



# Impact of Unplanned Service Disruption on Urban Transit Systems



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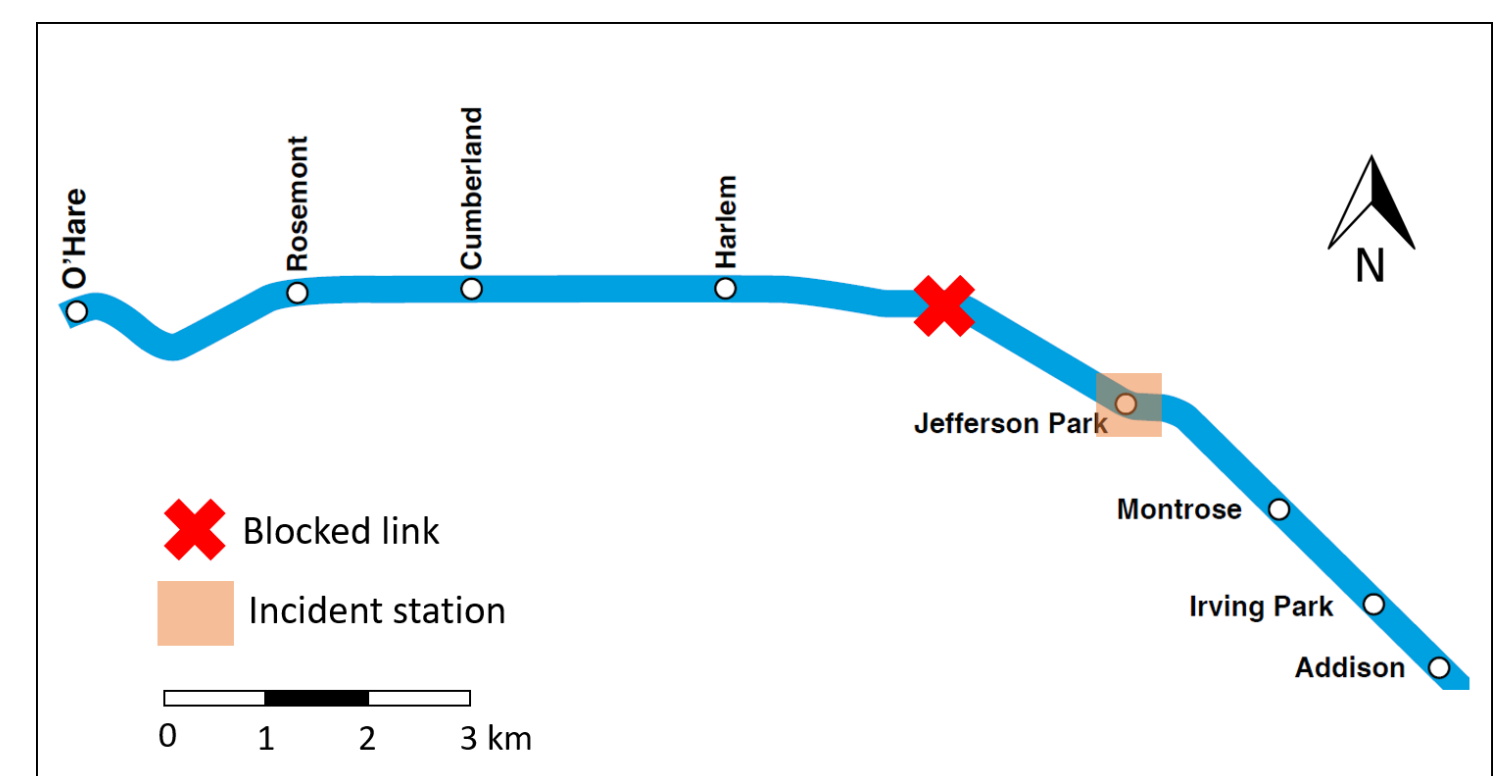
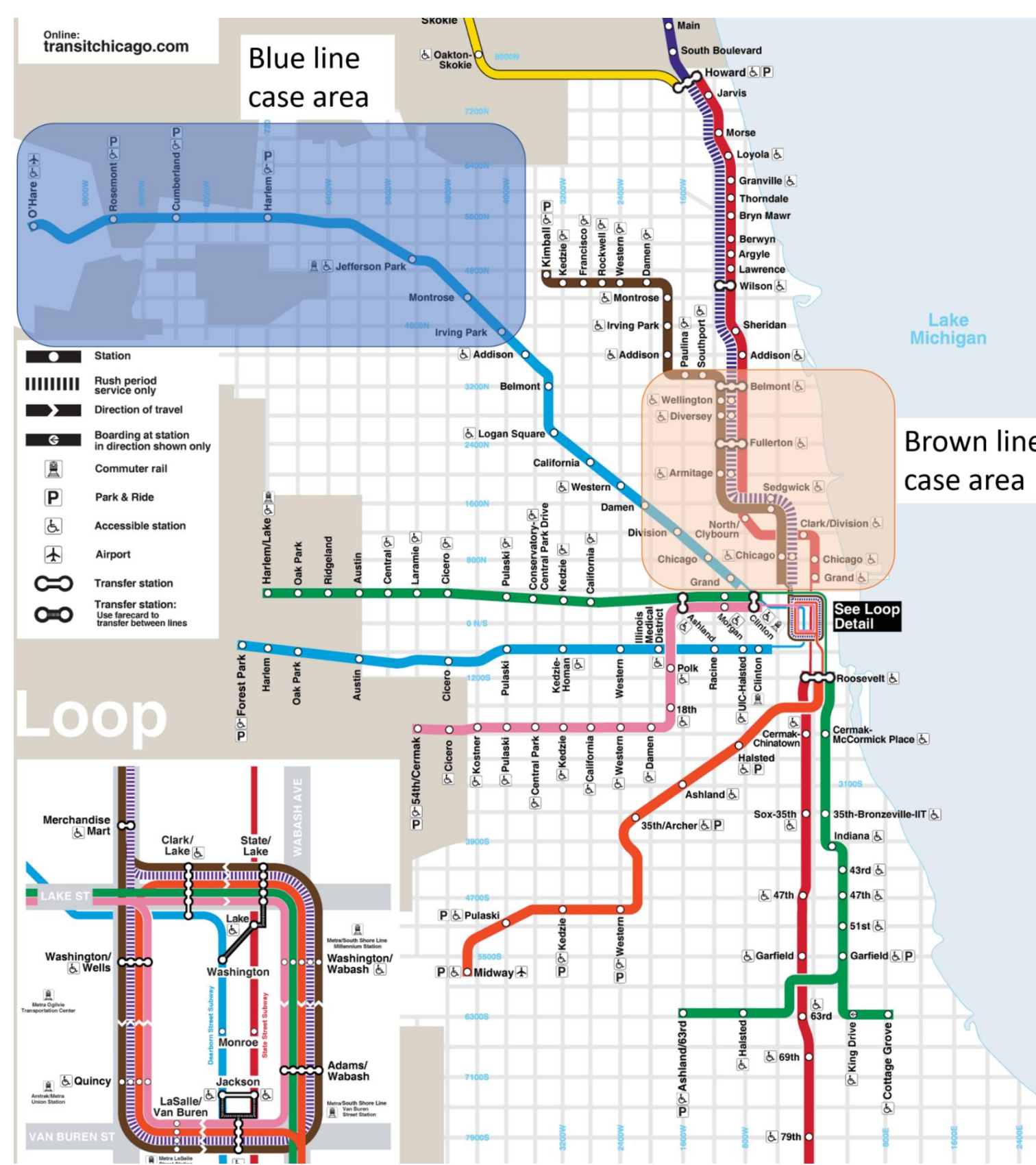
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## 1 INTRODUCTION

