delays of the seven days before the end of the disrupted period with the mean value of the seven days after the disruption (d_e). In Figure 5 these differences are explained visually. For comparing those differences in delay, we compute the difference of the means of any seven consecutive days (d_i). We then build the indicators I₁ and I₂ for the differences, given by

$$I_{1} = P[\min(|d_{b}|, |d_{e}|) > \min(|d_{i,1}|, |d_{i,2}|)],$$
(1)

$$I_2 = P[(|d_b| + |d_e|) > (|d_{i,1}| + |d_{i,2}|)].$$
⁽²⁾

Where $d_{i,1}$ and $d_{i,2}$ are randomly chosen samples of weekly mean changes. I_1 compares the minimal difference in delay at the begin or at the end of the disruption with the minimal difference of two random dates. I_2 considers, in opposition to I_1 , the sum of the two differences. The indicators can take values between 0 and 1. The higher the value is, the more infrequently such a distinct change happens. In reverse, this means that the dates of the disruption are more special compared with two random dates.



Figure 5 Visual explanation of the calculation of the differences of the weekly averages

In a second test, we compare the delay distribution during the disruption period with the delay distribution of the preceding and subsequent thirty days as Figure 6 shows. Note that by doing so, the dependencies of delays of consecutive days is removed. We assume that the delay distribution during 30 days before and after the disruption is a good proxy for the hypothetical delay distribution during the disruption period. Therefore, these two

distributions are compared by the aid of a two-sample Kolmogorov-Smirnov (KS) test. By this test, we check if the two samples are probable to come from the same distribution. The test is performed under the Null Hypothesis H₀ that the data comes from the same distribution. H₀ is rejected if the p-value is lower than the level of significance $\alpha = 0.01$.



Figure 6 Visual explanation of the two compared distributions

Third, to take into account the temporal dependencies of the time series, we determine the best fitting ARIMA model, based on the AIC, for the data of 2017, while excluding the disruption period. The mean value of the baseline time series during the disruption period, is estimated by Kalman smoothing on the state space representation of the ARIMA model. This is reported to be a powerful method for filling gaps in time series (Moritz et al., 2015). In the following, we compare the baseline time series in the disruption period with the real measured values. We conduct a t-test under the assumption of equal variances on a significance level $\alpha = 0.01$. If the p-value is smaller than the significance level, we reject the H₀, which proposes that there is no difference between the mean of the baseline time series and the observed time series.

5 Results

5.1 Arriving Trains from Germany to Basel SBB

The daily median delay of trains arriving to Basel SBB is shown in Figure 7. The red line shows the delays during the disruption period, the blue lines show delays when the disruption was not present. The change in timetable years, which is in December, is indicated by a slight change of the blue color. Furthermore, a black line, representing the simple moving average with a period of 7 days (average over the course of a week) is introduced.

The pattern is quite distinct; the highest delays of this observation period of two years are reached just before and after the disruption, presumably due to the construction works in southern Germany. Then, during the disruption, when extra trains where running, the delay dropped remarkably.



Figure 7 Daily median delays of trains arriving from Germany to Basel SBB

Figure 8 shows the time series of further percentile values of the weekly moving average of the daily delay distributions. It shows the 20th, 40th, 60th, and 80th percentile values of those values over the course of the timetable years 2017 and 2018. The blue curves show moving averages of delays at dates, which were not influenced by the disruption, the red curves show moving averages of disrupted dates. The grey values represent the transition phase, or in other words, they are computed with delays of dates that were affected by the disruption and such that were not.

The different percentile values show a similar course. All percentile time series have distinctly higher delays before and after the disruption period, than during the period. Furthermore, the variation of the delays is remarkably smaller during the disruption period.



Figure 8 Moving average (period of 7 days) of the percentile values (p = 20, 40, 60, 80) of arrival delays at Basel SBB

This change can be underlined in a statistical way. In Table 3 the indicators I_1 and I_2 , as well as the result of the KS-test and the t-test for the 20th, 40th, 50th, 60th, and 80th delay percentiles are shown. The I_1 - and I_2 -values are rather high (often 0.8 and more). This indicates that the change during this period is remarkable and comparatively high. Also, the KS-test and the t-test clearly indicate a significant change in the time series. The KS-test

states, that the distribution changes while the disruption is present and the t-test indicated that the time series have different means.

	Basel SBB					
р	I_1	I_2	p-value KS-test	p-value t-test		
0.2	0.86	0.80	$7.2 imes 10^{-3}$	$8.9\times10^{\text{-16}}$		
0.4	0.80	0.93	$2.4 imes10^{-6}$	$1.8 imes 10^{-21}$		
0.5	0.81	0.93	$1.2 imes 10^{-6}$	$6.5 imes 10^{-25}$		
0.6	0.79	0.95	$3.6 imes 10^{-7}$	$7.7 imes 10^{-25}$		
0.8	0.64	0.70	$2.0 imes 10^{-9}$	$1.3 imes 10^{-24}$		

Table 3: Indicators I₁ and I₂ and test results of KS- and t-tests for Basel SBB

This distinct change is most likely due to the fact that trains were running along a much smaller network, i.e. short turning at Baden-Baden (1.5 hours away from Basel) instead of Hamburg (7 hours away from Basel). This caused that these trains did not arrive in Switzerland with their potentially accumulated delays as they would if there were no interruption.

