Denne artikel er publiceret i det elektroniske tidsskrift **Artikler fra Trafikdage på Aalborg Universitet** (Proceedings from the Annual Transport Conference at Aalborg University) ISSN 1603-9696 www.trafikdage.dk/artikelarkiv



Impacts of long-term service disruptions on passenger travel behaviour: A smart card analysis from the Greater Copenhagen area

Morten Eltved^{1,2} (morel@dtu.dk), Nils Breyer³ (nils.breyer@liu.se), Jesper Bláfoss Ingvardson² (jbin@dtu.dk), Otto Anker Nielsen² (oani@dtu.dk) ¹ MOE Tetraplan, ² DTU Management, Technical University of Denmark, ³ Linköping University

1 Introduction

Disruptions in public transport are the major cause of passenger dissatisfaction (van Lierop et al., 2018) and they result in decreased public transport usage (Nazem et al., 2018). Much of the research on disruptions has focused on robustness of networks (Cats, 2016), network planning during disruptions (van der Hurk et al., 2016), and passenger information provision (Bruglieri et al., 2015). However, limited focus has been on understanding the changes to travel behaviour caused by planned long-term disruptions, such as closures due to construction work. Hence, this study analyses the effects of a long-term closure of an important suburban railway line in the Greater Copenhagen area (Denmark) on the travel behaviour of public transport passengers. Using a large-scale smart card dataset, the travel behaviour before and after the closure is compared and analysed across different groups of travellers focusing on changes to the travel patterns across groups.

2 Background

Disruptions in public transport systems can be unplanned, for example due to an accident, or planned, for example due to construction works. Planned disruptions, such as the closure of a station or an entire corridor, are not uncommon and can often last over a long period. However, the effects of planned long-term disruptions have not yet been studied extensively.

In Denmark, the Copenhagen S-train network has had several maintenance and other construction projects affecting the operations, both short-term such as closures of short segments during weekends and longer term such as track renewal on entire S-train lines. While there is much information on changes to actual usage within the corridors and network-wide during these disruptions less is known on how the disruptions influence travel patterns of various passenger types; both on the short term (e.g. changed routes or mode) and on the longer term in terms of whether (and when) passengers return to the public transport system.

Previous studies show numerous uses of smartcard data for strategic, tactical and operational public transportation planning (Pelletier et al., 2011). Only a few studies have used smart card data to investigate the effect of long-term disruptions (Yap et al., 2018). Nazem et al. (2018) analysed travel behaviour changes due to a closure of a single metro station and showed that even a mid-term disruption can have long-term impacts on travel behaviour. Clustering of travellers based on travel characteristics has been studied well, e.g. El Mahrsi et al. (2017), Briand et al. (2017), Kieu et al. (2015). However, these studies have not focused on analysing changes of travel patterns due to such disruptions, and specifically how patterns vary across user groups. Hence, this study also fills this gap in literature.

3 Case study

The project utilises the Danish public transport smart card data, Rejsekortet. This data includes complete information on route choices of the public transport passengers as it requires passengers to check-in at origin and transfer stations, and check-out at the destination station. The study analyses the planned disruptions at the S-train line linking Frederikssund to Copenhagen, which was closed for three months due to track renewals in 2018 (see Figure 1). The line, which normally has 87,600 daily passengers (DSB, 2013), corresponding to 11.7% of total S-train passengers, was closed in the period June 1st - August 26th 2018. Replacement buses were operating in this period resulting in increased travel times, less comfort and additional transfers for passengers.



Figure 1; Map of the Copenhagen S-train (colours) and metro (grey) network including the closure of the Frederikssund-lines between Frederikssund and Valby during Summer 2018 (dark blue).

It is well known, that passengers change their behaviour frequently due to different seasons of the year, change of job or housing location, etc. (Egu et al., 2020). As such, it is not possible to directly analyse the changes on the Frederikssund line. The changes for passengers on the Frederikssund line are therefore compared to the changes for passengers on other S-train lines. It is important to compare with similar reference lines, and the analysis therefore include passengers on the lines to Høje Taastrup, Køge and Hillerød as reference group since these have many similarities in seasonality changes, number of alternative lines close by and especially that these lines did not have any major disruptions in 2018.