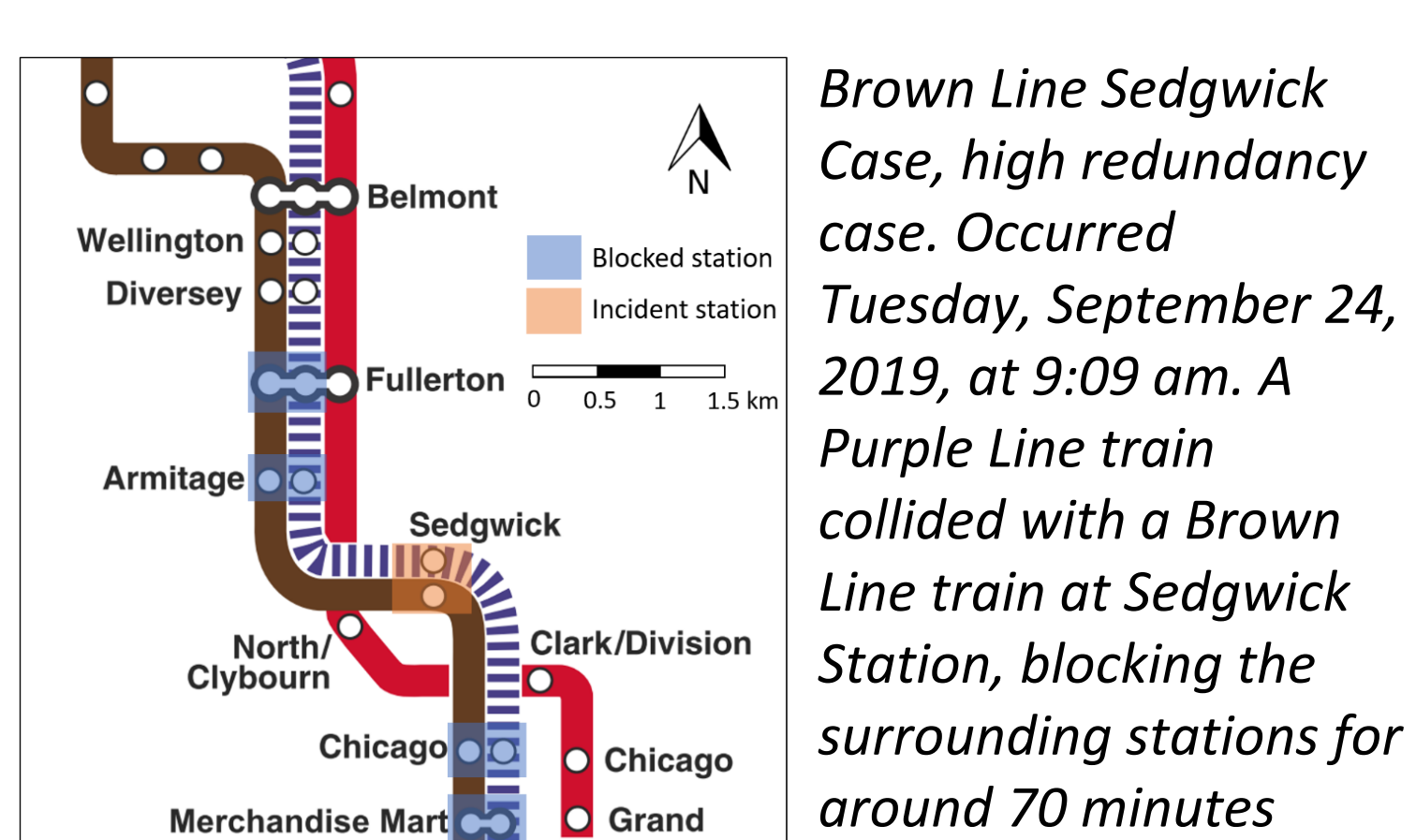
With advances in automated fare collection (AFC) and automated vehicle location (AVL) data, system-wide effects of transit network incidents can be investigated. In this study, we propose data-driven analysis frameworks from both supply and demand aspects to create a better understanding of incidents' impacts. The analysis includes quantifying network redundancy, analyzing passenger flows, and modeling individual choices. The framework is applied to two rail disruption cases from the Chicago Transit Authority (CTA) system.

