Optimization Framework for Recovery from Railway Freight Network Disruptions

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Nader Azad, Saint Mary's University

Change in Management Philosophy?

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- **Just-in-time to Just-in-case**

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- **Disruptions to railroad operations, are not infrequent. For example, 61 disruptions were registered for just the Seattle-Vancouver Amtrak operation between 2009 and 2013.**

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  - ***Example*: Re-routing strategy**

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- **Non-disrupted portion of the train (i.e., railcars with contents intact) could still be used to meet a portion of the overall demand.**

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  - **Developing appropriate mitigation and recovery strategies**

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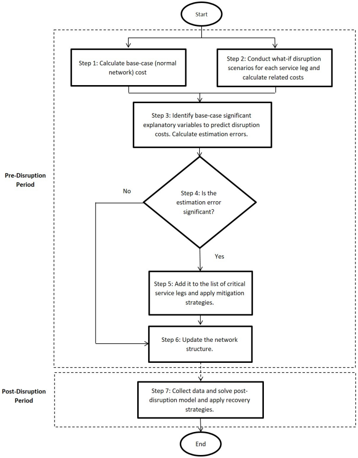
- Predictive model to identify critical service legs
- **Prescriptive model to find optimal recovery strategy with the least cost**

Flowchart


Start
Step 1: Calculate base-case (normal network) cost
Step 2: Conduct what-if disruption scenarios for each service leg and calculate related costs
Step 3: Identify base-case significant explanatory variables to predict disruption costs. Calculate estimation errors.
Pre-Disruption Period
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Step 4: Is the estimation error significant?
Yes
Step 5: Add it to the list of critical service legs and apply mitigation strategies.
Step 6: Update the network structure.
Post-Disruption Period
Step 7: Collect data and solve post-disruption model and apply recovery strategies.
End

