# Impact analysis of transport network disruptions using multimodal data: A case study for tunnel closures in Stockholm

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## Abstract

The paper explores the utilization of heterogeneous data sources to analyze the multimodal impacts of transport network disruptions. A systematic data-driven approach is proposed for the analysis of impacts with respect to two aspects: (a) spatiotemporal network changes, and (b) multimodal effects. The feasibility and benefits of combining various data sources are demonstrated through a case study for a tunnel in Stockholm, Sweden which is often prone to closures. Several questions are addressed including the identification of impacted areas, and the evaluation of impacts on network performance, demand patterns and performance of the public transport system. The results indicate significant impact of tunnel closures on the network traffic conditions due to the redistribution of vehicles on alternative paths. Effects are also found on the performance of public transport. Analysis of the demand reveals redistribution of traffic during the tunnel closures, consistent with the observed impacts on network performance. Evidence for redistribution of travelers to public transport is observed as a potential effect of the closures. Better understanding of multimodal impacts of a disruption can assist authorities in their decision-making process to apply adequate traffic management policies.

*Keywords:* Transport system disruptions; data-driven analysis.

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## 1. Introduction

Transportation networks in urban areas consist of a large number of components that are vulnerable to incidents and events, both natural and man-made. Some incidents may result in capacity reduction of specific links, disrupting their multimodal operations and the operations of the urban area (e.g. bridge collapses, tunnel closures), while others result in network-wide failures (e.g. adverse weather conditions). Incidents may also differ with respect to the amount of time available for response. This time dimension is very important and determines the type of strategies that may be used.

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The importance of a robust and reliable transport system from an economic and quality of life perspective has led to considerable research in order to understand the mechanisms and interrelationships that create its vulnerability, and to find ways to mitigate the consequences of incidents (Mattsson and Jenelius, 2015).

In general, traffic management for incidents involves the following phases:

- *Preparedness,* which takes place prior to an incident with the aim to support and enhance response. Developing plans for dealing with different types of incidents is an important component in this phase.
- *Response and mitigation* which address the immediate and short-term effects of the incident, with the aim to reduce the impacts and speeding up recovery.
- *Recovery* which involves restoring services to a nominal state.

The increasing availability of traffic information enables a data-driven analysis as a direct approach for understanding the network dynamics and traffic patterns in response to specific events. A number of studies exist in the literature using data-driven approaches to analyze transport systems disruptions. Schäfer et al. (2002) utilized floating car data (FCD) from taxis for different cities. The analysis showed that the speeds can vary from the normal conditions, representing the traffic situation in case of special events, bad weather conditions or roadwork. Calabrese et al. (2010) used location inference from anonymous cellphone data to analyze the spatial correlation between mobility choices of people and their origin patterns in the city of Boston during social events. Donovan and Work (2015) used GPS data from taxis to measure the resilience of the transport system in New York City to Hurricane Sandy. They analyzed the historical distribution of pace (travel time per mile) between various regions of the city, as well as the pace deviations during unusual events. In a similar context, Zhu et al. (2015) investigated recovery patterns based on taxi and subway ridership data in New York City after hurricanes Irene and Sandy. The findings showed that the recovery behavior varies spatially and temporally. Melnikov et al. (2015) analyzed the impact on the road traffic performance of a major power outage in North Holland which disrupted the electricity-driven public transport system for several hours, and forced people to travel by car. Traffic flow and speed data were used to highlight the most affected areas during the blackout and the propagation of traffic jams compared with days with normal traffic patterns.

Most of the studies in the literature focus on the impact of various disruptions with respect to one measure, e.g. the road traffic conditions or taxi ridership. This paper uses a data-driven approach to provide a better understanding of the broader multimodal impacts of events related to important transport facilities that may become capacity bottlenecks. The systematic analysis can provide decision makers with the tools required to develop mitigation strategies which are comprehensive in their scope and deal not only with mitigating the impacts on car traffic but also the services provided by alternative modes.

For this purpose, heterogeneous data sources are utilized. The feasibility and benefits of combining historical traffic information from various data sources are demonstrated through a case study, which examines the impact of temporary closures, due to recurrent congestion, of a freeway tunnel. This subject has not received a lot of attention in the existing literature. Specifically, the study aims at understanding and quantifying the impacts of tunnel closures in two aspects: (a) road network traffic conditions, and (b) other transport modes, e.g. public transport. The broader questions that are addressed are:

- What are the impacts of tunnel closures on the network performance and demand?
- Are there wider impacts on the performance of other transport modes or redistribution of demand to other modes due to the tunnel closures?

The paper is organized as follows. Section 2 introduces the proposed data-driven approach for the analysis of disruption impacts on network performance and demand patterns. Section 3 presents a case study focusing on tunnel closures in Stockholm, Sweden and discusses the scope of the impact analysis and the various data sources that are utilized. In Section 4 the data-driven analysis is presented, summarizing the impact of tunnel closures on network performance and demand. Section 5 concludes the paper.

## 2. Approach

The proposed methodology utilizes extensive historical information obtained from multiple traffic data sources for the identification of the impacts of a network disruption. The approach focuses on events that are not planned in advance (e.g. days or months ago), but are a result of recurrent traffic congestion or incidents. Hence, people may not have sufficient time to adpat their travel plans to the new conditions. The approach can be divided into demand and network performance analysis supported by adequate traffic metrics from heterogeneous data sources.

### 2.1 Dimensions of evaluation

A significant, localized, network disruption such as a tunnel closure has direct impact on travel demand patterns as drivers try to find alternative routes to reach their destination or switch to other transport modes (Jenelius and Mattsson, 2015). In order to observe how vehicles are redistributed during a tunnel closure, *vehicle count measurements* near the tunnel entrance and at critical diversion locations can indicate changes in the demand towards specific paths compared to regular days without disruption. *Turning fractions* at critical diversion locations can provide insights about the alternative routes that drivers take during a closure.

*Passenger load, boarding and alighting data* for select public transport lines and stops around the tunnel can be compared between closure and regular days and inform about redistribution of demand to public transport.

Moreover, studying *taxi trips* may reveal changes in the demand for taxis on closure days. A hypothesis is that travelers, who usually use car for their trip, may shift to taxi to reach the nearest public transport station, if their home location is not accessible by public transport.

Redistribution of demand to alternative paths due to a disruption may affect network traffic conditions. The impact of detouring is expected to appear near the tunnel entrances and in a wider area farther away. Information about the extent in time and space of the impacts can be provided by *speed and travel time* measurements.

Broader impacts on the performance of other transport modes are also of interest. Potential impacts on public transport performance may include increased travel time for passengers, especially on routes that cross detouring paths during tunnel closures. Deteriorating service reliability is another potential impact. Information about such impacts can be provided by *bus travel time data*, and data on *headway distributions*.

### 2.2 Data sources

Advances in sensor technologies enable the collection of data that can be used for the analysis of complex network dynamics and mobility patterns. Traffic sensors may be categorized based on their functionality as point, point-to-point and area-wide sensors (Antoniou et al., 2011). A description of the data sources that can provide the aforementioned metrics to support the impact analysis of tunnel closures is presented below.

A. Point sensors

Point sensor technologies have been widely used for traffic data collection (e.g. inductive loop detectors, radar sensors). These sensors can provide accurate vehicle counts and average speed measurements per lane, usually in fine aggregation periods (e.g. 1-minute interval). Moreover, turning percentages can be calculated if sensors are properly positioned.

B. Point-to-point sensors

Point-to-point sensors can be used to extract traffic information at the link or route level, depending on the location of the cameras. This type of sensor can be used to infer route travel times based on recorded timestamps of vehicles at the beginning and the end of the routes. *Automatic number plate recognition (ANPR)* systems are roadside cameras that use image processing to identify vehicles by recording their license plate. One example of such application is congestion pricing systems that are based on license plate recognition through video technology. Other point-to-point sensor technologies include Bluetooth and Wi-Fi sensors.

C. Area-wide sensors

The use of area-wide, non-infrastructure based sensors (in contrast to point or point-to-point sensors) is becoming more popular due to their potential to provide cost-effective spatiotemporal traffic and mobility information. These sensors are based on technologies such as Global Positioning Systems (GPS), and mobile phones. The network coverage includes the areas where GPS-equipped vehicles or mobile phones travel. The vehicles whose positions are tracked are called probe vehicles and the type of data is commonly referred as floating car data (FCD) (Rahmani et al., 2010). The raw data is processed to estimate the distribution of travel times and speeds for links in the network (Rahmani and Koutsopoulos, 2013; Jenelius and Koutsopoulos, 2013).

