

# Assessing the customer impact of service disruptions on the London Underground network using Automated Fare Collection data

Ioannis Kaparias <sup>1</sup>, Chi Xu <sup>1</sup>, Richard Smith <sup>2</sup>, David Winslett <sup>2</sup>

<sup>1</sup> Transportation Research Group, University of Southampton, UK

<sup>2</sup> London Underground, Transport for London, UK

## Abstract

Service disruptions are a common undesirable occurrence in urban public transport networks, in response to which passengers often take action. This may involve changing their route, altering their origin and/or destination, switching to other modes or even cancelling their trip altogether. The aim of this study is to provide an insight into the factors that influence this behaviour. Using the London Underground network as an example, passenger responses to incidents are inferred by analysing an eight-week dataset of the “Oyster” Automated Fare Collection system, while service disruptions are extracted from London Underground’s CuPID database of incidents during the same period. Binary logistic regression is used to fit models describing passenger responses to disruptions in terms of continuing their journey, changing origin or destination station, or leaving the network altogether. The results suggest that passengers are more likely to take action in response to a service disruption if this has a delay of less than 5 mins or more than 20 mins, but more likely to stick to their original route for delay durations in between. Also, passengers are more likely to change station or leave the network if the disruption occurs at the origin station of their journey.

## Introduction

Public transport networks can be affected by service disruptions, ranging from platform closures on rail networks to diverted routes on bus networks, and it is broadly acknowledged that from an operational perspective these are undesirable and should be avoided as much as possible. From the point of view of the passengers, however, the impact of these service disruptions, whether minor or major, can be detrimental with respect to their travel experience [1-2]. As a result, passengers already en-route may decide to not take any action in response to a disruption and continue their journey as normal, in which case they will experience a considerably longer journey time. Alternatively, they may choose to re-route, re-mode or even delay or cancel their journey, in which case they may switch to a different station or stop, or they may leave the network altogether. All of these introduce great inconvenience.

But while it is widely acknowledged that disruptions can severely impact the journey experience of customers, the prevailing data scarcity in the public transport field up until recently has meant that the exact nature of this impact, as well as the ways that it may manifest itself, have been mostly analysed at a theoretical level (e.g. stated-preference surveys). Past research has also concentrated on assessing and quantifying this impact (e.g. [3]), but more practical aspects (i.e. what do passengers actually do in the event of a service disruption), have received relatively little attention.

The aim of this study is, therefore to address this gap and explore the “customer impact” of incidents (e.g. signal failures, temporary station closures, etc.) using the London Underground network as a case study. The objective is to develop quantitative models to describe the real relationship between service incident characteristics and customer experience, as expressed by revealed-preference data from records of Transport for London’s (TfL) “Oyster” Automated Fare Collection (AFC) system. Such analysis can be of value to public transport operators, as the results