## 2 STUDY DESIGN

### CTA Case Study Areas



Blue Line Jefferson Park Case, low redundancy case. Incident. Occurred Friday, February 1, 2019, at 8:14 am. The inbound track between Harlem and Jefferson was closed due to an infrastructure problem. This lasted a little under 4 hours

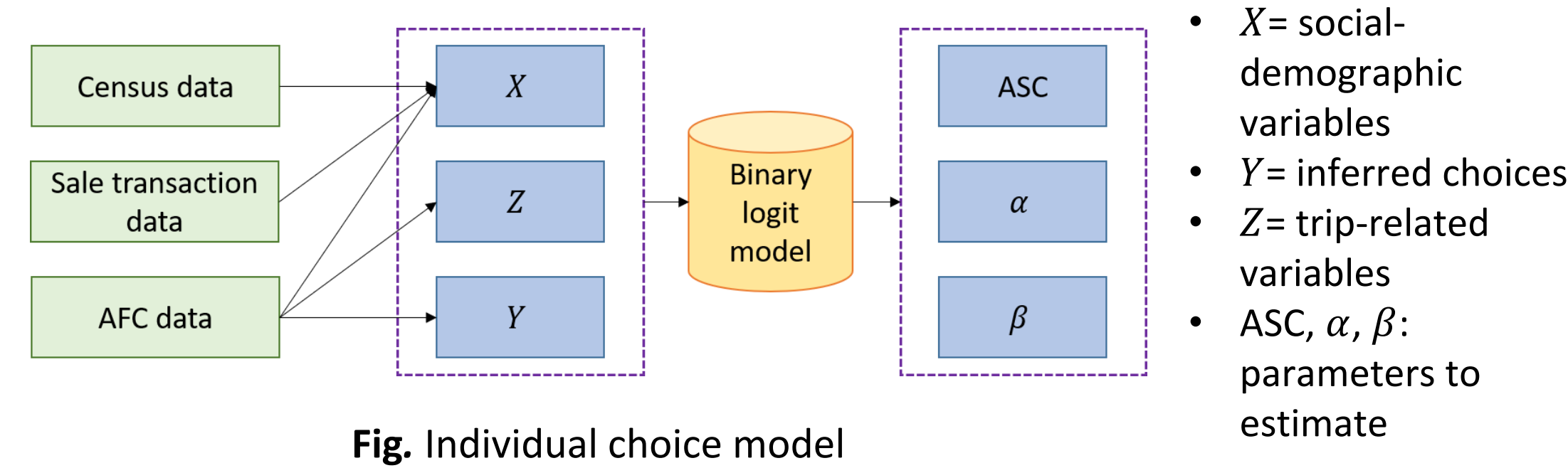


Brown Line Sedgwick Case, high redundancy case. Occurred Tuesday, September 24, 2019, at 9:09 am. A Purple Line train collided with a Brown Line train at Sedgwick Station, blocking the surrounding stations for around 70 minutes

### Main Analysis Framework

	Analysis tasks	Description
Supply	Network properties	Calculate indicators such as resilience, vulnerability, redundancy
	Operations	Analyze changes of agency's operations (e.g., headway, routing)
Demand	Passenger flows	Analyze demand changes of different stations, lines
	Individual behavior	Analyze people's response behavior under incidents

- Supply Analysis:** We propose an incident-based network redundancy index to analyze the network's ability to provide alternative services under a specific rail disruption. The impacts on the operation are analyzed through headway changes.
- Demand Analysis:** We calculate the demand changes of different rail lines, rail stations, bus routes, and bus stops to better understand the passenger flow redistribution under incidents. Individual behavior is analyzed using a binary logit model based on inferred passengers' mode choices and socio-demographics using AFC data.