Vehicle fleets equipped with GPS are frequently used as an FCD source for the collection of traffic information. Information regarding the impact on the demand for taxis can be obtained by analyzing the number of taxi trips and their origin-destination patterns.

*Automatic Vehicle Location (AVL)* and *Automatic Passenger Count (APC)* systems have been widely used in public transport systems to provide information on the system's performance.

However, they can also be used to evaluate the network traffic conditions or potential short-term demand redistribution to other modes due to traffic disruptions. AVL data provide information regarding vehicles' positions, speed, and arrival and departure times (e.g. at different stops), which can be further processed to extract travel times on select bus routes, as well as headways at different stops. APC contain information about passenger demand (boarding, alighting), loads, etc. Smart card transactions from Automated Fare Collection (AFC) systems are another reliable and detailed source of information about passenger demand, which can be used in combination with AVL data to provide boarding and alighting times and locations, infer origin-destination matrices, passenger travel times, etc. (Gordon et al., 2013).

The combination of the different data sources can enhance and complement the analysis of traffic impacts. Traditional point sensors provide important information about local traffic conditions at the link level and can be used to identify impacts of traffic disruptions over time at select locations. However, one limitation is that the sensors are installed at predefined locations. Moreover, they do not reveal much about the network travel demand patterns and the behavior of travelers. Traffic information at a route level (point-to-point sensors) can better reflect the traffic conditions than measurements at single links. Finally, network-wide measurements can provide an overall perspective of the potential impacts on network traffic conditions in space and time. Nevertheless, the penetration rate is an important factor regarding the coverage and accuracy of the estimated traffic measurements. Fig. 1 presents a summary of the available sensors and the traffic metrics they provide for the analysis.

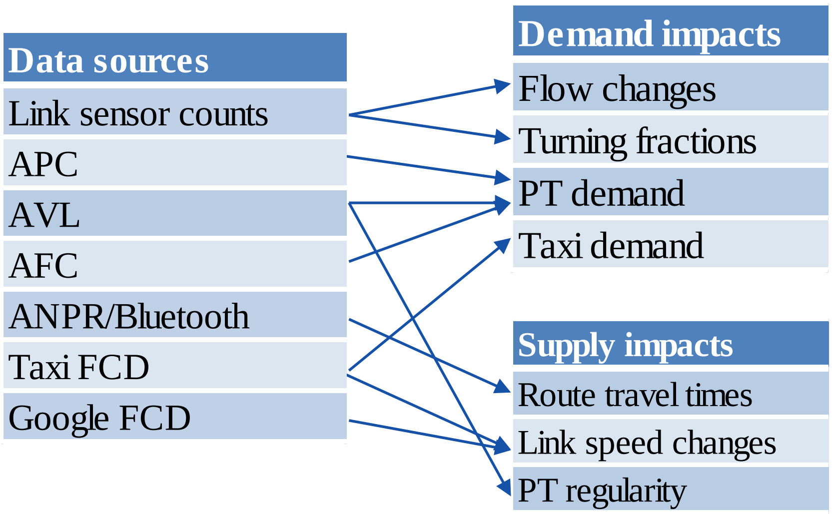


**Fig. 1** Summary of data sources and relevant traffic metrics.

## 3. Case study

### 3.1 Background

The analysis approach outlined in Section 2 is applied to a tunnel on the Södra Länken (Southern Link) freeway section in Stockholm, Sweden (Fig. 2). The Södra Länken freeway is 6 km long, of which 4.7 km is in tunnels. It connects Essingeleden (E4) freeway with Värmdöleden in Nacka municipality (Fig. 2). In the westbound direction, Södra Länken merges with flow coming from the south (E4). The tunnel has in general two lanes in each direction and a speed limit of 70 km/h. There are six entry points and six exit points (including the mainline entrance and exit). Södra Länken was designed to serve 60,000-70,000 vehicles per day when it opened in 2004. Today, however, the traffic demand is 90,000-100,000 vehicles per day.

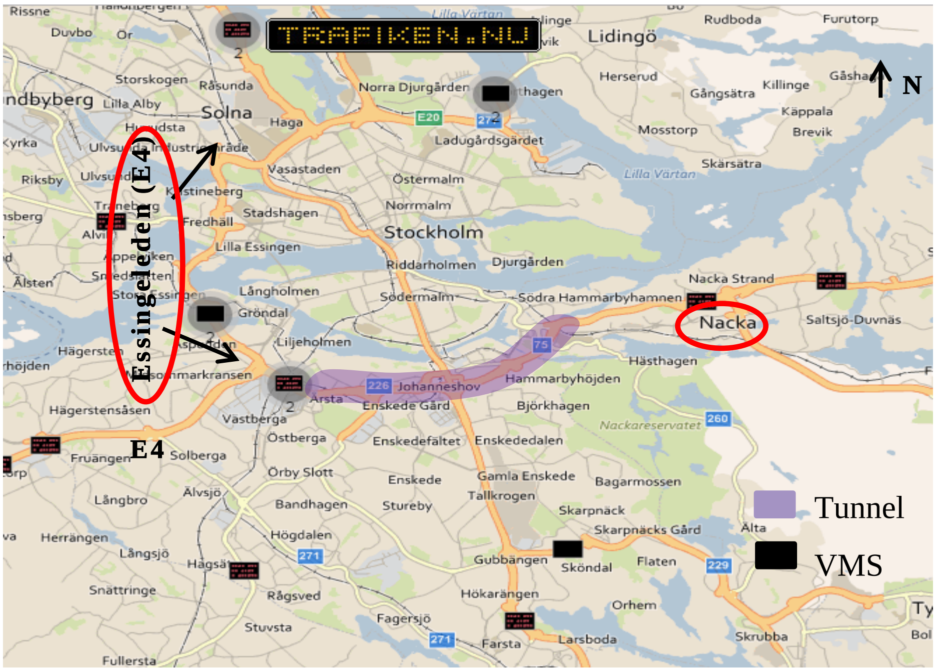


**Fig. 2** Södra Länken tunnel, Stockholm, Sweden (shaded area).

For safety reasons, closures of tunnel entrances are often used to prevent still-standing queues forming inside the tunnel due to the high demand in the tunnel and the downstream freeway. Fig. 3a summarizes the number of tunnel closures due to recurrent congestion only per year between 2005 and 2015; other causes of closures, e.g. incidents, are not included. There is an increasing trend in the number of closures over time. As Fig. 3b illustrates, the average closure time is about 45 minutes. Closures occur most commonly during the morning peak between 6-8 am, and occasionally in the evening peak. A recent study (Tympakianaki et al., 2017) investigated the causes leading to tunnel closures using data-driven analysis and evaluated different tunnel traffic management strategies through simulation.

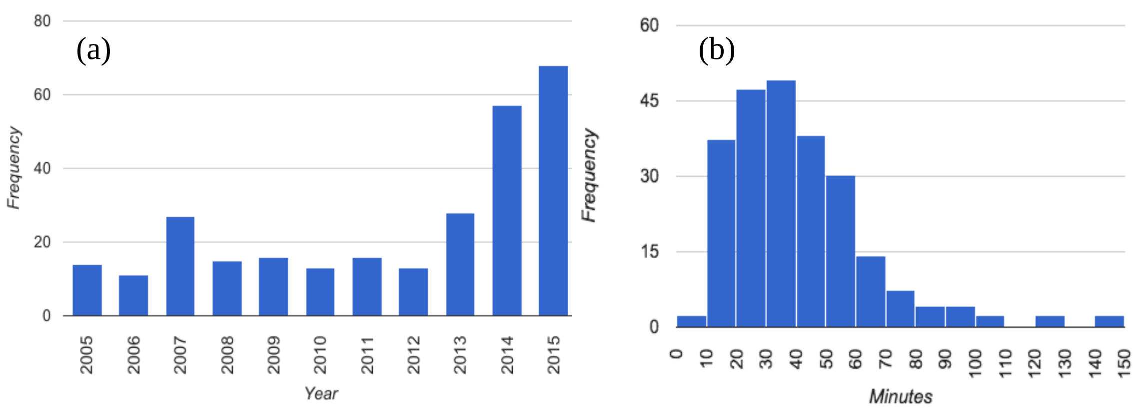


**Fig. 3** (a) Tunnel closures per year. (b) Duration of tunnel closures.

Before any tunnel closure takes place, warning messages informing drivers about the congestion in the tunnel are broadcast via radio, posted on Stockholm’s traffic information website, and displayed on variable message signs (VMS). The VMS locations are indicated in Fig. 2. A sketch of the tunnel entrances and exits is presented in Fig. 4, with the main tunnel entrances numbered. Based on the current traffic management strategy, two tunnel entrances are normally closed (entrances 1 and 3). However, when tunnel congestion is very severe, a third entrance may also be closed (entrance 5).