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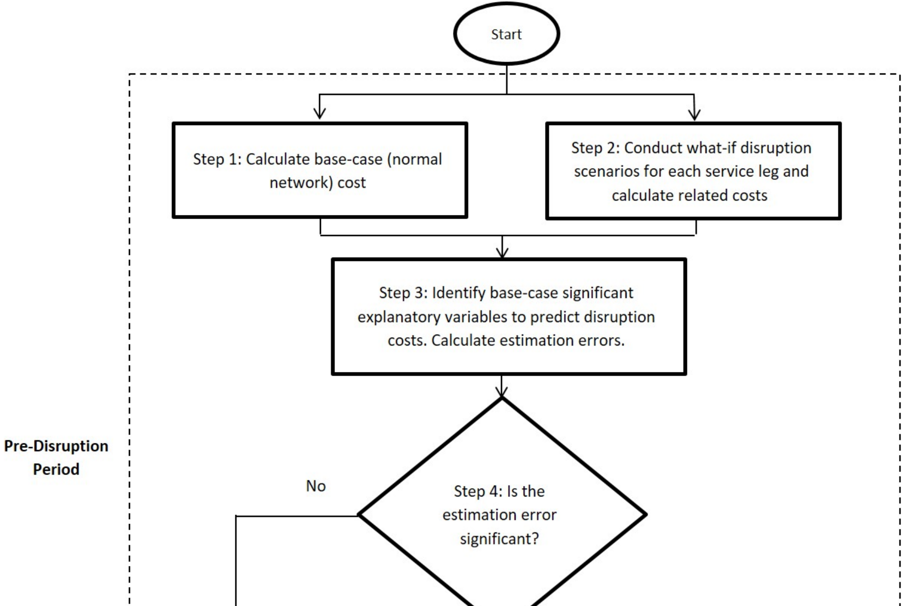
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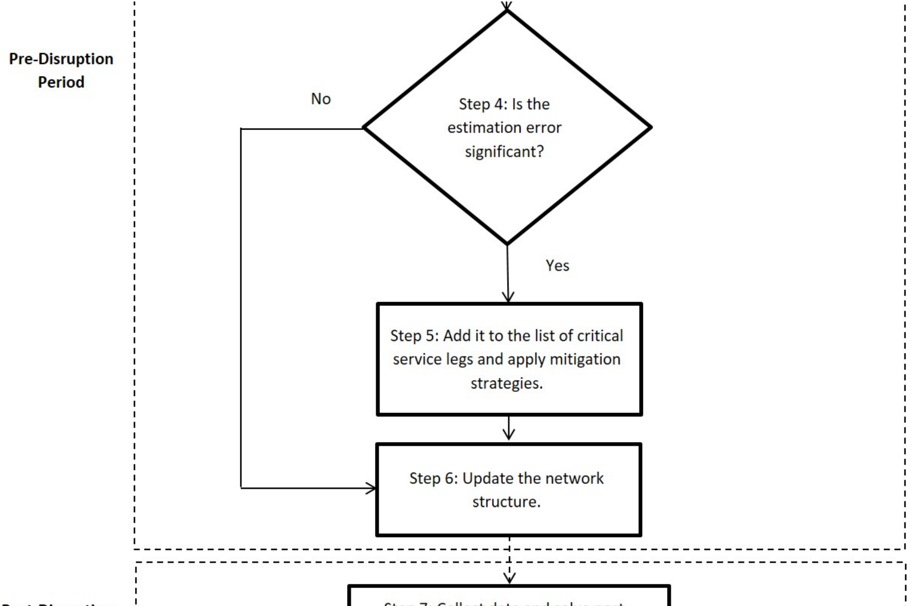
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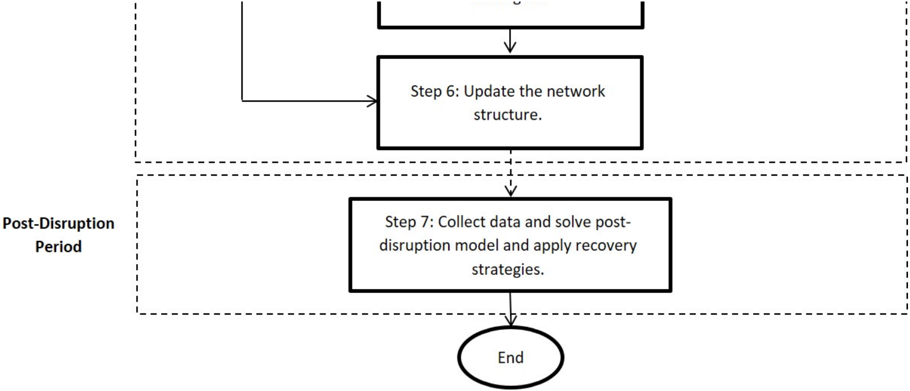
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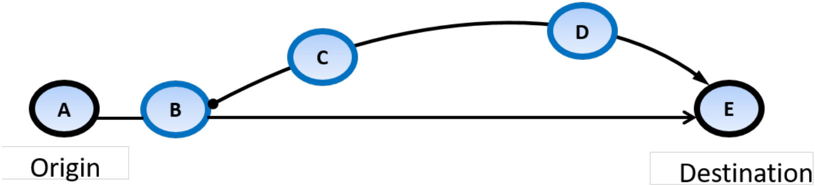
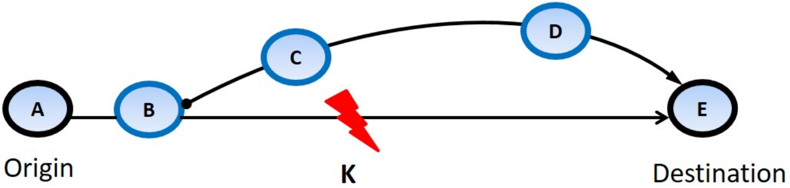


Pre-disruption:

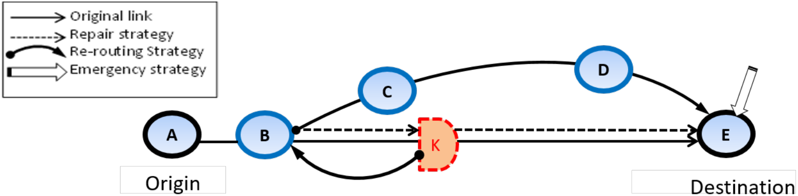
100 railcars have to be sent every week from yard A to yard E.
The time to delivery before disruption is seven days.
The current network has two itineraries: A-B-E; and, A-B-C-D-E.
We assume that the itinerary A-B-E is being used before disruption

