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Enhancing Travel Resilience: Integrating Alternative Path-Based Robustness Metric in Route Optimization

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Abstract

Unforeseen disruptions, including accidents, adverse weather conditions, and temporary construction, frequently hinder traffic flow in road transportation, forcing passengers to alter their routes. These incidents impart stress and delays on travelers.

This article delves into the optimization of itineraries to minimize the impact of disruptions on passengers' journeys, with a focus on the criteria to be considered.

We present a new metric for topological robustness that focuses on alternative paths and can be integrated into passengers' decision-making processes for choosing a route.

Our simulations, based on static traffic assignment and varying levels of robustness, demonstrate that these robust paths are an effective way to mitigate travel delays and excessive travel time during disruptions.

1 Introduction

In contemporary societies, passenger transport is a crucial aspect, serving as a cornerstone of human activity. The efficient movement of individuals is of utmost importance, not only for personal convenience but also for wider implications concerning the economy, public health and overall well-being. Passenger mobility facilitates economic growth by promoting trade and tourism, enables access to healthcare, education and leisure, and underpins professional interactions. In this context, effective allocation of passenger traffic is key to addressing the challenges of population growth and increasing urbanization while meeting societal needs.

Despite its undeniable importance, passenger traffic management faces many challenges and obstacles. Road congestion has become common in urban areas, resulting in wasted time, increased air pollution, and a declining quality of life for residents. Public transport delays can inconvenience passengers, and current infrastructure can become overwhelmed, causing traffic congestion and disrupting travel schedules. Addressing these complex issues requires innovative solutions to improve passenger traffic management in the modern era. With that in mind, significant advances in traffic assignment can provide a meaningful response to mitigate the impact of such disruptions on passenger travel.

In addressing these complex challenges, it becomes evident that one potential solution lies in a fundamental shift of the passenger journey decision paradigm. Traditionally, cost and travel time have been the primary determinants when selecting modes of transport. However, to improve mobility and create intelligent transport systems, it's crucial to broaden the range of factors influencing passengers' choices. Considerations beyond mere economic and time efficiency, such as environmental impact, accessibility and rerouting capacity, should play a crucial role in the decision-making process. This change in perspective demands innovative policies as well as a fundamental alteration in how we view and prioritize the factors that define our travel choices. By acknowledging and catering for these varied requirements, we can facilitate the development of a robust transportation system that satisfies the needs of contemporary society.

In this paper, we investigate events that have the potential to completely block a road link in a transportation network. These events may include bad weather conditions, temporary constructions, or accidents. Passengers affected by such disruptions are required to seek alternative routes. The aim of this paper is to address the following question: How can passengers choose an itinerary that minimizes the effect of disruptions on their trip? Therefore, we have designed a model that focuses on the passenger and measures the robustness of a route by the number of alternative options available.

The paper is structured as follows: Section 2 provides an objective overview of existing robustness models in the literature. Then, Section 3 presents a clear and concise mathematical formulation of the robustness model. Next, Section 4 displays the results of various robust assignment applications to the Sioux Falls road network. Finally, we conclude with a summary of the work in Section 5.

2 Related work

The section explores the diverse models of robustness in transportation networks. It is organized into two main categories commonly adopted in the literature: transportation and topological models.

2.1 Transportation robustness models

Robustness models rooted in transportation theory prioritize simulation. Typically, these models evaluate a measure prior to and after removing transportation elements in the network. The network robustness index (NRI) is the most well-known measure of this kind. It represents the difference in system assignment cost prior to and after eliminating a link [1, 2]. The robustness of the air transportation network can be measured by the increase in total cost resulting from link removal, as demonstrated by [3] using this approach to quantify the vulnerability of the European network through delays caused by the closure of key airports. [4] present a vulnerability model for air transportation networks that estimates the impact on network flow when node capacities are reduced over a wide range. [5] present two models for analyzing road vulnerability: a global demand-weighted model and a relative model examining importance and exposure. The primary contrast between the two models is that importance is deterministic while exposure is stochastic. Importance measures the change in weighted total travel cost between all origin-destination pairs due to disruption, while exposure quantifies the impact of disruptions on all users of the transportation network. [6] proposed a model consisting of three components: additional travel time, additional travel distance, and additional accident cost as a way to measure vulnerability. [7] measured vulnerability by evaluating the change in topological accessibility due to a breakdown. [8] found critical elements using a bi-level MILP problem where the traffic assignment optimization was conducted in the master problem and the connectivity minimization was performed in the slave problem.