The passengers who travel mostly on any of the affected or reference lines (i.e. more than 50% of their public transport trips include this line) are included in the study. To study the effect on different types of passengers (for example daily commuters or leisure/weekend travellers) the smart cards are clustered using three relevant travel characteristics: *share of active weeks in a period, active days pr. active week in a period, and share of trips made on the weekend*. K-means clustering (Ma et al, 2013) is used to cluster the passengers in two time periods – *pre* and *post* disruption. The *pre* period is set to the 12 weeks from January 1st to March 25th, as there were preliminary works with many smaller closures on the track to Frederikssund in the spring before the affected period, and the *post* period is set to the 12 weeks from August 27th to November 18th. Passengers are clustered into eight groups in each of the periods based on their travel behaviour. The characteristics for the groups are shown in Figure 2. Passenger clusters 7 and 8 are the most active travellers who travel regularly and in almost all weeks in a period. On the other hand, clusters 1-4 are rare and occasional users who only travel in few of the weeks and only one or two days in the active weeks. Passenger clusters 5 and 6 are users, who travel regularly but only few days in the active weeks and respectively either only on weekdays or both on weekdays and weekends.



Figure 2; Travel behaviour characteristics for passenger clusters

Table 1 shows the distribution of passengers (only personal cards) across the clusters for respectively the affected line to Frederikssund and for all the reference lines combined in the pre period. The distribution of passenger across the groups is very similar for the affected and reference lines, where for example commuters account for approximately 6.5% of the passengers, but up to 35% of the trips made. The two most active passenger groups (7 and 8) account for 15% of the passengers but more than 55% of the trips. On the other hand the four least active groups (1-4) account for 65% of the passengers, but only around 20% of the trips. With the groups established, it is possible to look at the changes from the pre to the post period and compare these changes on the affected and reference lines.

Table 1; Distribution of passengers and number of trips across passenger clusters on the affected line (Frederikssund) and reference lines (Køge, Høje Taastrup, Hillerød) in the pre period

	Frederi	kssund	Reference lines		
Cluster	Card share	Trip share	Card share	Trip share	
1: Rare weekday	32.2%	7.0%	33.7%	7.6%	
2: Rare weekend	12.5%	2.6%	10.7%	2.3%	
3: Occasional leisure	18.4%	7.1%	17.2%	6.5%	
4: Irregular workers	4.3%	5.0%	4.4%	5.0%	
5: Weekly-Biweekly	12.6%	12.9%	13.6%	13.7%	
6: Regular leisure	4.9%	6.4%	5.3%	7.1%	
7: Part-time workers	8.5%	23.4%	8.8%	24.1%	
8: Commuters	6.6%	35.6%	6.2%	33.7%	

4 Results of analysis of changes

By analysing the changes for both the overall composition of passenger clusters in the pre and post period and the individual changes for passengers from pre to post period, it is possible to give some clear indications on the effect of the track closure on travel behaviour. Table 2 shows the overall composition of passengers in the different clusters in the pre and post period. The number of commuters and part-time workers decreased on the Frederikssund line from pre to post period, while the those groups increased on the reference lines. This indicates a loss of commuters due to the track closure, which cannot be explained by the overall trends in the public transport system. In general it is found that all groups increase (or decrease less) on the reference lines compared to the groups on the line to Frederikssund.

Table 2; Changes in number of passengers in the passenger clusters on Frederikssund and reference lines from pre to post period

	Frederikssund			Reference lines		
Cluster	Pre	Post	Change	Pre	Post	Change
1: Rare weekday	10,642	9,916	-6.8%	33 <i>,</i> 595	34,055	1.4%
2: Rare weekend	4,122	4,205	2.0%	10,653	11,441	7.4%
3: Occasional leisure	6,103	6,601	8.2%	17,158	19,852	15.7%
4: Irregular workers	1,430	1,304	-8.8%	4,424	4,295	-2.9%
5: Weekly-Biweekly	4,166	4,182	0.4%	13,564	15,022	10.7%
6: Regular leisure	1,616	1,843	14.0%	5,320	6,562	23.3%
7: Part-time workers	2,828	2,753	-2.7%	8,803	9,188	4.4%
8: Commuters	2,178	1,906	-12.5%	6,230	6,311	1.3%
Total	33,085	32,710	-1.1%	99,747	106,726	7.0%

It is also possible to track the individual card holders from the pre to the post period. Figure 3 shows an alluvial diagram, where it is possible to see how travel behaviour changes for passengers from group 7 and 8 (part-time workers and commuters) between the pre- and post-period. As shown in the left figure for passengers on the Frederikssund line only 36% of the commuters in the pre-period are also commuters in the post-period. On the reference lines (shown in the right figure) 44% of the commuters in the pre-period are still in the commuter cluster in the post-period. Many commuters and part-time workers stop travelling in the post-period (to group *NA*) and this group of passengers is bigger on the Frederikssund line compared to the reference lines. This again indicates a loss of passengers due to the track closure.