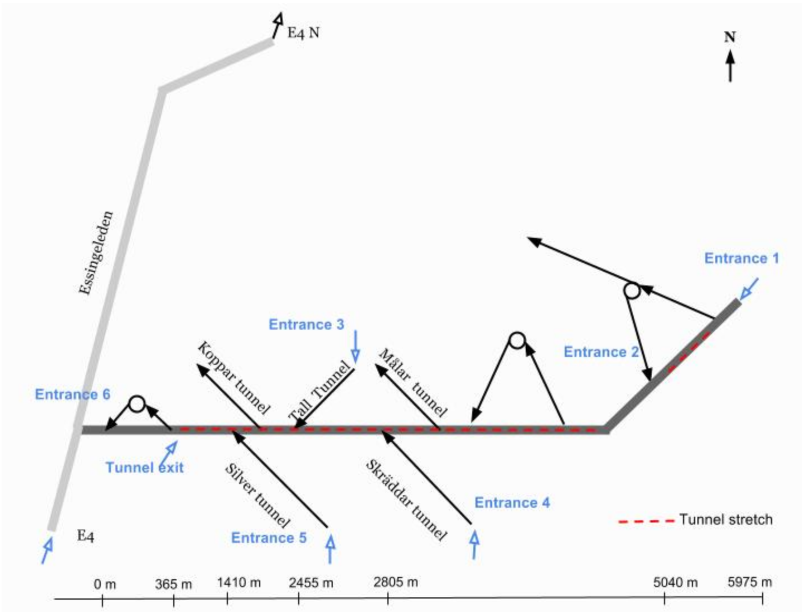


**Fig. 4** Sketch of Södra Länken tunnel.

The tunnel warnings and closures may have significant impacts for travelers since the surrounding local network is not designed to handle large volumes of rerouted traffic. Impacts are expected on both, the demand and the network performance.

### 3.2 Data

The westbound tunnel direction and the morning period is used for the analysis. The morning period 6:00 – 10:00 am and a set of 40 weekdays in April and October 2014, including days with and without tunnel closures, is selected as the study period.

In order to identify general changes in network traffic conditions, as well as the alternative paths that vehicles may take during closures, traffic measurements are first analyzed at the network level. A radius of approximately 10 km is defined as the study area. Depending on the origins and destinations of vehicles, several alternative paths exist. The most likely diversion locations and paths around the tunnel are shown in Fig. 5. The locations of the entrances that bring the highest inflow into the tunnel are also marked.

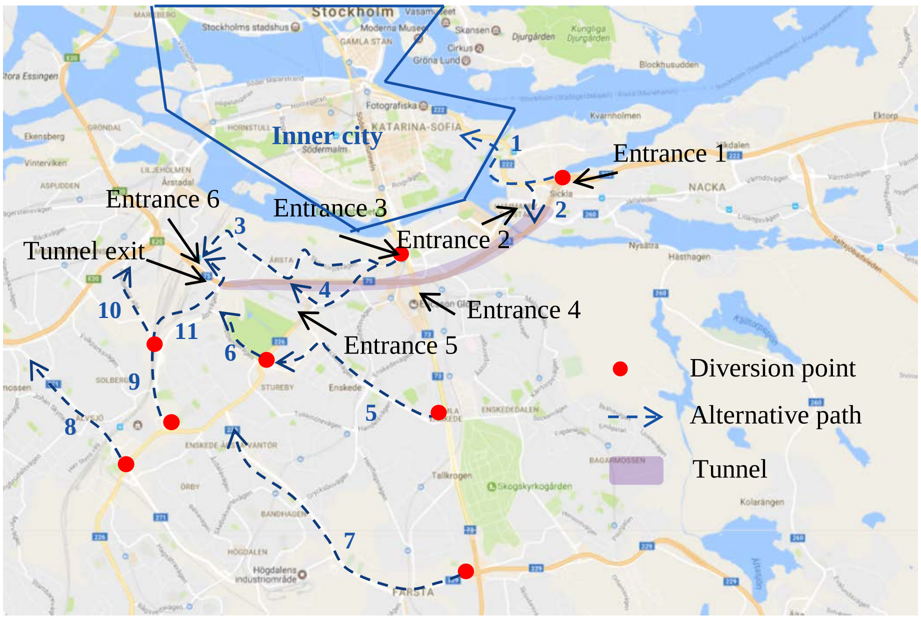


**Fig. 5** Potential alternative paths during tunnel closures.

The data sources used for the analysis are illustrated in Fig. 6. They include infrastructure sensors, AVL, APC and AFC data for select bus and light rail lines, ANPR routes, congestion pricing stations, and FCD.

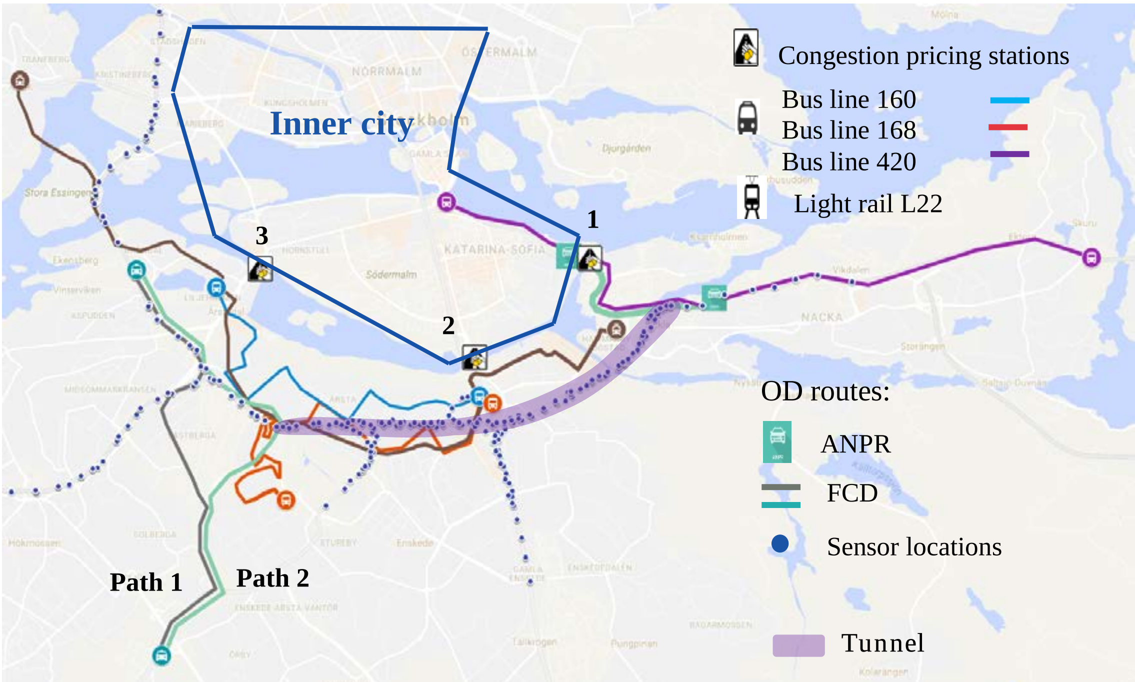


**Fig. 6** Location and coverage of data sources.

The highway network, including Södra Länken and Essingeleden, is equipped with radar sensors every 500 meters, which report counts and speeds per minute and per lane. Count measurements from the congestion pricing system are available from 18 locations around the city. The inner city and several important routes to and from the city center are equipped with ANPR cameras. For each monitored route, travel times of individual vehicles are recorded.