### Redundancy Equation

$$R_I = \frac{\sum_{w \in \mathcal{W}_I} \sum_{p \in \tilde{\mathcal{P}}_w} A_p}{\sum_{w \in \mathcal{W}_I} \sum_{p \in \mathcal{P}_w} A_p} = \frac{\text{Total capacity of available paths after the incident}}{\text{Total capacity of available paths before the incident}}$$

$$A_p = \sum_{k=1}^{\lfloor D_I/H_p \rfloor} \min\{D_I - (k-1)H_p, L_p\} \cdot C_p$$

$A_p$  = Time-sensitive path capacity of path  $p$  under incident  $I$

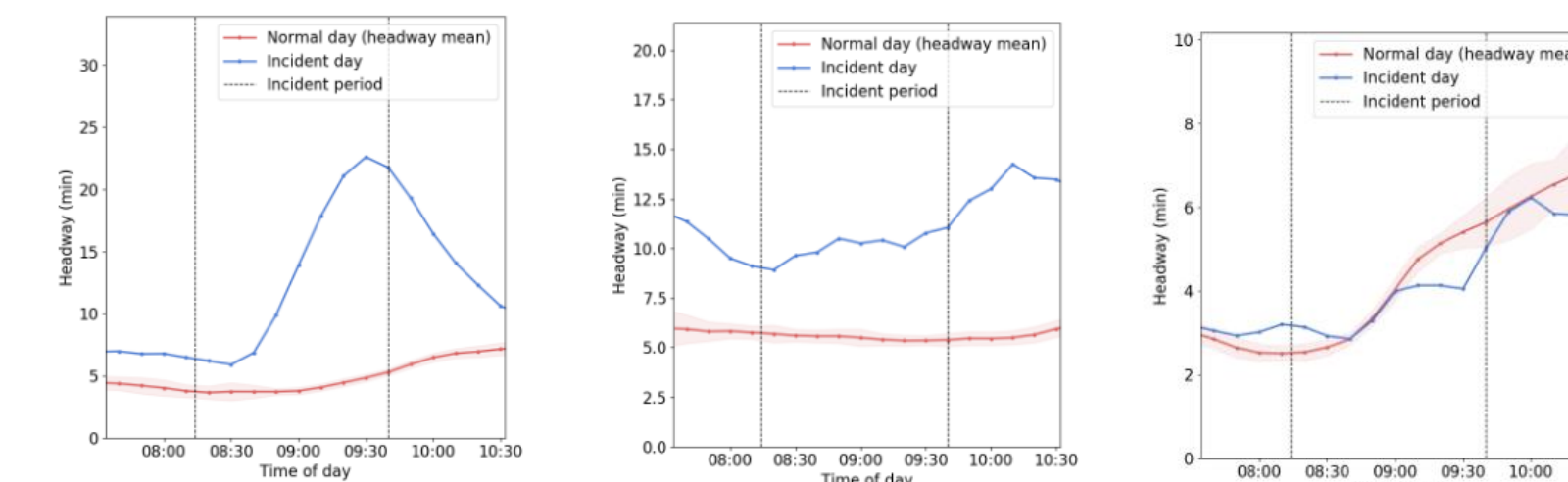
$\mathcal{W}_I$  = set of all OD pairs of the rail network that are affected by the incident  
 $\mathcal{P}_w$  = set of available paths for  $w$  before the incident  
 $\tilde{\mathcal{P}}_w$  =  $\mathcal{P}_w$  without blocked paths and augmented paths added  
 $D_I$  = duration of the incident,  
 $H_p$  = headway of the path 'p'  
 $L_p$  = travel time of path 'p'  
 $D_I/H_p$  = # of vehicles dispatched during incident  $I$