2.2 Topological robustness models

Topological models are based on graph properties, rooted in complex graph theory. Centrality measures are a well-known example of such models [9–12]. They originate from social network analysis and quantify the centralization of elements within a graph. The most commonly used centrality measures in vulnerability analysis are degree, closeness, eigenvector, and betweenness centrality. The centrality degree measures a node’s accessibility. Closeness centrality calculates how closely connected an element is to all other nodes. Eigenvector centrality represents an element’s influence within the network. Betweenness quantifies the number of times a node serves as a bridge on the shortest path between any two other nodes.

Betweenness centrality appears to be the standard measure. It either serves as a comparison and validation tool for newly developed models [4] or plays a role in these models. [13] propose a link robustness model that utilizes betweenness centrality, node degree, and clique size. Due to its time-consuming nature and impracticality in analyzing large-scale networks, computing clique size is avoided. Three additional models were employed for comparison: the Jaccard coefficient, bridgeness index, and reachability index. The Jaccard coefficient is a statistical metric used to compare the neighborhood of the links’ nodes. The bridgeness index estimates the degree to which a link acts as a bridge between cliques. Reachability assesses the accessibility of the nodes in the network after a link is disrupted. Kivimki (2016) defined two betweenness

centrality models based on randomized shortest paths. These models have the potential to converge to the betweenness centrality depending on the parameters.

However, robustness models extend beyond centrality indices. According to Vodk et al. (2019), a loss function is defined to illustrate vulnerability by identifying the minimal link cut set that maximizes disintegration of a network into multiple components. Nevertheless, this method appears to be suitable solely for undirected networks. [14, 15] utilized percolation theory in order to detect bottleneck links from analyzing the network before and after it reaches the critical threshold. These links appear to be the cause of network disintegration into connected components.

2.3 Mixed models

Robustness analysis is a multifaceted process that requires capturing various aspects of system resilience. To address this complexity, several papers recommend utilizing multiple measures to comprehensively evaluate robustness. This approach provides a more comprehensive understanding of robustness, ensuring that all critical aspects are carefully considered. To address this complexity, several papers recommend utilizing multiple measures to comprehensively evaluate robustness. In their analysis of the metro network, [16] employed ten robustness metrics, including centrality indices, clustering coefficients, and spectral indices. Another option is to consolidate the various measures into one formula to obtain a comprehensive understanding of robustness as suggested by [17]. Each measure can be weighed to encompass all the aspects being analyzed. However, this method can be challenging as it is influenced by the weight assigned to each measure and the measures’ independence. In [13], the authors establish a novel measure of link centrality that merges betweenness centrality and the quantity of cliques comprising the link. This combination employs two established topological metrics to uncover previously unexplored vulnerabilities. Similarly, in [18], the authors employ two topological analyses (betweenness centrality and percolation theory) to identify critical links within airspace networks.

3 Model

In this section, we present the definition of a transportation network (Table 1) and a well-established traffic assignment model from the literature. Route choice is deeply connected to the traffic assignment problem. Then, we present the passenger-centric robustness model as the central contribution of this research.

3.1 Transportation network

A transportation network can be defined by a triplet $\mathcal{T} = (\mathcal{G}, t, d)$ with :

- $\mathcal{G} = (\mathcal{N}, \mathcal{A})$: a strongly connected digraph where \mathcal{N} is the set of nodes and \mathcal{A} the set of links.
- t : vector of the transportation network link travel cost.
- d : vector of the user demand which is the number of people traveling from an origin p to a destination q .