In addition to the above, data are also provided by Google (Better cities, 2015) in the form of aggregate, historical traffic statistics such as travel times and turning percentages at various locations. A validation study of the Google traffic measurements is described in Haak and Emde (2016). Moreover, taxi data are available in Stockholm from 1500 GPS-equipped taxis. Each taxi reports its location, timestamp and status (free/hired) every two minutes on average (see Rahmani et al., 2010). Google and taxi traffic information are combined to identify and understand the impact of tunnel closures. With respect to the penetration rate, Google data represent a larger sample of the population compared to taxi data, hence, the accuracy of the estimated traffic metrics is expected to be higher. On the other hand, the coverage of the taxi data is denser providing additional information on the affected areas and paths. Nevertheless, the travel patterns of taxis may be different from regular vehicles, which may result in potential biases in the observed traffic conditions. In Rahmani et al. (2015) these biases are identified and a method is proposed to reduce their impact.

Data from public transport buses provide traffic information that is useful to measure the impact of tunnel closures on the network conditions, but also on the public transport service performance. Historical records from AVL, AFC and APC data were available with information on dwell times, departure times (actual and scheduled), number of passengers boarding and alighting at each stop, and bus loads.

# 4 Analysis

The evaluation of the different dimensions of impacts is presented separately for demand and network performance. However, changes in the network performance may be related to different factors: (a) propagation of congestion due to downstream bottlenecks not related with the tunnel closures or (b) generation of temporary bottlenecks due to the demand redistribution, i.e. higher demand on some paths, during the closures. Therefore, the information obtained at each level is used to associate the impacts on the traffic conditions and redistribution of demand to other modes with the tunnel closures. The most significant results are presented here.

## 4.1 Demand impacts

*Car traffic*

Turning fractions are calculated upstream of entrance 1, representing the proportion of vehicles that take the alternative path as opposed to the tunnel entrance (Fig. 5). Before a closure, the turning percentages towards the alternative path are very similar for closure and regular days, indicating that drivers do not react to the warnings regarding congestion inside the tunnel.

The demand for alternative path 2 towards entrance 2 is further analyzed (Fig. 5). The average flow entering the on-ramp is 1664 veh/h during closures and 1196 veh/h for the corresponding periods on regular days. Thus, there is an approximately 40% flow increase on closure days. Fig. 7 illustrates flow as a function of time for a closure day (April 1$^{st}$) based on the sensors at entrance 2. The red line represents the flow on the closure day, while the green line represents the average flow on regular days. The bars indicate the standard deviation. The warning and closure periods are marked with orange and red rectangles, respectively. Significant flow increase is observed on the on-ramp during the closure period, indicating that the temporary closure of some of the entrances may not have the expected reduction in the tunnel inflow.

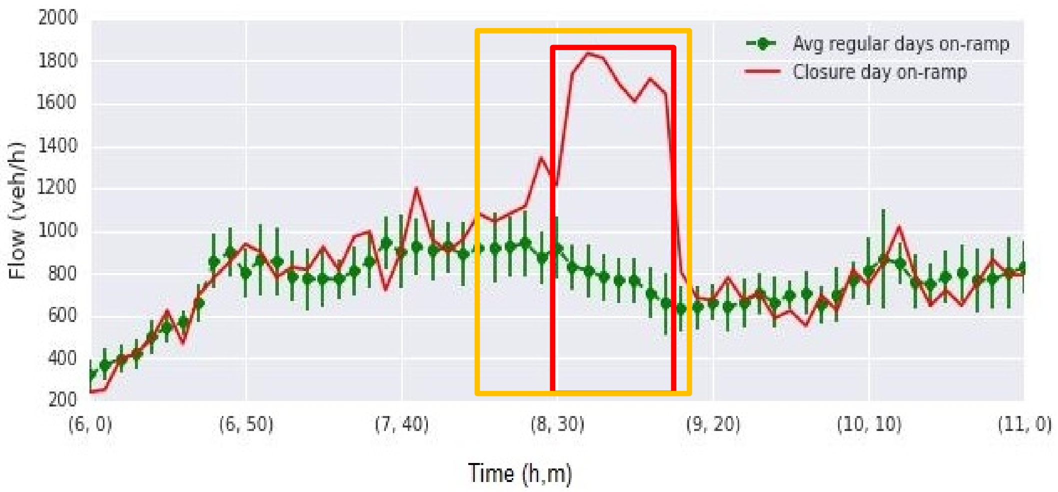


**Fig. 7** Comparison of flow at entrance 2 of a closure day (April 1st) and regular days.

Redistribution of vehicles is also expected on alternative path 1 (Fig. 5) towards the city center when entrance 1 is closed. In the examined set of days, half of the closures are triggered around 7:00 am and half around 8:00 am. Hence, the closure days are further categorized based on the time window when they take place: days with closures between 7:00–8:00 am (group 1) and days with closures 8:00–9:00 am (group 2), respectively. This categorization will help to associate potential impacts in space and time with the tunnel closures and minimize the influence of unrelated factors due to variations in the closure time windows.

The data are aggregated over 15-minute intervals for each day in the data set. Fig. 8 shows the distributions of counts at congestion pricing station 1 (Fig. 6) as box-and-whisker plots for regular days, as well as for the two groups of closure days. The red lines inside the box correspond to the median of the observed counts among days. The bottom and top box boundaries represent the 25th and 75th percentiles, respectively. The whiskers span from either end of the box to the smallest and largest data points that are non-outliers, where "outliers" are defined as any points that are more than 1.5 interquartile range away from the top and bottom of the box. Individual outliers, if any, are marked as points.

The median values (generally close to the average) in Fig. 8 confirm that the traffic flow on closure days is higher than on regular days. Higher variation of flow is observed on regular days, as indicated by the corresponding percentiles. On average the flow increase during closure days is 200 veh/h. Moreover, the mean flow on closure days during and after the closure is higher for days in group 1, compared to days in group 2.

Similar analysis is carried out for locations 2 and 3 in the direction towards the city (Fig. 6). These stations are located near entrance 3 which is one of the entrances that are often closed (Fig. 5). The comparison of vehicle counts between regular and closure days indicate on average higher number of vehicles on closure days, at both stations. The highest increase is observed between 8:00–9:00 am, with a 19% and 23% increase at locations 2 and 3, respectively.

No significant demand changes between closure and regular days are identified at other stations around the city. This result strengthens the conclusion that the observed flow increase at the three stations near the tunnel is mainly a result of the tunnel closures.