## 3 RESULTS

### Supply Analysis

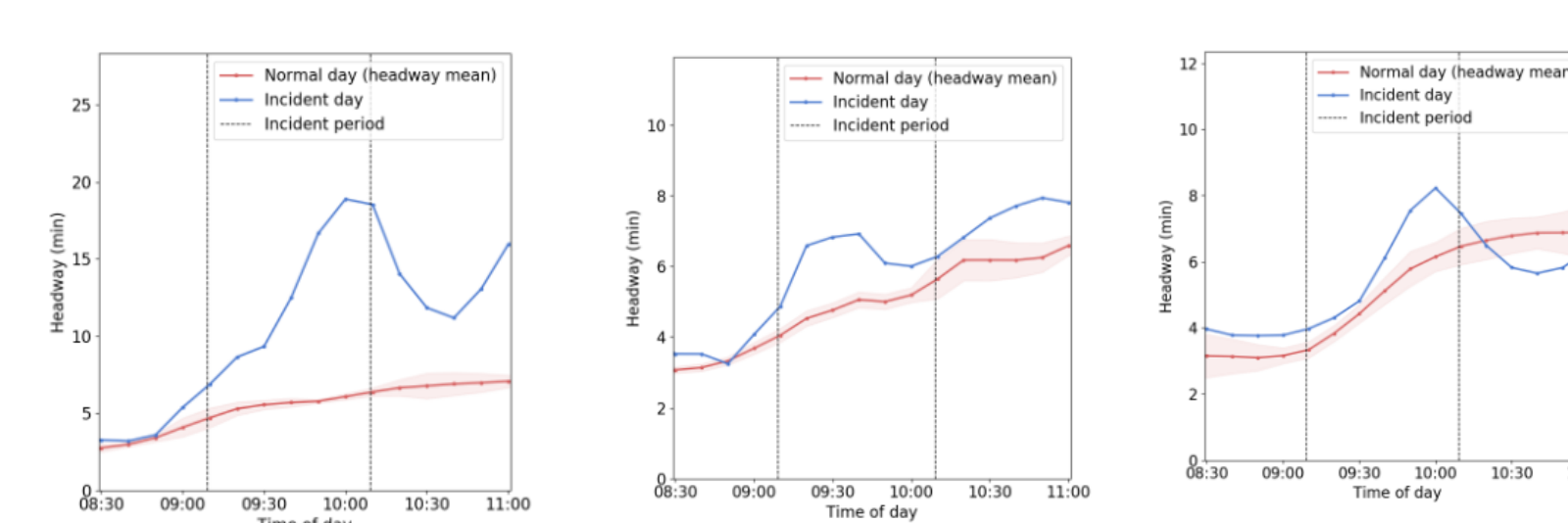
- Redundancy Index:** The Blue Line and Brown Line cases, scored 9.3% and 74.7% capacity to transport passengers during the incident, respectively.

- Headway Analysis: Blue Line**



As the incident proceeded, inbound delays rose, while outbound delays remained relatively constant. Unaffected Brown Line headways were typical