Table 1: Notations

Variable	Description
$\mathcal{T} = (\mathcal{G}, t, d)$	Transportation network
$\mathcal{G} = (\mathcal{N}, \mathcal{A})$	Strongly connected digraph of nodes and links
\mathcal{N}, \mathcal{A}	Set of nodes and links
$\mathcal{P}, \mathcal{Q}, \mathcal{C}$	Set of origins, destinations, and OD pairs
\mathcal{R}_{pq}	Set of simple routes between nodes p and q
$d = (d_{pq})$	User fixed demand
$t = (t_a)$	Link travel cost
$\tau_a, \beta_a, \gamma_a$	Link travel time parameters
$f = (f_a)$	Link flow
$k = (k_a)$	Link capacity
$c = (c_{pqr})$	Route travel cost
$h = (h_{pqr})$	Route flow
$\pi = (\pi_{pq})$	Shortest route cost
$s = (s_{nq})$	Number of alternative routes between n and q
$w = (w_{pqr})$	Route robustness
$v = (v_{pqr})$	Route vulnerability
$\nu = (\nu_{pq})$	Maximum route robustness
$z = (z_{pqr})$	Multi-objective route cost
$\zeta = (\zeta_{pq})$	Shortest multi-objective route cost

We distinguish two types of transportation networks according to whether the transportation cost of a link depends or not on its flow. If it depends on the flow the transportation network is congested otherwise it is not which means $t_a(f_a)$ is constant.

In our case, we consider the well-known Bureau of Public Roads (BPR) cost function to force congestion by making the cost too high when it is busy:

$$t_a(f_a) = \tau_a \left(1 + \beta_a \left(\frac{f_a}{k_a} \right)^{\gamma_a} \right) \quad (1)$$

with τ_a , β_a , and γ_a being data of the link a . The constant τ_a is known as the free flow travel time.

Often, the transportation demand (d_{pq}) between an OD pair pq can be distributed among several paths r connecting p to q . Let's note h_{pqr} the flow along the path r leading from p to q then:

$$d_{pq} = \sum_{r \in \mathcal{R}_{pq}} h_{pqr} \quad (2)$$

The cost associated with the route r is equal to the sum of the costs of the links belonging to this route.

$$c_{pqr} = \sum_{a \in \mathcal{A}} \delta_{pqr a} t_a \quad (3)$$

$\delta_{pqr a}$ equals 1 if the link a belongs to path r and 0 otherwise.

Moreover, the flow on the link a is the sum of the flows of the paths passing through this link:

$$f_a = \sum_{r \in \mathcal{R}_{pq}} \delta_{pqr a} h_{pqr} \quad (4)$$

3.2 Deterministic user equilibrium

Many models (static, dynamic, deterministic, stochastic...) were defined to tackle traffic assignment problems. This paper pays attention only to the static deterministic user equilibrium.

The problem consists in determining the distribution of demand flows on the equilibrium network. In order to do so, two assumptions must be formulated:

1. each user has a global knowledge of the network (links, paths, costs ...)
2. all users have the same behavior

Furthermore, users are expected to choose the path with the least cost. Although this may not be the most realistic strategy, it is still a reasonable approximation. An equilibrium is achieved when users cannot reduce their transportation costs by selecting an alternate path from the one they are currently using. As a result, all paths within the same origin-destination pair that are utilized have identical costs, while unused paths incur higher costs. Wardrop's first principle summarizes this equilibrium [19]:

"Travel times on all used roads are equal to and smaller than those of unused roads."

The user equilibrium is obtained by solving the following system:

$$(\mathcal{P}) \begin{cases} c_{pqr} = \pi_{pq} & \text{if } h_{pqr} > 0 & \forall p, q, r \\ c_{pqr} > \pi_{pq} & \text{if } h_{pqr} = 0 & \forall p, q, r \\ d_{pq} = \sum_{r \in \mathcal{R}_{pq}} h_{pqr} & & \forall p, q \\ f_a = \sum_{r \in \mathcal{R}_{pq}} \delta_{pqr a} h_{pqr} & & \forall a \\ f_a \geq 0, h_{pqr} \geq 0, d_{pq} \geq 0 & & \forall a, p, q, r \end{cases} \quad (5)$$

3.3 Passenger-centric robustness model

The effect of a disruption of a roadway link on the flow of traffic along a path connecting an origin-destination pair is linked to the flow density and the availability of alternate routes. Specifically, as density increases, costs increase as well. Additionally, when there are fewer shorter alternate routes, disruptions in flow have greater consequences for rerouting, resulting in increased congestion, and greater delays.