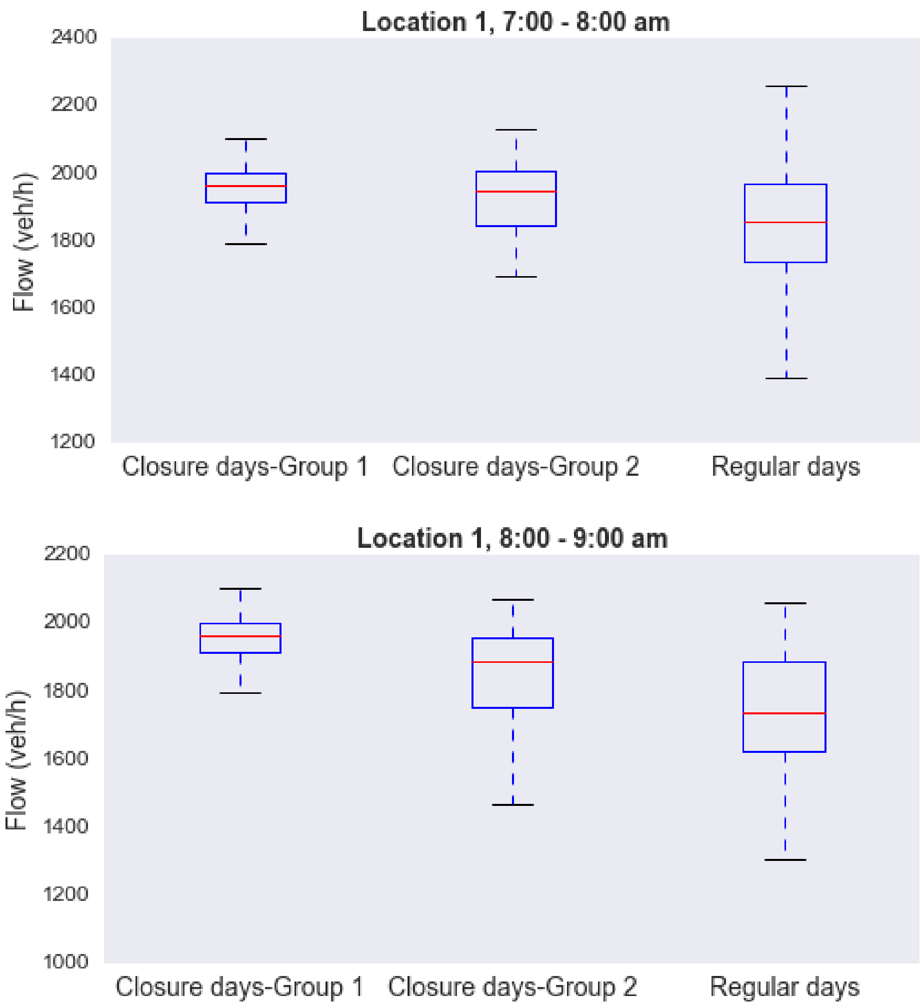


**Fig. 8** Comparison of flows at congestion pricing station 1 on regular and closure days for the 7:00–8:00 am, and 8:00–9:00 am periods.

*Public transport*

Data from the public transport system are used to analyze potential changes in the passenger demand patterns, although it is not very likely that individuals will change their travel habits, despite being aware of the congestion inside the tunnel. Aggregated data in 15-min intervals for the days in the data set for all the stops on select lines are used for the analysis. In particular, the light rail line 22 and eight bus lines with similar origins and destinations (one of the lines, 420, is indicated in Fig. 6) are analyzed. These lines cover routes related to the tunnel entrances and the alternative paths. For line 22 passenger loads on closure and regular days during the period 7:00 – 8:00 am are compared for each stop along the line. No statistically significant differences are observed in the average number of passengers between closure and regular days, indicating no major redistribution of demand to public transport modes.

The number of passengers is also analyzed for eight bus lines with origins east of entrance 1, where most of the inflow into the tunnel comes from. The destination of all lines is the city center. The average number of passengers boarding the eight bus lines is obtained from the AFC system. The analysis shows slightly higher number of passengers on closure days (1627 on average) compared to regular days (1564 on average) for the period 7:30-8:15 am; however, the difference is not statistically significant. There is thus no clear indication of redistribution of demand to public transport for the examined bus lines.

*Taxi trips*

Taxi patterns in the network are analyzed to examine whether there is evidence of travelers switching to other transport modes on days with congestion. In particular, individual taxi trips are analyzed for different time periods before, during, and after the closures for select origin-destination zones. As expected, the analysis indicates no significant change in the demand for taxis or any differences in the origin-destination trip patterns on closure days compared to regular days.

*Summary*

The analysis of demand impacts reveals important implications for traffic management and the public transport system:

- Drivers seek alternative routes, not only to their final destination, but also to reenter the tunnel at other downstream entrances.
- The traffic information system may not be very effective, as many vehicles ignore the warnings for congestion inside the tunnel and, during the closures, enter the tunnel from other entrances.
- There is no evidence of significant demand redistribution to public transport modes or taxi services on closure days. However, a spatial redistribution of the demand is observed.

### 4.2 Impact on network performance

The impact on the network performance is analyzed for car traffic and public transport. The redistribution of traffic is expected to affect traffic conditions near the entrances and at diversion locations. The most significant results are presented below.

*Car traffic*

Network traffic dynamics are analyzed in order to observe significant changes in the overall traffic conditions between regular and closure days and to identify the most impacted areas. For this purpose, FCD from the available data sources in Stockholm are analyzed. Aggregated link speed measurements in 30-minute intervals are collected for regular and closure days. For every link in the network and time interval, the average speed across the corresponding days in each data set is used (calculated as in Rahmani et al., 2015). The analysis is conducted separately for the two groups of closure days (closures around 7:00–8:00 am and around 8:00–9:00 am, respectively).

The ratio between the average link speed on closure days and regular days for different time intervals is used as performance metric. Fig. 9 shows the calculated ratios for group 1 and the time interval 7:30–8:00 am. The results are similar for the other intervals in both groups of closure days.

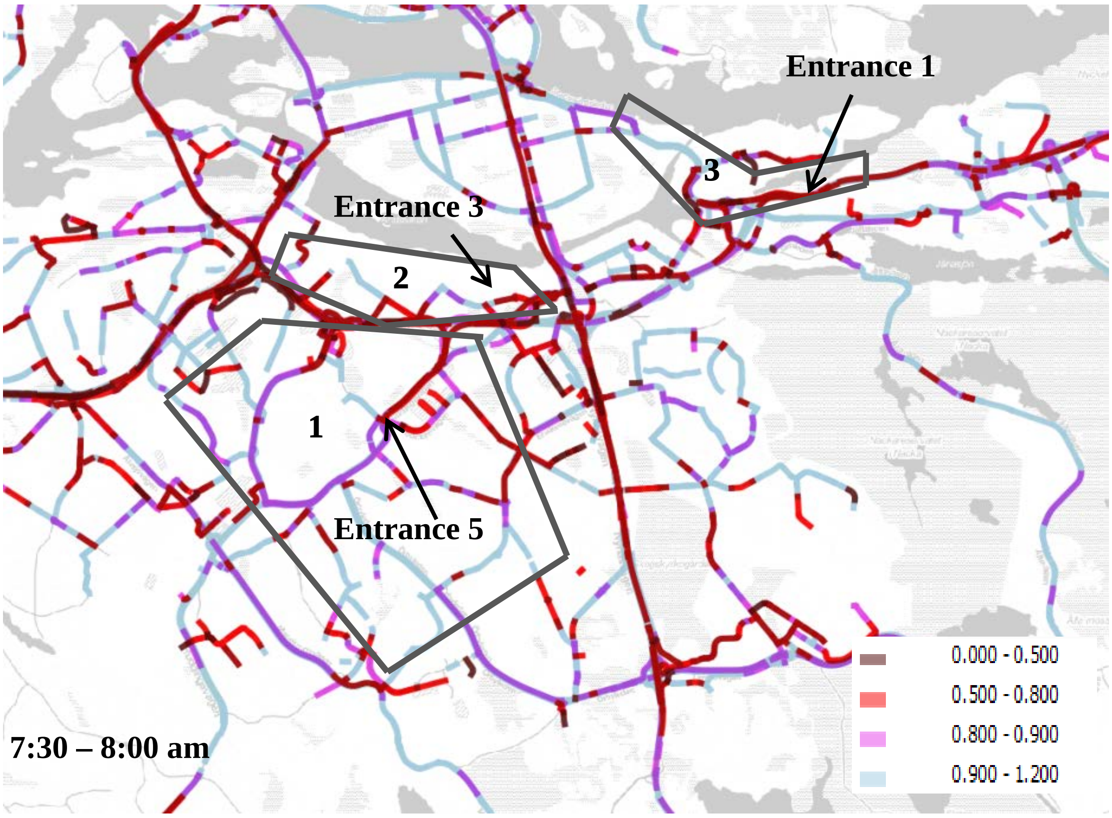


**Fig. 9** Average link speed ratios (closure to regular days, 7:30–8:00 am).

Overall, the speed ratios are mostly less than 1 and quite low for the entire network. Differences are observed for several areas both near and farther away from the tunnel. These changes are most likely associated with the closures, since measured flows and speeds at central locations reveal that conditions are similar on regular and closure days before the warning and closure periods. The areas geographically related to the three tunnel entrances that are usually closed are shown in Fig. 9. In particular, entrance 1 and the associated alternative paths 1 and 2 are included in area 3, while entrance 5 and paths 5 to 11 belong to area 1. This observation is consistent with the results of the demand analysis, which show that detouring of vehicles occurs at entrance 2 (path 2, Fig. 5) when entrance 1 is closed (Fig. 7). Worsened traffic conditions are also evident near entrance 3 (area 2), which is connected to paths 3 and 4.

Select routes related to alternative paths are analyzed using ANPR and FCD data. In particular, route travel times are compared between regular and closure days, over different time periods (before, during, after closures). A few individual days are also analyzed. The analysis of one ANPR route and two routes using FCD are presented here.