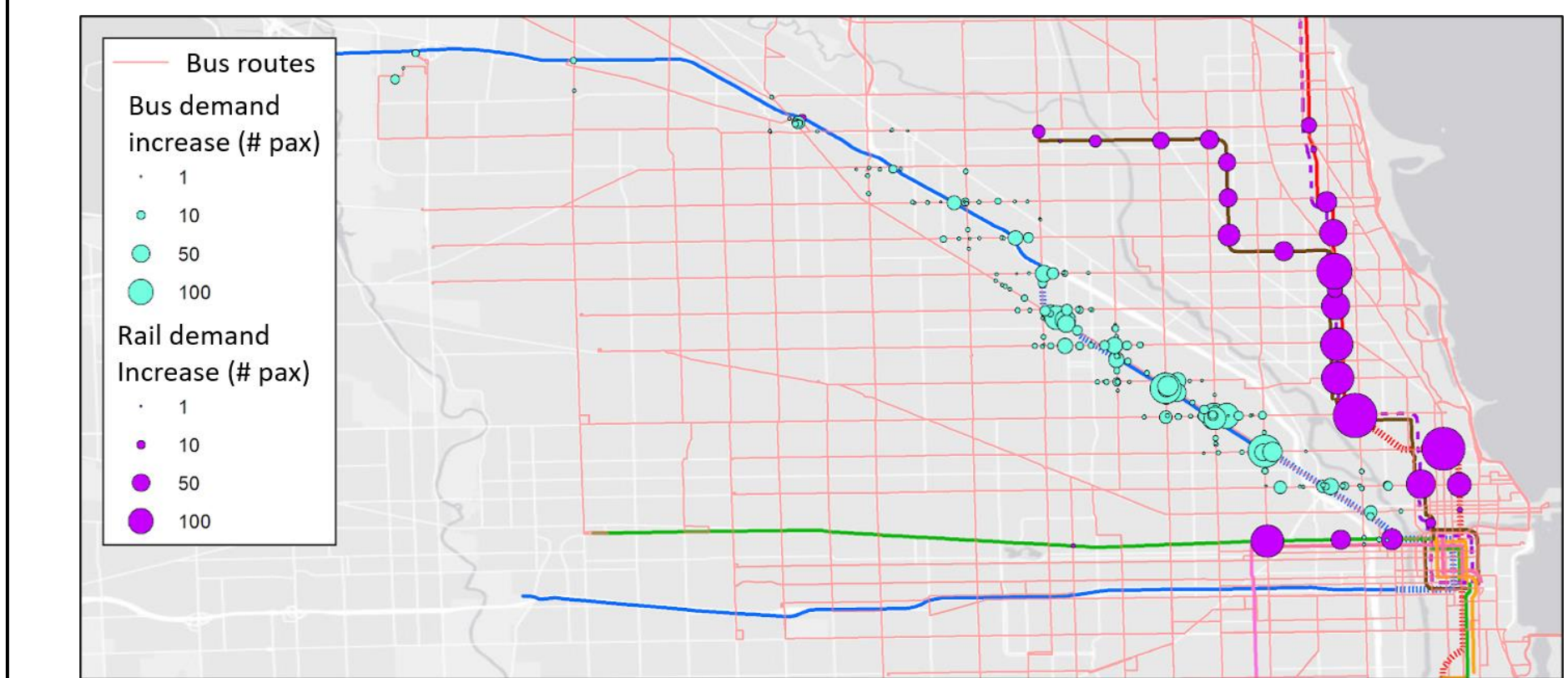
- Headway Analysis: Brown Line**



As the incident proceeded, affected route headways increased. Unaffected Red Line headways also increased, most likely due to increased ridership from Brown / Purple line passengers