Example



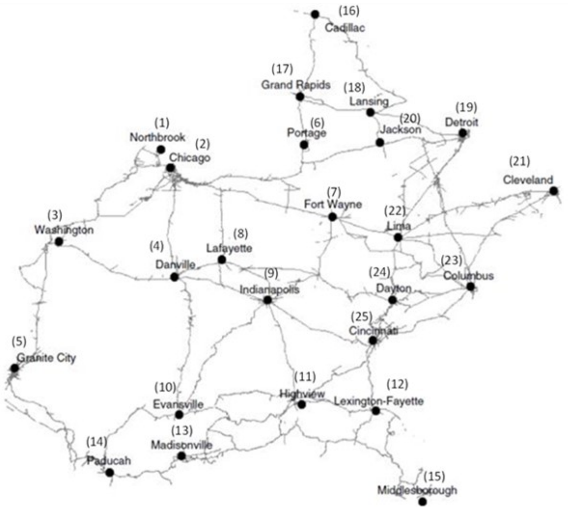
Disruption:
A disruption occurs for a train service passing the service leg B-E with capacity of 100 railcars.
The disruption occurs at site K on the third day of the week, and results in the loss of 40% of railcars.

Example



Post-disruption:
Add the disruption point K as a virtual node to the network whose capacity is equal to the 60 undamaged railcars.
The time to delivery post-disruption is only 4 days.
The available itineraries are: A-B-E, A-B-C-D-E (existing itineraries from pre-disruption), K-B-C-D-E (re-routing strategy) and K-E (repair strategy).
Capacity for KB and KE is 60 railcars.

Case Study: Railroad Network in the Midwest United States



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- 600 origin-destination pairs, and each has between 1 to 4 itineraries for a total of 1338.
- **The yards are connected by thirty-one train services, which amongst them share 53 service legs.**

Case Study: Predictive Model Results

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Regression statistics				
Multiple R	0.77			
R Square	0.59			
Adjusted R Square	0.58			
Standard Error	90729.98			
Observations	53			
	Coefficients	Standard Error	t Stat	P-value
Intercept	15654518.21	21225.82093	737.5223914	1.3639E-102
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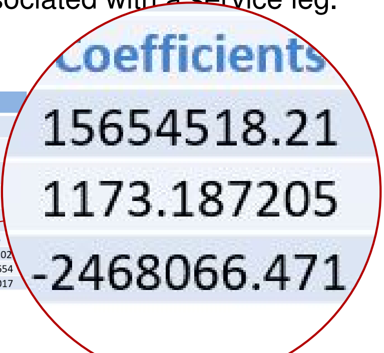

Case Study: ABC Analysis

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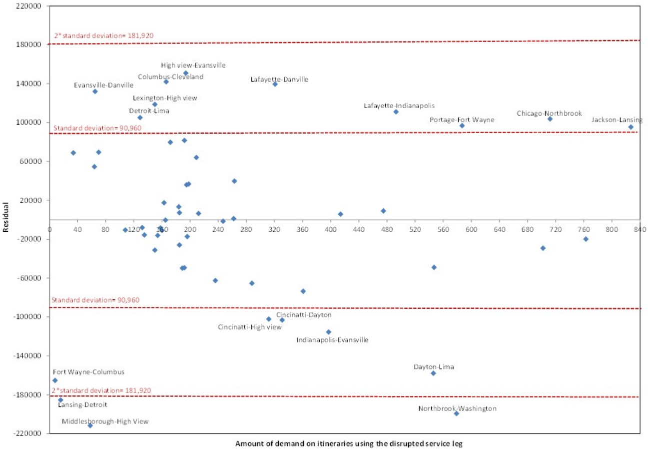