The model concentrates on exploring substitute routes linking any transit node with the final destination node. No attention is given to the resilience of the origin node since passengers can easily opt for other available routes at this point. However, once the journey has begun at the first transit node, there is no turning back. Furthermore, starting from the origin node, calculating the robustness of a path would consider other paths used to assign demand for the OD in question. This presents an issue when seeking path robustness measures that are independent of one another.

More formally, if we note s_{nq} the number of alternative routes connecting nodes n and q whose cost is less than a threshold (Figure 1); let us consider the route $r \in \mathcal{R}_{pq}$ then the robustness w_{pqr} of the route r is:

$$w_{pqr} = \sum_{n \in r \setminus (p, q)} s_{nq} \quad (6)$$

The variable s_{nq} renders the model passenger-centric. Disruptions may occur at each node n on the route; therefore, a robust path should suggest at least one alternative in the event of such an occurrence. Not all routes are feasible alternatives, and the costs associated with alternative paths must be reasonable in comparison to the cost of the shortest path connecting node n to the destination node.

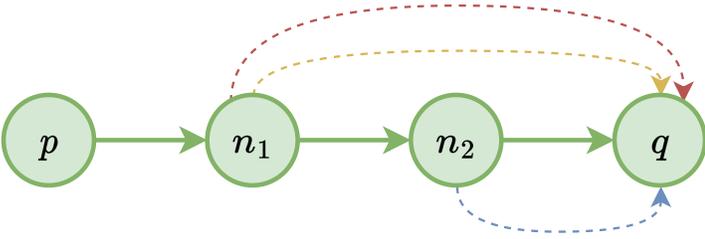


Figure 1: An example of the computation of w_{pqr} of the green path $r = (p, n_1, n_2, q)$. Two alternative paths (dashed yellow and red paths) connect node n_1 to node q and one (dashed blue path) connects node n_2 to q , so $w_{pqr} = 2 + 1 = 3$.

So far, the model is purely topological. The transportation part which involves the flow assigned to the path is to be included.

For each path, a vulnerability measure is defined. This measure takes into account the flow of passengers on the path and its robustness. Usually, traffic assignment problems are minimization problems. So, we define a model that fits this kind of optimization. The vulnerability of a path r during the path selection process of a path connecting an OD pair pq is defined as follows:

$$v_{pqr} = (h_{pqr} + 1)(\nu_{pq} - w_{pqr}) \quad (7)$$

As a practical implementation of the robustness model presented in Equation (7) for the passenger route decision process, we suggest a resilient static traffic assignment model grounded on the same model. The passengers' aim is to opt for the route that minimizes the linear combination of cost and vulnerability.

By integrating the route vulnerability in the cost function, we define a new generalized bi-objective route cost:

$$z_{pqr} = \alpha v_{pqr} + (1 - \alpha)c_{pqr} \quad (8)$$

where α is a parameter to be set according to the importance one wishes to give to robustness.

Finally, the robust version (\mathcal{P}_r) of the problem (\mathcal{P}) can be formulated the following way:

$$(\mathcal{P}_r) \begin{cases} z_{pqr} = \zeta_{pq} & \text{if } h_{pqr} > 0 & \forall p, q, r \\ z_{pqr} > \zeta_{pq} & \text{if } h_{pqr} = 0 & \forall p, q, r \\ d_{pq} = \sum_{r \in \mathcal{R}_{pq}} h_{pqr} & & \forall p, q \\ f_a = \sum_{r \in \mathcal{R}_{pq}} \delta_{pqra} h_{pqr} & & \forall a \\ f_a \geq 0, h_{pqr} \geq 0, d_{pq} \geq 0 & & \forall a, p, q, r \end{cases} \quad (9)$$

4 Results

The open database [20] gathered several road transportation network data: network, demand, and the node coordinates. The size of these networks varies from 4 to 33837 nodes.

We decided to test our model on the Sioux Falls road network. This network is composed of 24 nodes and 76 links. All the nodes are origins and destinations of at least one OD pair. Figure 2 plots the demand to assign between the OD pairs. We can remark there is no loop demand, the diagonal values of the matrix are null. Moreover, nodes 10, 16, and 22 have the highest number of departing and arriving passengers.