The ANPR route of interest is 2.58 km long (Fig. 6) and directed towards the city center. The travel time distributions for regular days and closure days in group 1 are presented in Fig. 10

and indicate no statistically significant difference between regular and closure days before the closure (6:00–7:00 am) at the 95% confidence level (same level used for all the statistical tests that follow). However, travel times during (7:00–8:00 am) and after (8:00–9:00 am) are significantly higher on closure days, with absolute average travel time differences 5 min (*p-value* < 0.000) and 8 min (*p-value* < 0.000), respectively. Similar results are obtained for the closure days in group 2. The corresponding absolute differences are 2 min (*p-value* < 0.000) and 4 min (*p-value* < 0.000) during and after the closure, respectively. Hence, traffic conditions on the ANPR route are significantly worse during closures and the impact is sustained even after the tunnel is reopened.

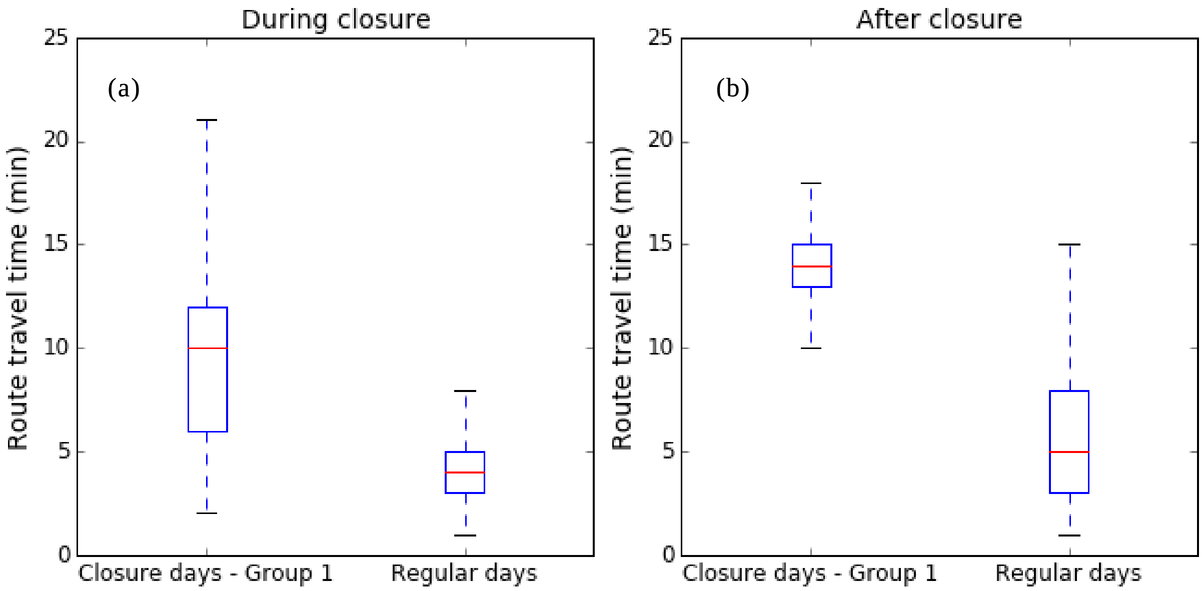


**Fig. 10** Distributions of travel times for regular and closures days in group 1: (a) before; (b) during; and, (c) after closures.

These results are consistent with the FCD speed ratios (Fig. 9). The speed ratios in area 3, which includes the ANPR route, show lower speeds during the closure periods compared to regular days. Moreover, the demand analysis indicates significant increase of flow at the congestion pricing station 1, which is part of the examined route.

Further analysis is presented for individual closure days. Fig. 11 shows the travel time for the morning period and for select closure days compared to regular days. The warning and closure periods are also marked for each closure day. For the two days with early warning and closure periods (April 7th, 9th, and 29th) the travel times are significantly higher during and after the closure periods. As shown on Table 1, the average travel times during the closures on these days increase by 175% (11 min) compared to the corresponding average travel time on regular days (4 min). There is an obvious post-effect due to the closures indicated by the increased travel times, which remain high for one more hour after the closure periods. On April 1st, travel times increased by 140% (12 min) during the closure; however, the network conditions recover fast after the closure. This may be related to the fact that the closure on that day was towards the end of the morning peak.

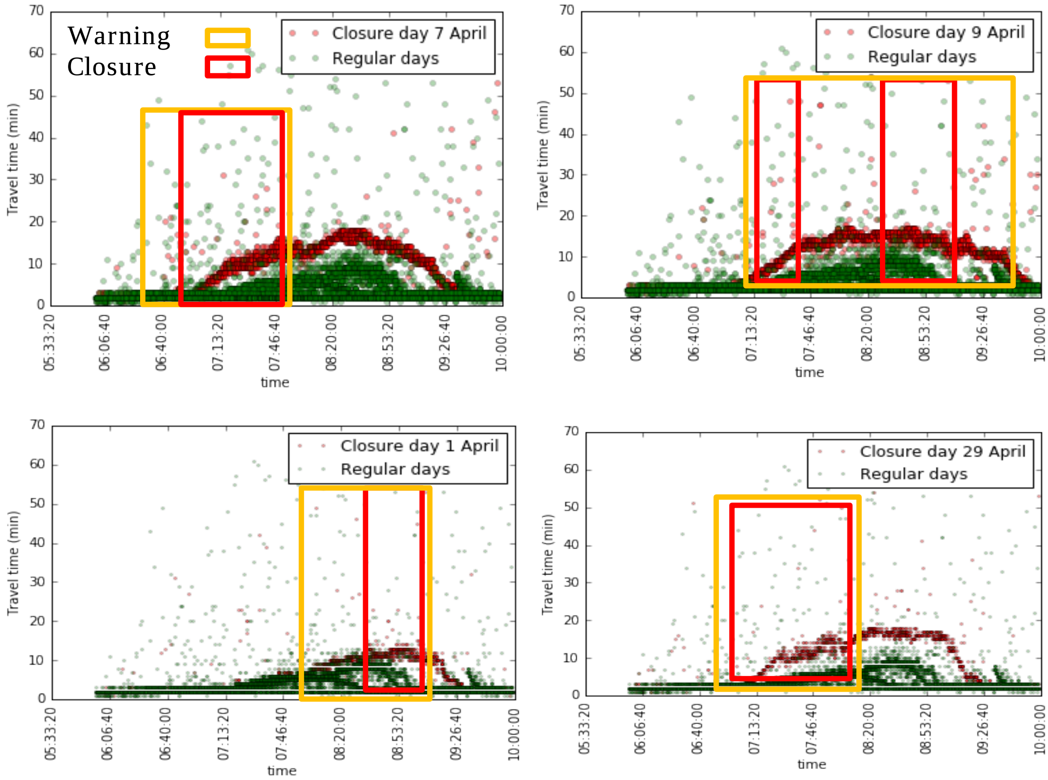


**Fig. 11** Travel time for regular and closure days for the ANPR route.

**Table 1** Average travel time for regular and closure days for the ANPR route.

| Time intervals | Regular days (min) | April 7th (min) | April 9th(min) | April 1st (min) | April 29th(min) |
|---|---|---|---|---|---|
| 7:00 - 8:00 | 4 | 11 (+175%) | 11 (+175%) | 5 (+0.25%) | 11 (+175%) |
| 8:00 - 8:30 | 6 | 16 (+166%) | 15 (+150%) | 10 (+0.66%) | 17 (+183%) |
| 8:30 - 9:00 | 5 | 13 (+160%) | 14 (+180%) | 12 (+140%) | 15 (+200%) |
| 9:00 -10:00 | 3 | 6 (+100%) | 9 (+200%) | 5 (+0.66%) | 4 (+0.33%) |

The travel times on two different paths for an Origin-Destination (OD) pair are analyzed based on FCD data aggregated over 15 minutes. The OD paths are 5.5 km long (Fig.6). Fig. 12 presents the box-and-whisker plots for the travel times on the two paths between 7:00 – 8:00 am for the two groups of closure days and regular days. The median is higher for closure compared to regular days, especially for days in group 1 for OD path 2, which is probably due to higher demand during this period.