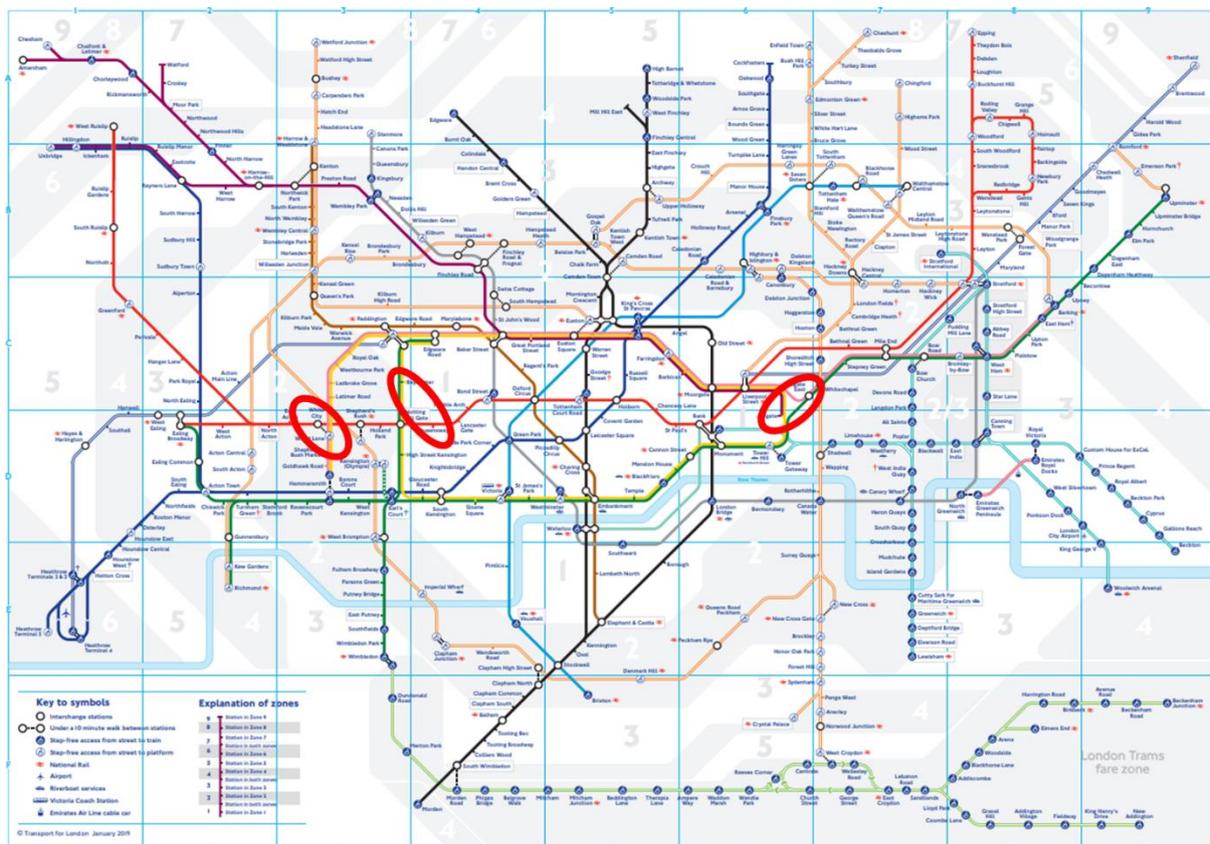
could serve as input to the calibration and validation of models used to assess the effect of planned and unplanned disruptions.

### Study area and datasets

The study uses the London Underground network (Figure 1) as a case study, which consists of 11 lines covering 402 km and serving 270 stations across the Greater London area. The network facilitates up to 5 million passenger journeys per day, having carried a total of 1.36 billion passengers in the 2017-18 period [4-5].

Data from two sources are obtained for the whole of the London Underground network over an eight-week period, and specifically between 15 January and 11 March 2019:

- An anonymised log of all journeys carried out on the network, as recorded by the “Oyster” AFC system. For each journey, the log contains information on the origin and destination stations, as well as the times of entry and exit (i.e. the times of departure and arrival). As a result, the log consists of some 200 million entries.
- A log of all service disruption incidents that occurred on the network, as recorded on London Underground’s CuPID database. Among 41 parameters, each record contains information on the location of the incident, the date and time, the duration, the corresponding initial delay to passengers, the type of the incident and a free text description of what happened. 5734 service disruption incidents have been entered in CuPID during the study period and are available here.



**Figure 1:** The London Underground network, with the three selected station pairs [4]

In order to simplify the analysis, only the journeys to and from three specific station pairs (i.e. six stations) are considered. These station pairs are selected across the network on the basis of their suitability to act as alternative origin or destination stations for re-routed passengers as a result

of a service disruption (Figure 2). For two stations to be selected, they must be served by different lines and the actual walking distance between them should be less than 300 m. The selected station pairs are:

- Wood Lane (served by the Circle and the Hammersmith & City Lines) and White City (served by the Central Line), located 210 m apart.
- Aldgate East (served by the District and the Hammersmith & City Lines) and Aldgate (served by the Circle and the Metropolitan Lines), located 270 m apart.
- Queensway (served by the Central Line) and Bayswater (served by the District and the Circle Lines), located 215 m apart.