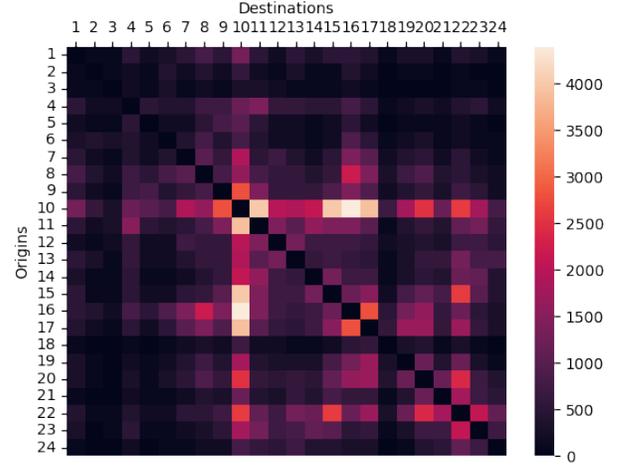


Figure 2: OD matrix of the Sioux Falls road network

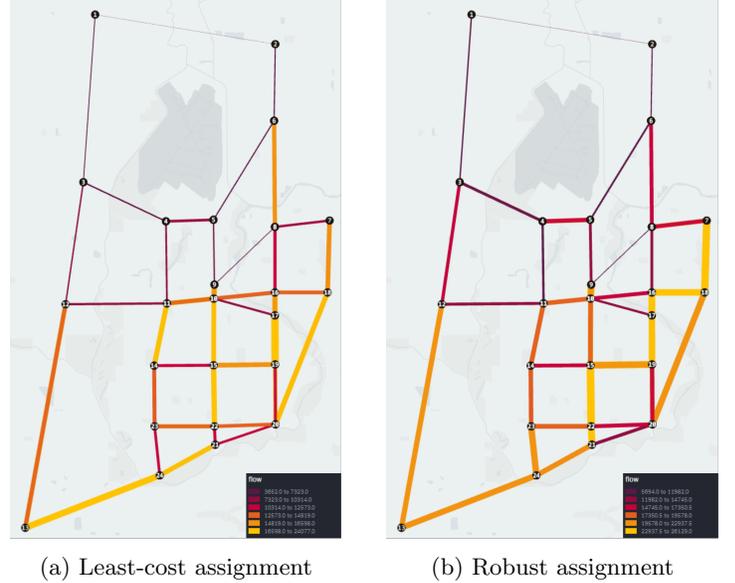


Figure 3: Flow comparison between least-cost and robust assignment on the Sioux Falls road network

The graph depicted in Figure 3 illustrates two types of assignments: the least-cost assignment and the robust assignment. The latter is derived from the alternative paths model presented in Section 3. The links of the robust assignment are more heavily loaded, resulting in thicker widths and increased costs based on the flow (refer to Equation (1)). This behavior was anticipated. The cost and alternative options along the path are taken into account in the robust assignment, resulting in a longer selected path compared to the least-cost option.

As shown in Figure 4, the robust model assigns passengers to more paths than the least-cost model. Moreover, since the demand is the same for both assignments, we can infer that fewer people are on these routes. This implies that there will be fewer people to re-route in case of a disruption, and alternative costs will be close to the disrupted path. Nevertheless, utilizing multiple routes to assign passengers from the same OD pair heightens the probability that some of them encounter a disturbance. Nonetheless, it minimizes the resources

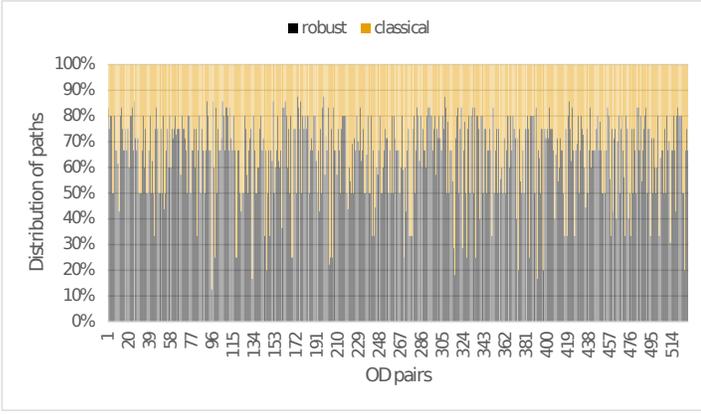
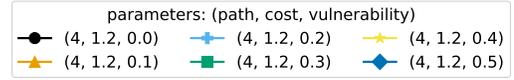