Figure 3; Change for passengers in clusters 7 and 8 in the pre period (S indicates all other clusters and NA indicate that the passenger did not travel in the post period) – Frederikssund line on the left – Reference lines on the right.

5 Conclusion

The proposed methodology of clustering passengers in different groups based on their travel behaviour has been used to analyse the changes due to the track closure on the Frederikssund line compared to the overall trends in the public transport system. The analysis shows that a small share of individuals constitute a major part of the trips taken in the system.

By analysing the change in the overall composition of passenger clusters it is clear that there was a drop in the number of commuters on the line to Frederikssund, which is opposite to the increase in commuters on the reference lines. Also the analysis of individual passengers and their travel behaviour pre and post the disruption shows that more commuters stopped commuting on the Frederikssund line than what can be explained by the overall trends on the reference lines.

The results shown in this study is useful for the public transport agencies, since it is important to keep the commuters in the public transport system, as a loss of commuters will also result in a permanent decrease in passengers compared to the overall trends in the public transport system.

References

Briand A.S., Côme E., Trépanier M., Oukhellou L. (2017). Analyzing year-to-year changes in public transport passenger behaviour using smart card data. Transp Res Part C Emerg Technol 79:274–289. <u>https://doi.org/10.1016/j.trc.2017.03.021</u>

Bruglieri, M., Bruschi, F., Colorni, A., Luè, A., Nocerino, R., & Rana, V. (2015). A real-time information system for public transport in case of delays and service disruptions. Transportation Research Procedia, 10, 493-502.

Cats, O. (2016). The robustness value of public transport development plans. Journal of Transport Geography, 51, 236-246.

DSB. (2013). Passenger numbers 2009-2013 (in Danish). Accessed February 17, 2020, from https://www.dsb.dk/globalassets/kommunikation/tal-om-togrejser/af--og-pastigere-s-tog-hverdagsgennemsnit-pr--station.pdf

Egu, O., Bonnel, P., 2020. Investigating day-to-day variability of transit usage on a multimonth scale with smart card data. A case study in Lyon. Travel Behav. Soc. 19, 112–123. https://doi.org/10.1016/j.tbs.2019.12.003

El Mahrsi, M. K., Come, E., Oukhellou, L., & Verleysen, M. (2017). Clustering Smart Card Data for Urban Mobility Analysis. IEEE Transactions on Intelligent Transportation Systems, 18(3), 712–728. https://doi.org/10.1109/TITS.2016.2600515

Kieu, L. M., Bhaskar, A., & Chung, E. (2015). Passenger segmentation using smart card data. IEEE Transactions on Intelligent Transportation Systems, 16(3), 1537–1548. <u>https://doi.org/10.1109/TITS.2014.2368998</u>

Ma, X., Wu, Y. J., Wang, Y., Chen, F., & Liu, J. (2013). Mining smart card data for transit riders' travel patterns. Transportation Research Part C: Emerging Technologies, 36, 1–12. <u>https://doi.org/10.1016/j.trc.2013.07.010</u>

Nazem, M., Lomone, A., Chu, A., & Spurr, T. (2018). Analysis of travel pattern changes due to a mediumterm disruption on public transit networks using smart card data. Transportation Research Procedia, 32, 585 - 596. <u>http://www.sciencedirect.com/science/article/pii/S235214651830173X</u>

Pelletier, M.-P., Trépanier, M., & Morency, C. (2011). Smart card data use in public transit: A literature review. Transportation Research Part C: Emerging Technologies, 19(4), 557 - 568. <u>http://www.sciencedirect.com/science/article/pii/S0968090X1000166X</u>

van der Hurk, E., Koutsopoulos, H. N, Wilson, N, Kroon, L. G., Maróti, G. (2016). Shuttle planning for link closures in urban public transport networks. Transportation Science, 50(3), 947-965. <u>https://doi.org/10.1287/trsc.2015.0647</u>

van Lierop D., Badami M. G., El-Geneidy A. M. (2018). What influences satisfaction and loyalty in public transport? A review of the literature. Transp Rev 38:52–72. <u>https://doi.org/10.1080/01441647.2017.1298683</u>

Yap, M. D., Nijënstein, S., & van Oort, N. (2018). Improving predictions of public transport usage during disturbances based on smart card data. Transport Policy, 61, 84 - 95. <u>http://www.sciencedirect.com/science/article/pii/S0967070X16307648</u>