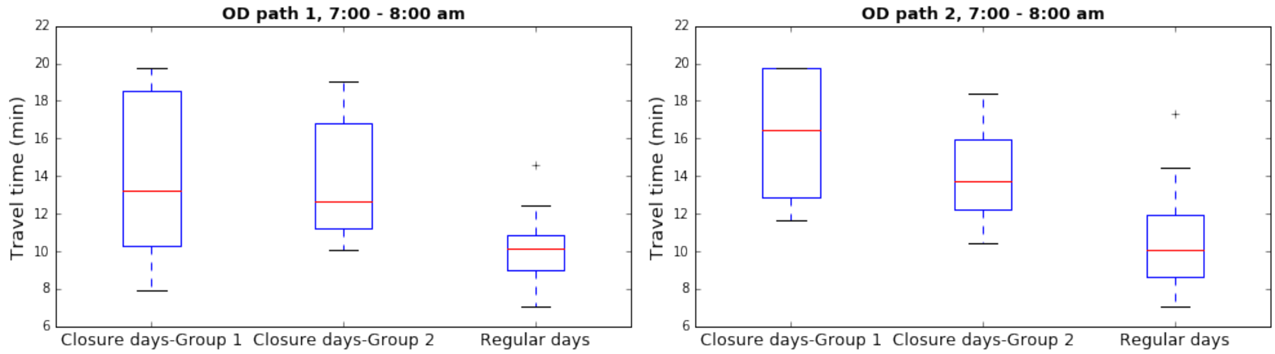


**Fig. 12** Comparison of travel times for regular and closure days.

Aggregated speed data from FCD measurements indicate impacts in areas farther away from the tunnel entrances. The statistical tests indicate significantly lower speeds on closure days (*p-value* < 0.000) on a link at the beginning of alternative path 7 (Fig. 5) that vehicles can take towards area 1, however, the absolute average speed difference is only 3 km/h. Nevertheless, the box-and-whisker plots of speeds presented in Fig. 13 indicate greater lower speed variability across closure days compared to regular days. A few outliers are also observed on regular days.

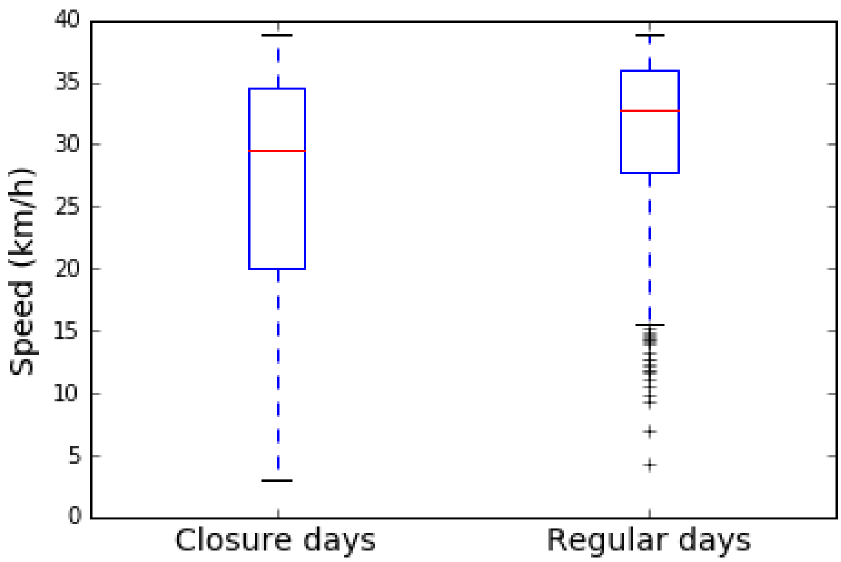


**Fig**. **13** Comparison of link speed distributions for closure and regular days on path 7.

*Public transport*

Running times between terminals and intermediate stops on select bus lines serving routes related to vehicles' detouring are derived from the AVL data, by calculating the difference in reported departure times minus the total intermediate dwell time. Bus headways are calculated to evaluate the impact of tunnel closure on public transport reliability. Bus lines 160 and 168 are selected for the analysis. Their routes are part of area 2, which is identified as one of the impacted areas during closures in Fig. 9. The first and last stops of each line, as well as a few intermediate stops are numbered on Fig. 14 to indicate the direction of the trip. The scheduled frequency of line 160 varies between 3-10 minutes during the morning 7:00–9:00 am period. The frequency of line 168 is between 15-20 minutes.

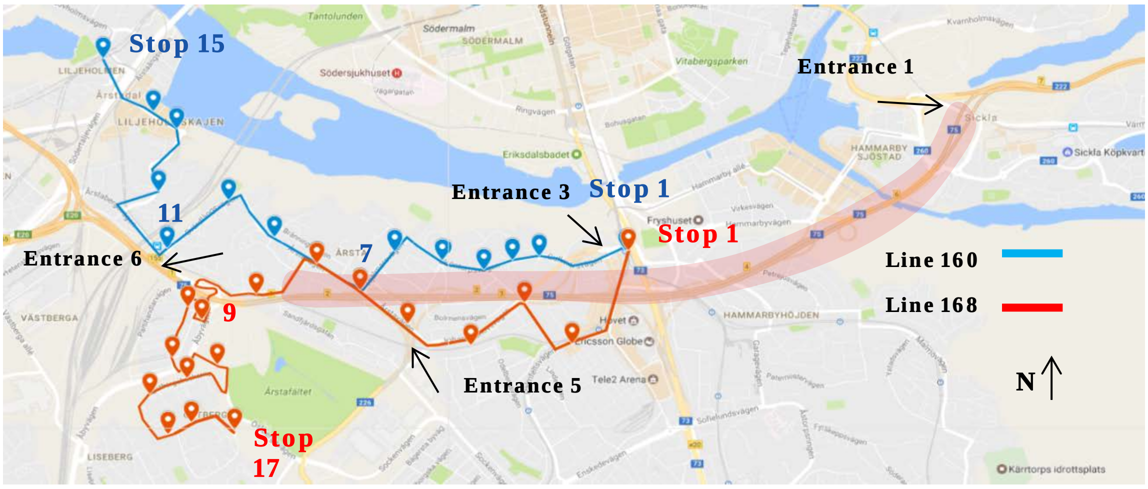

**Fig. 14** Bus lines around the tunnel.

When entrances 1 and 3 are closed, one potential alternative path near entrance 3 is path 3 (Fig. 5), which follows bus line 160 (Fig. 14). Fig. 15 presents the box-and-whisker plots for running times for line 160 between 8:00–9:00 am for closure and regular days. Higher median values are observed for closure days. Moreover, closure days in group 1 indicate higher running times variability. The absolute differences in average running times for groups 1 and 2 are 2 and 1 minute, respectively, and are found to be statistically significant (*p-value* < 0.000). The corresponding difference between 7:00 – 8:00 am is statistically significant only for closure days in group 1 and it is 3 minutes (*p-value* < 0.000), suggesting that the impact is most likely due to the tunnel closures. One reason is that alternative path 3 merges with path 4 (Fig. 5) at stop 7, hence, congestion may occur if there is higher demand on closure days. Another reason may be the detouring of vehicles from south (path 11), especially on days when entrance 5 is closed. Moreover, line 160 shares the path towards congestion pricing station 3 (Fig. 5) which indicates higher flow towards the city during the closures (see Section 4.1). The coefficients of variation are also calculated as a measure of reliability and are 0.17 for days in group 1, 0.13 for days in group 2 and 0.09 for regular days. The coefficients indicate higher travel time variability on closure days compared to regular days.