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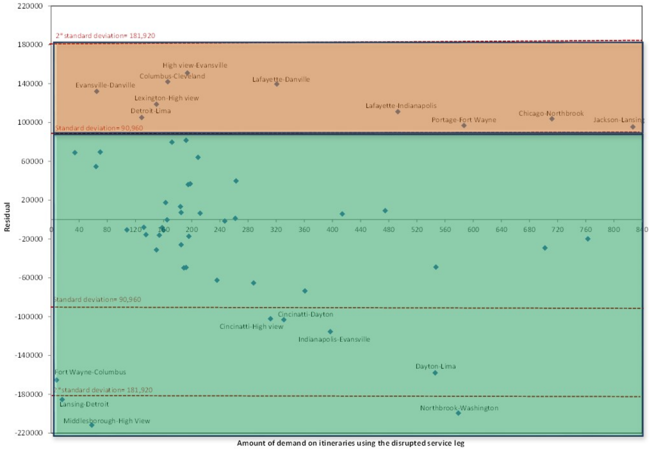

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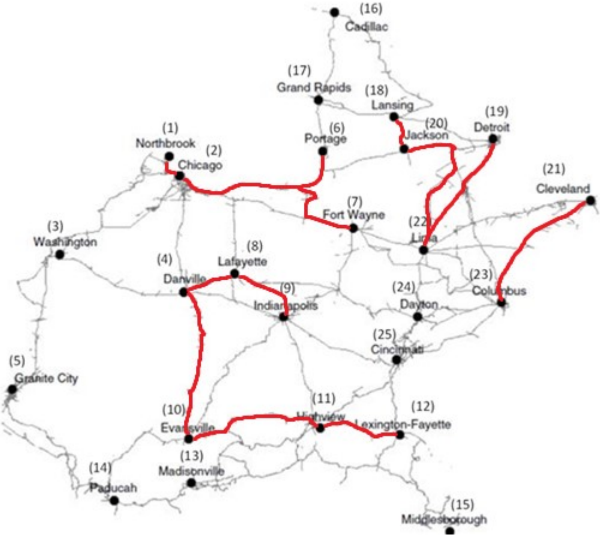

Case Study: Mitigation Strategy

Mitigation strategy for critical service legs: Add new itineraries by renting the tracks owned by competing railroad operators

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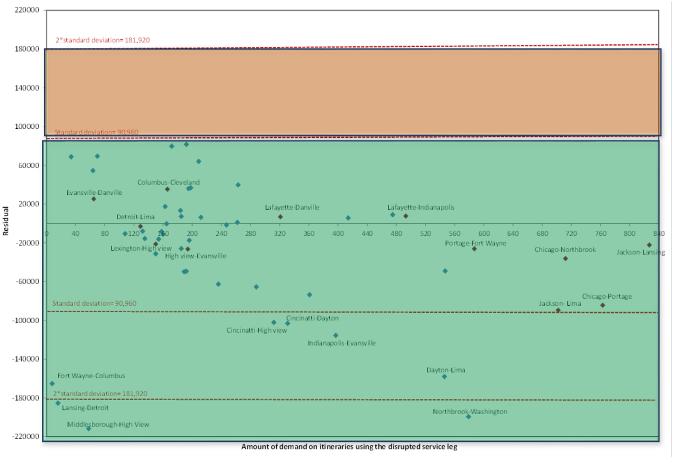
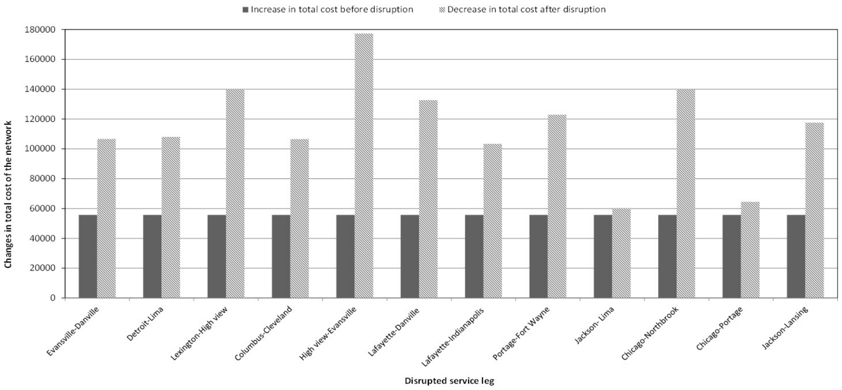


Case Study: Resuts



Case Study: Conclusion

The mitigation strategy implementation results in significant enhancement to the railroad transportation resiliency with minimal changes to the existing infrastructure and insignificant increase in the pre-disruption transportation costs