5.2 Delay Pattern One Stop Away

After assessing the entrance delay at Basel, we look at the delay propagation in the Swiss Railway network. We look at the first stop of direct trains from Basel. Figures 9 - 12 show, under the same styling convention as Figure 7, moving average of the percentile values of daily delays. The investigated percentiles are 20^{th} , 40^{th} , 60^{th} , and 80^{th} percentile.

For the two groups of stations with direct train connections from Basel, namely Zürich HB and Olten, as well as Liestal and Rheinfelden a relatively clear trend of lower delays during the disruption period can be recognized. The average delays during the disruption is as low as the minimum delay recorded throughout the year. The variability is actually much smaller during the disruption period, than throughout the rest of the year.

For comparing these observations, a placebo test was conducted with the train station that have direct connections from Lausanne. Neither the farther away located major stations, as Fribourg / Freiburg and Yverdon-les-Bains, nor the nearer and less important stations Vevey, Morges, and Palézieuz show a clear influence of the Rastatt disruption. These stations are far enough away from the disruption there the effects of the disruptions cannot be quantified anymore.



Figure 9 Moving average (period of 7 days) of the percentile values (p = 20, 40, 60, 80) of arrival delays at Zürich HB and Olten



Figure 10 Moving average (period of 7 days) of the percentile values (p = 20, 40, 60, 80) of arrival delays at Liestal and Rheinfelden



Figure 11 Moving average (period of 7 days) of the percentile values (p = 20, 40, 60, 80) of arrival delays at Yverdon-les-Bains and Fribourg / Freiburg



Figure 12 Moving average (period of 7 days) of the percentile values (p = 20, 40, 60, 80) of arrival delays at Vevey, Morges, and Palézieux

In Table 4 the indicators I_1 and I_2 , as well as the result of the KS-test and the t-test for the 20th, 40th, 60th, and 80th delay percentile are shown for the stations with direct services to Basel SBB (left) and the stations far away (right). The values in the table are highlighted with color. A green color is an indicator for an influence of the disruption, red is an indicator that the disruption had no influence, yellow is in between.

The groups of stations close to Basel SBB exhibit clearly higher I_1 - and I_2 - values for all investigated percentile values compared with the stations close to Lausanne. Also considering the results of the KS-tests and t-test the difference between the groups is evident. While the groups close to Basel SBB show almost always significant differences between the disrupted and non-disrupted periods, for the groups close to Lausanne this is rarely the case.

We don't find evidence, that the stations near to Lausanne were influenced by the Rastatt disruption, whereas we find strong indication that stations near to Basel SBB felt an effect. The indicators and statistical tests are show a clear difference between the two groups of stations.

Table 4: Indicators I_1 and I_2 and test results of KS- and t-tests for groups close to Basel SBB (Liestal & Rheinfelden and Olten & Zürich HB) and for groups close to Lausanne (Yverdon & Fribourg / Freiburg and Morges, Vevey, & Palézieux)

	Liestal & Rheinfelden						
р	I_1	I_2	p-value KS-test	p-value t-test			
0.2	0.87	0.89	3.1×10^{-4}	$8.7 imes10^{-4}$			
0.4	0.86	0.97	$2.3 imes 10^{-4}$	$4.7 imes 10^{-2}$			
0.5	0.92	0.94	$8.2 imes 10^{-4}$	$1.0 imes 10^{-2}$			
0.6	0.94	0.93	$7.0 imes 10^{-3}$	$3.4 imes 10^{-4}$			
0.8	0.87	0.91	$4.7 imes10^{-4}$	$1.0 imes 10^{-5}$			

Yverdon & Fribourg / Freiburg						
р	I_1	I_2	p-value KS-test	p-value t-test		
0.2	0.70	0.80	4.7×10^{-2}	2.8×10^{-3}		
0.4	0.71	0.31	$2.6 imes 10^{-1}$	3.4×10^{-2}		
0.5	0.59	0.32	$4.1 imes 10^{-1}$	$1.5 imes 10^{-1}$		
0.6	0.60	0.49	$8.0 imes 10^{-2}$	$3.5 imes 10^{-1}$		
0.8	0.58	0.15	$6.1 imes 10^{-2}$	$1.9 imes 10^{-2}$		

Olten & Zürich HB						Ν	
р	I_1	I_2	p-value KS-test	p-value t-test		р	Ι
0.2	0.71	0.90	$2.3 imes 10^{-2}$	2.9E-03		0.2	0.
0.4	0.93	0.99	$1.6 imes 10^{-3}$	1.8E-07		0.4	0.2
0.5	0.88	0.88	$6.8 imes 10^{-5}$	2.2E-07		0.5	0.3
0.6	0.84	0.74	$7.1 imes 10^{-4}$	2.4E-07		0.6	0.2
0.8	0.88	0.90	4.3×10^{-3}	1.6E-09		0.8	0.