Figure 4: Distribution of paths used for least-cost (orange) and robust (black) assignments depending on the OD pairs

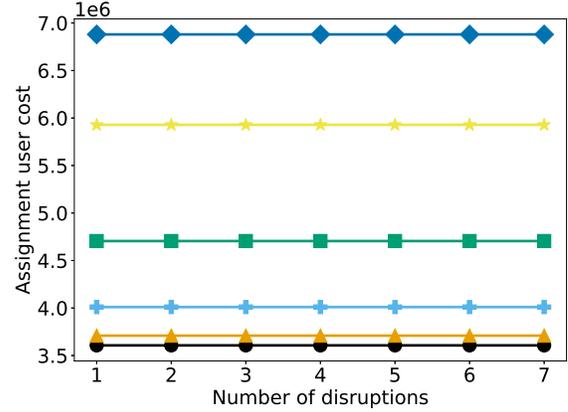
required to reassign them.

We were interested in analyzing the global cost of the traffic for different disruption cases. The disruptions here are complete road closure. In Figure 5, we ran several simulations with different values of parameters. A simulation is a three-step process. It starts with an assignment for a given cost and vulnerability parameter. Then, some links of the network are disrupted. And finally, the stranded passengers are reassigned from the node where the disruption happens. The cost parameter is used to compute the alternative paths so that their costs do not deviate too far away from the least-cost path. This parameter is related to s_{nq} in Equation (6). The vulnerability parameter is exactly the parameter α in Equation (8). We set the cost parameter to 1.2 so that the cost of the alternatives is at a maximum 20% higher than the least-cost path and made the vulnerability parameter vary from 0 to 0.5. The vulnerability parameter set to 0 means that the robustness is not considered therefore it is equivalent to a least-cost assignment.

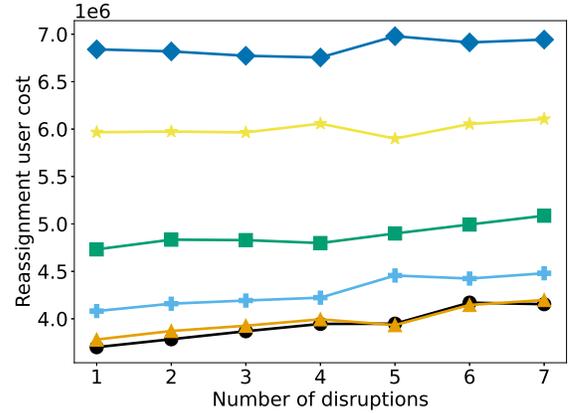
The cost of the network after the robust assignment process is shown in Figure 5b. Notably, the cost increases in proportion to the level of robustness considered. For a given set of parameters, irrespective of the number of disruptions to be carried out, the cost remains constant. The global reassignment cost after network disruptions is illustrated in Figure 5c, where it is generally observed to slightly increase. There is a noticeable decline seen on the blue and green curves from 1 to 4 and 2 to 4, respectively. The orange and yellow curves both show a decreasing at 5. Lastly, the orange curve dips below the black curve at 5 and 6 disruptions, indicating that reassignment becomes more cost-effective with greater robustness. The extra cost is the difference between the cost of reassignment following a disruption and the cost of assignment. The extra cost of reassignment is depicted in Figure 5d. Similar to reassignment, the extra cost generally rises with the number of disruptions, but it may occasionally decrease. Notably, the extra cost exhibits the same variation patterns as reassignment. The curves in this graph are sorted in the opposite direction as the previous two graphs, with the least robust (black curve) at the top and the most robust (blue curve) at the bottom. The cost of reassignment decreases as assignments become more robust. Occasionally, the extra cost is negative (blue and yellow curve), meaning the paths used for reassignment are less