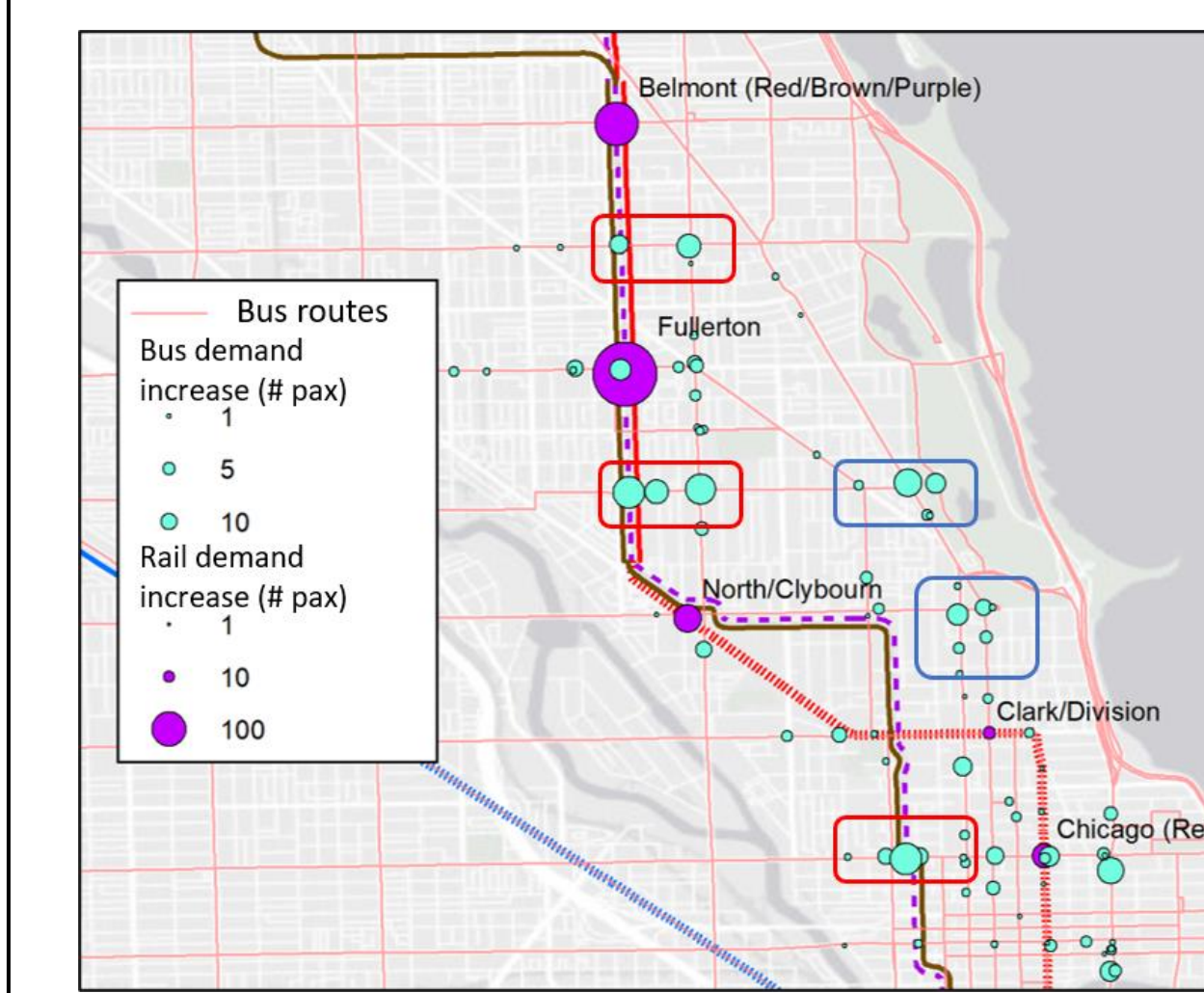
### Demand Analysis

#### Passenger Flow: Blue Line Incident



Passenger flow increases across the CTA Network during Blue Line Incident, with an increase in nearby bus routes and Red/Brown/Purple Lines, but a smaller increase in the Green Line, which in some cases was actually closer than the Red/Brown/Purple Lines

#### Passenger Flow: Brown Line Incident



Passenger flow increases across the CTA Network during Brown Line Incident, with key clusters highlighted. Many transferred to the Red Line or nearby bus routes.

#### Individual Choice Model

- Higher income riders were less likely to use CTA post incident
- CTA pass and reduced fare pass users were more likely to continue to use CTA post incident

## 4 DISCUSSION

### Major findings

- Results show that service frequencies were reduced on incident lines (by around 30%~70%). Nearby lines are also slightly affected. Passengers showed different behavioral responses in the two incident scenarios. In the low redundancy case, most of the passengers chose to use nearby buses to move, either to their destinations or to the nearby rail lines. In the high redundancy case, most of the passengers transferred directly to nearby lines.
- Passengers did not always act rationally, especially when redundancy was low. Some alternative routes, which were less crowded, were not chosen. A lack of understanding of the bus network or transit network in general may be the cause.
- A passenger's socioeconomic status, along with the role CTA played in their everyday life, affected their retention rate to using the service post-incident. Higher-income riders were hypothesized to be able to change their mode of transport, whereas pass holders and reduced fare passengers understood the system better and/or relied on the system primarily.

### Policy implications

- Data like this can be utilized by agencies to better understand how passengers move, both rationally and irrationally. This allows agencies to better prepare and execute system fixes during service disruptions. It also allows agencies to make long term plans and service changes, allowing for greater resiliency in the future.

## 5 CONCLUSION

- Using AFC and AVL data, a comprehensive analysis can be conducted for the impact of incident on urban rail systems from both demand and supply perspectives.
- Transit agencies can apply similar techniques to better understand how their dynamic networks operate in the face of both known and unknown variables, allowing for better transit planning.