The Oyster AFC records for all individual journeys on the London Underground network involving the six chosen stations are aggregated into 5-min intervals covering the entire study period. As such, for each 5-min period an average travel time and standard deviation value is obtained, along with the number of trips. Instances of invalid or insufficient data (e.g. unrealistically short or long travel times, or very small numbers of trips) are filtered out and are not considered. Moreover, the study period includes certain days when adverse weather (heavy snowfall) has been reported, and since this is associated with abnormal travel patterns, these days are also excluded.

Considering the service disruption data, it is assumed that an incident at a certain station affects all passengers starting their trip from or being already en-route to the station in question during the time that the incident is in progress (i.e. start time plus duration). It is also recognised that incidents occurring at stations en-route other than the origin and destination may well have an impact on passengers travelling through them, and that spatial dependence effects may result in trips elsewhere on the network to also be affected; however, the consideration of these is much more complex and is beyond the scope of this study. Finally, it should be mentioned that incidents having a low frequency of occurrence or affecting a small number of passengers (e.g. early morning or late night) are not considered, and that only the five most common incident types are investigated, namely: train delay; train cancellation; train withdrawn from service; escalator downtime; and partial line suspension.

### **Customer impact evaluation methodology**

In general, when faced with a service disruption incident in an urban metro network while en-route, passengers will in most cases respond in one of the following three ways:

1. *Continue*: the passenger continues his/her journey to his/her original destination station, either on the original route or by re-routing;
2. *Change station*: the passenger continues his/her journey, but changes his/her origin and/or destination station; or
3. *Leave network*: the passenger does not continue his/her journey and leaves the metro network, opting to either re-mode (e.g. to the bus network) or cancel his/her trip altogether.

Nevertheless, the chosen response strongly depends on the location of the incident in relation to the entire journey, and this translates to different patterns in the AFC data for the passengers taking a specific journey between two stations in the network. For instance, if the incident occurs near the origin station, response 1 is likely to result in an increase in travel time, while responses 2 and 3 will be associated with a decrease in the entry volume of the origin station for that specific journey. If that decrease is coupled with an increase in the entry volume of a paired station, then this shows that passengers opted to change their origin station for that specific journey; if not, then passengers have likely chosen to leave the network.

On the other hand, if the incident occurs away from the origin station along the journey,

passengers are well under way and are therefore unlikely to leave the network, so only responses 1 and 2 are likely. Again, response 1 will result in increased travel time for that specific journey, whereas response 2 will be associated with a decrease in the exit volume of the destination station, coupled with an increase in the exit volume of a paired station. It should be noted, however, that in some cases passengers have no choice but to stick to their original route (e.g. if there is no transfer station in the rest of their trip).

The entire Oyster dataset for the selected stations during the study period is used in order to establish the “normal” conditions (number of passenger entries and exits) for each day and 5-min time period. Then, during a service disruption at, say, Station A, potentially different conditions may be exhibited, not just for the trips starting/ending at Station A itself, but possibly also at its paired Station B. Paired sample hypothesis tests are used in this case, whereby it is checked whether there are statistically significant differences (at the 5% level) between the recorded entry/exit volumes during the disruption and the corresponding values at normal conditions.

Depending on the results of the tests, the relevant passenger response can be inferred, namely:

1. If no statistically significant difference to normal conditions in the entry/exit volume is found for Station A, then the prevailing passenger response is inferred as “Continue”.
2. If the entry/exit volume at Station A is found to be statistically significantly lower than normal conditions, and the entry/exit volume at Station B is statistically significantly higher, then it is inferred that the prevailing passenger response is “Change station”.
3. If the entry/exit volume at Station A is found to be statistically significantly lower than normal conditions, but the entry/exit volume at Station B is not statistically significantly different, then it is inferred that the prevailing passenger response is “Leave network”.

### Analysis and results

Two binary multinomial logistic regression models are derived from the data, each expressing the probability of changing the origin/destination station (“Change station”: Yes = 1, No = 0) and that of leaving the network (“Leave network”: Yes = 1, No = 0) respectively, in comparison with continuing the journey with no change (“Continue”). The results of the models are shown Table 1, where the effects of the various incident parameters (day of week, time of day, incident type, initial delay, incident location, and the need of transferring) can be found as the coefficients of relevant binary dummy variables. Effects with positive coefficients increase the probability of the dependent variable being 1 (i.e. of changing station or leaving the network), whereas negative ones decrease that probability and therefore reinforce the “Continue” response.