Morges, Vevey, & Palézieux						
р	I_1	I_2	p-value KS-test	p-value t-test		
0.2	0.18	0.45	$1.8 imes 10^{-1}$	5.4E-01		
0.4	0.23	0.20	$7.5 imes 10^{-2}$	1.6E-01		
0.5	0.35	0.37	$2.0 imes 10^{-1}$	1.1E-02		
0.6	0.22	0.37	$8.9\times10^{\text{-}2}$	2.0E-07		
0.8	0.33	0.33	2.6×10^{-2}	4.4E-04		

5.3 All IC Lines Departing from Basel SBB

In a third step we look at all train lines from Basel. We compute for all stops of the lines the difference of the delays during the disruption and non-disruption period for different percentile values. This difference in delays is shown color coded in Figure 13. Additionally, the number of daily trains per station is shown by the size of the circle.

It is visible that near to Basel SBB the trains reduced their delay during the period. Farther away, the pattern is not so clear anymore. The line running to St. Gallen eastern Switzerland even performed worse in the disruption period compared to the rest of the year.

Furthermore, it can be seen that for high percentile values the gains and reduction respectively were more than for low percentile values, meaning particularly the strongly delayed trains performed better in the disruption period.



Figure 13: Evaluation of arrival delay difference given different percentile values (p = 25, p = 50, and p=75)

6 Discussion

From the analysis performed, a few points are worth being discussed. The variability of delays in real life operations is extremely high; no model of first order or second order, or with a time series analysis with one week or one day fit could explain the variance of the observed data. In fact, the realized delay is the product of so many factors, some of which are correlated to a certain extent over space, day, days, weeks (like weather; holiday seasons; maintenance actions) and some are more of a random components related to demand, some other to operational process. Further steps based on delay distributions or fitting functional relations to discover or highlight root causes in the variable performance are an interesting follow-up (see for instance Cerreto et al, 2018).

Also due to this high variability, the strength of typical statistical tests to identify the difference in samples and relate them to underlying changing in organizational pattern is quite limited. Moreover, each test can be performed at different percentile level, and maybe spurious phenomena can be pinpointed. It is difficult to clarify the philosophical dilemma between what is in the reality, what is in the data and what is in the eyes of the observer.

The study of the relation between different input conditions and the performance of the network is very crucial in reliability assessment, in economic appraisal of new projects. Most of the studies of complex network and service level based on topological structure or on service structures also do not go in detail in discussing the microscopic impact that the relation traffic-performance has to a railway network. To this end, simulated operations would need to consider an enlarged set of parameters of random processes, to result in a

performance directly comparable with the observed real life.

Another limitation or feature of the approach is the fact that every disruption is one-ofa-kind, and its impact is so large that it unavoidably changes the conditions under which the system is operating. This includes for instance running speed, planned stops, travel time, passenger demand, flow over links, and mitigation actions. The interaction of all those aspects is so intricate that is almost impossible to identify all contributions, unless a set of simulations based on some assumptions could be replicated, to isolate those components. The reasons why some mitigation actions have been chosen, what the objective was, and to which extent those mitigation actions reached their goal is something, which is very relevant for design of future contingency schemes (see for instance BLS cargo 2018). It is furthermore relevant from a process point of view, to identify bottlenecks and enable exchange of best practices, but also from a traffic planning and dispatching point of view, where there is strong need for smart decision support (see for instance Ghaemi, 2018).

7 Conclusion

From the analysis performed, the Rastatt disruption did not degrade the punctuality of the Swiss passenger trains at Basel SBB. On the contrary, it even improved it. The long train section from the Netherlands and northern Germany to southern Germany, Switzerland and Italy was split into two, what caused trains to arrive in Switzerland with lower potentially accumulated delay. A further reason for the consistently lower delays is the secondary delay, which was reduced due to much more punctual trains arriving from Germany.

Additional effects that should be investigated are the effects to passengers, in terms of additional travel time in Germany, which were related to the disruption, as the costs for the planned unreliable services in the non-disrupted situation was then felt directly by passengers as extra connection time. This analysis of disruption can be performed post-eventum only by replicating behavior of people, for instance via agent-based models, and assuming that sufficiently accurate modelling of the non-equilibrium (Malandri et al, 2018) behavior of passengers during disruptions can be replicated properly (see for instance Leng et al, 2018).

It would be very interesting to clarify the impact of freight trains, which were running in a very different pattern during the disruption, and partially cancelled or rerouted to other different parts of the network. The main limitation for this is the unavailability of sufficiently accurate data, which also includes the probabilistic chance of delay propagation by freight train under normal operating conditions, something which so far addressed large attention, but delivered few clear conclusions (Andersson et al, 2015). The possibility to fit stochastic models to the two situations, and derive parameters linking traffic, buffer time and observed delay propagation can open up a field of operational analysis of networks and their vulnerability.

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