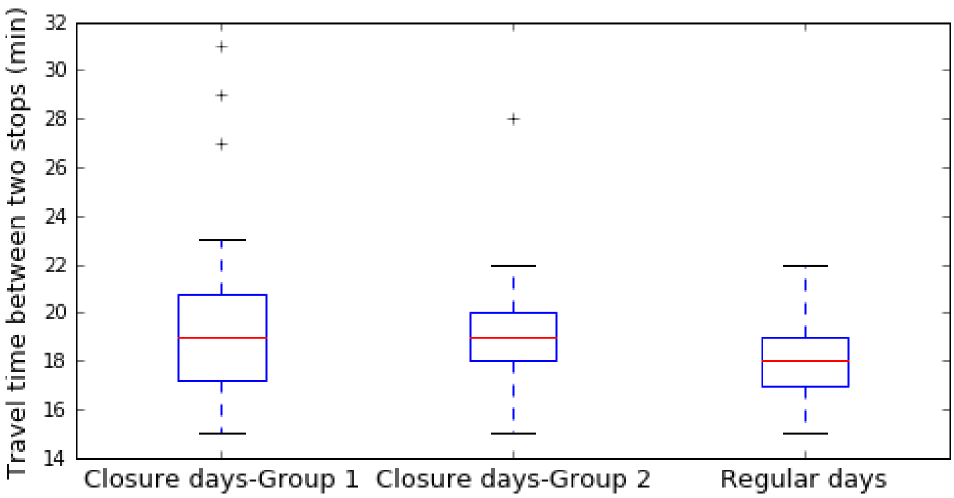

**Fig. 15** Travel time distributions for bus line 160 (trips from 8:00 - 9:00 am).

The results for line 168 (Fig. 14) are consistent with the line 160 and show statistically significant increases of bus running times. This is probably due to traffic exiting the tunnel merging at the roundabout with traffic on paths 11 and 3 and entrance 6 (Fig. 5).

Headway distributions calculated for select stops on bus lines 160 and 168 (Fig. 14). Higher variation of headways is observed on closure days. The coefficient of variation of headway for line 160 at stop 7 is presented in Fig. 16 as well as the corresponding average headway and standard deviation values (in minutes). Higher variability is observed during the closure periods (8:00–8:45 am) compared to regular days. However, these differences are not statistically significant. The analysis of individual days shows that the highest variation of headways is observed on very congested closure days. Hence, tunnel closures have a negative impact on the service reliability of the public transport system, mainly on closure days with severe traffic congestion.

The analysis of line 168 indicates similarly higher headway variability on closure days. The highest variation is observed for days in group 1 between 7:30–8:00 and 8:00 – 8:30 am. The headway coefficients of variation are 0.38 and 0.40, respectively, while the standard deviations are 6.27 and 6.24 minutes, respectively. The corresponding coefficients for the regular days are 0.20 and 0.35, respectively, with standard deviation of 3.27 and 5.6 minutes, respectively. Nevertheless, the statistical tests indicate no significant difference in the variation of headways. Similarly to the results for line 160, there are a few closure days with high impact on the headways during the closure period.

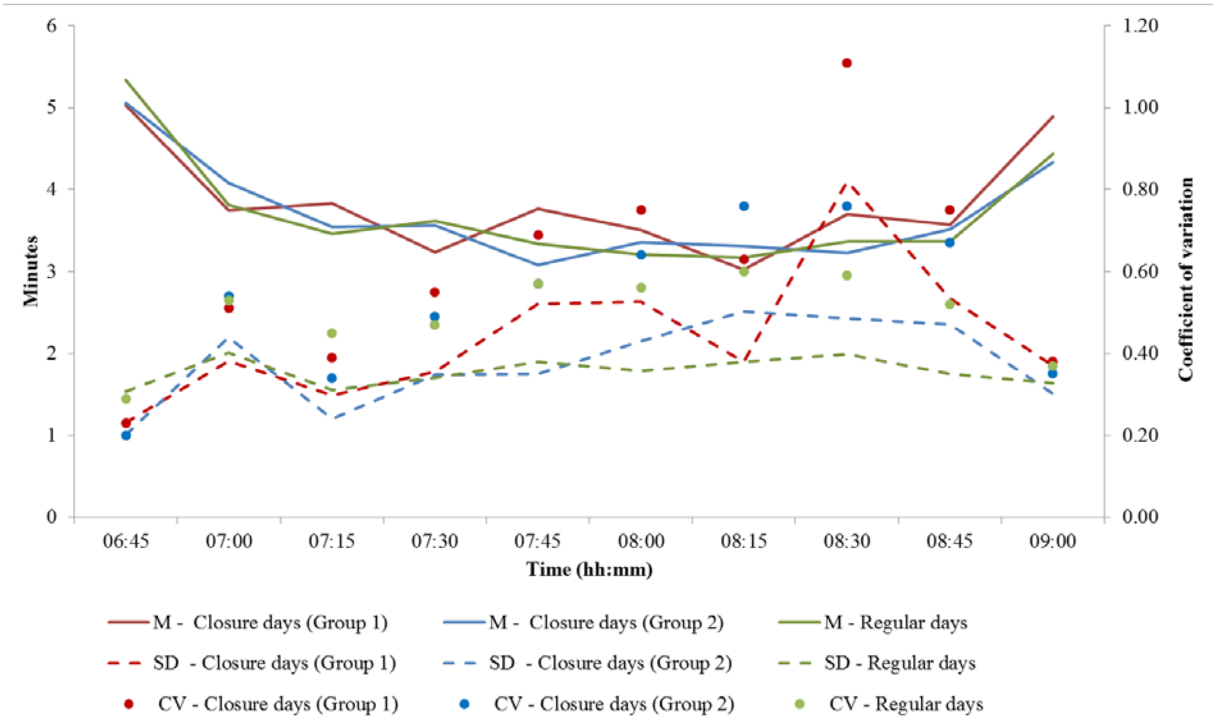


**Fig. 16** Bus headway variability for line 160 (coefficients of variation (CV), average headways (M), and standard deviations (SD)).

*Summary*

Substantial impacts are identified for the network performance as well as the public transport system performance and reliability. This implies that better information sharing and coordination between traffic and public transport authorities is needed, in order to mitigate these impacts. The impacts on traffic conditions may also suggest that tunnel closures as a policy may be too drastic and other, less impactful but equally effective tunnel traffic management strategies should be considered (Tympakianaki et al., 2017). Furthermore, during closures the traffic control system can be adjusted to accommodate for the increased traffic flows in the specific directions and/or to better facilitate bus movements.

**Discussion**

The results from the demand and network performance analysis presented above highlight the need for:

- Utilization of multimodal traffic data sources for the identification and comprehensive understanding of the associated spatiotemporal impacts on demand and network performance.
- More effective tunnel traffic management to improve the traffic conditions inside the tunnel and avoid the impacts from tunnel closures on the local network. Drastic measures such as closures may be replaced by equally effective ramp metering strategies.
- Refinement of traffic control at local streets impacted by the redistribution of traffic during closure days, to account for increased flows in specific movements, and provide improved bus priority signals.
- Accurate and timely traffic information sharing between public transport and traffic management to mitigate the impacts on public transport system performance due vehicles redistribution.
- Evaluation of traffic information provision to drivers to ensure greater response. The evaluation should focus on several design aspects, including location of VMS and information content.

## 5. Conclusion

The paper presented a data-driven approach to the analysis of multimodal impacts of transport network disruptions. The impacts are investigated at two levels: (a) spatiotemporal changes in network performance and demand, and (b) effects on other transport modes. For this purpose, heterogeneous data sources are used in a systematic way to measure changes in network traffic conditions, demand patterns, and performance of multiple transport modes.

The approach was used for the study of the impacts of closures of a tunnel in Stockholm, Sweden, where some of the tunnel entrances are frequently closed due to congestion. Heterogeneous historical traffic data from sensors, taxi FCD, traffic cameras (ANPR and congestion pricing) and public transport AVL, AFC, and APC data sources, were combined in order to identify and analyze the impacts of the tunnel closures.

The demand patterns and network traffic conditions were analyzed for critical locations near the tunnel but also farther away from the tunnel. The analysis revealed significant impacts on both traffic conditions and the performance of the public transport system due to redistribution of traffic. In particular, higher travel times and lower speeds are observed on closure days compared to regular days. Moreover, bus routes following potential alternative paths during closures were analyzed, indicating higher travel times on days with closures. Finally, the headways on several bus routes were also affected on highly congested closure days.

These findings can provide traffic authorities with valuable insights into the impacted areas and the extent of effects under a network disturbance and assist them to make better decisions about tunnel traffic management and mitigation of congestion. Indications about the extent of post-effects on the transport system are also provided; suggesting that the impacts of closures remain even after the tunnel is reopened. The recovery ability of the system after the closures is another interesting dimension that can be further studied.

**Acknowledgements**

This research was co-funded by Google through the Better Cities program, the Swedish National Transport Administration, and the TRENoP Strategic Research Area. The authors would like to thank Trafik Stockholm and Stockholm Public Transport, SLL Trafikförvaltningen, for providing the data and for their valuable input.

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