**Table 1: Multinomial logistic regression model coefficients for passenger choices**

	“Change station”		“Leave network”	
	Coeff. ( $\beta$ )	Sig.	Coeff. ( $\beta$ )	Sig.
Intercept	-7.535	.991	-37.900	.947
Day - Weekday	-1.936	.894	-1.845	.197
Time - AM peak	-.095	.384	.429	.193
Time - Inter-peak	-1.503	.091	.971	.085
Time - PM peak	-.702	.241	-.778	.132
Time - Evening	-.151	.097	1.092	.079
Incident type - Escalator downtime	-1.156	.999	.004	.993
Incident type - Partial line suspension	.198	.929	.258	.983
Incident type - Train cancellation	1.672	.983	.301	.971
Incident type - Train delay	.346	.983	.560	.893
Initial delay - Long	-3.487	.000	-1.176	.000
Initial delay - Medium	-4.083	.040	-1.947	.001
Incident location - Origin	1.511	.000	.825	.000
Incident location - Destination	-.277	.137	-2.604	.081
Transfer needed to destination - No	.253	.532	.528	.044
More transfers needed to re-route - Yes	.038	.250	-.741	.000

Looking at the results, it can be observed that a number of characteristics have no significant impact at the 5% level on the probability of a passenger changing origin/destination station or leaving the network altogether as a result of a service disruption. These are: the day of the week (weekday or weekend); the time of day (AM peak, inter-peak, PM peak, evening, other times); and the incident type (escalator downtime, partial line suspension, train cancellation, train delay and train withdrawal from service). It can also be seen that the intercept of both models is insignificant, which suggests that passengers are initially indifferent to the choice they will make.

On the other hand, there appears to be a significant impact of the initial delay imposed by the disruption on the passenger choice. Specifically, it can be observed, perhaps paradoxically, that passengers are more likely to take action when the initial delay is short (i.e. less than 5 mins) compared to when it is medium (5-20 mins) or long (more than 20 mins). Also, interestingly, a medium delay is less likely to result in a passenger changing station or leaving the network compared to a long one. In other words, passengers are more likely to choose to take action in response to short and long delays, and less so for medium delays.

This finding can be attributed to the fact that passengers are unlikely to know in advance how long the delay is going to be, and they can only assess it from clues based on the different types and locations of disruption that may have experienced in the past. As such, most passengers are very likely to either change station or leave the network immediately (not knowing that the delay may turn out to be short, which is the case for the majority of the disruption incidents). Those who stay, on the other hand, only take action after a long time, i.e. after they have established with certainty that the delay is long; if the delay turns out to be of medium duration, then they stick to their original route.

A further significant effect is that of the incident location. As can be observed, passengers are more likely to take action and change station or leave the network if the disruption occurs at the origin station compared to midway. On the other hand, there is no significant impact on a passenger's choice if the incident occurs at the destination station. This is sensible, as a disruption at the origin station often means that this becomes unusable, so passengers are forced to look for alternatives.

Finally, the required transfers have significant effects on passenger choices. Specifically, a passenger is more likely to leave the network as a result of a disruption if his/her original route did not include a transfer, and more likely to continue his/her journey if re-routing would mean that an additional transfer would be required.

### **Concluding remarks**

The initial results from this study provide an interesting insight into the customer impact of service disruptions on the London Underground and identify a number of relevant effects that could potentially be taken into account by public transport operators. However, passenger choices can be much more variable and irrational at times, and are also likely to be influenced by numerous other factors that have not been considered here, such as crowding levels at stations, availability of other modes, additional costs associated with re-routing and re-moding, as well as personal attributes, such as individual preferences and trip purpose. It is, hence, the objective of future work to explore these.

### **Acknowledgements**

The authors would like to thank London Underground for providing the Oyster and CuPID data used in the study.

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