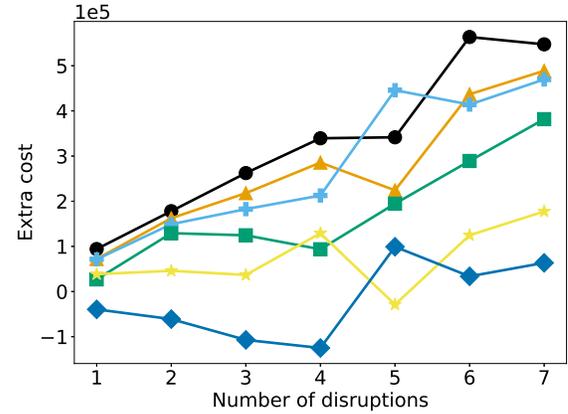
(a) Parameters used for the different curves: the path parameter is the number of paths computed at each iteration, the cost parameter is used to compute s_{nq} in Equation (6), and the vulnerability parameter is α in Equation (8)



(b) Assignment cost



(c) Reassignment cost



(d) Extra cost

Figure 5: Overall transportation cost after the traffic assignment and reassignment steps of the Sioux Falls road network disruption simulation for different parameter values

Table 2: Scenarios simulated in the Sioux Falls road network where five roadway links were fully closed. The subscript LC and R refer to Least-Cost and Robust, respectively. R_* represents the reassignment cost, EC_* denotes the extra cost incurred due to the disruption, and A_* represents the assignment cost.

Scenario	R_{LC}	R_R	EC_{LC}	EC_R	$\Delta = A_R - A_{LC}$	$EC_{LC} - EC_R - \Delta$
1	4114519,96	3979736,108	507892,6309	270688,3211	102420,4579	134783,8519
2	3959245,719	4110710,804	352618,3905	401663,0172	102420,4579	-151465,0846
3	4014468,303	3838573,41	407840,9746	129525,6228	102420,4579	175894,8939
4	3831719,568	4096622,027	225092,2389	387574,2405	102420,4579	-264902,4595
5	3935039,539	3953570,813	328412,2101	244523,0266	102420,4579	-18531,27432
6	3809941,809	3907289,247	203314,4804	198241,4601	102420,4579	-97347,43759
7	3938988,687	3964626,708	332361,3583	255578,9211	102420,4579	-25638,02071
8	3906298,91	3954667,289	299671,5815	245619,5023	102420,4579	-48368,37873
9	4078718,237	3875316,617	472090,908	166268,8299	102420,4579	203401,6203
10	3893070,07	3651187,3	286442,7414	-57860,48722	102420,4579	241882,7707

expensive than the initially assigned paths. This results in shorter travel times when network disruptions occur.

The most remarkable result from these tests is the orange curve falling below the dark curve in Figure 5c. The orange curve represents a 10% robust assignment whereas the black curve is a non-robust least-cost assignment. We plot in Table 2 the ten scenarios used to compute the average black and orange curves in Figure 5. As we can remark, the robust extra-cost EC_R , which is cost generated by the reassignment of the passengers, is often lower than the least-cost extra-cost EC_{LC} . Besides, we compute the initial cost difference between the robust and the least-cost scenario in column Δ . Finally, we calculate the difference between the least-cost extra-cost and the robust extra with the initial cost difference. It is remarkable to note for the scenarios with the green cells, the least-cost extra-cost is far greater than the robust assignment combined with the initial cost difference. This final result shows that a robust strategy can absorb both the initial extra-cost and the generated delays. This result is not reflecting the benefit of such a strategy on one route plan but on the whole transportation network.

The most significant outcome of the examinations is the orange curve's descent below the dark curve in Figure 5c. The orange curve exhibits a 10% robust assignment, while the black curve illustrates a non-robust least-cost assignment. We have included in Table 2 the ten scenarios utilized to calculate the average black and orange curves in Figure 5. As we can observe, the additional cost incurred by reassigning passengers, known as robust extra-cost (EC_R), is frequently lower than the least-cost extra-cost (EC_{LC}). Additionally, we calculate the initial cost difference between the robust and least-cost scenarios in column Δ . Lastly, we determine the difference between the least-cost extra-cost and the robust extra-cost with the initial cost difference. For the scenarios with green cells, it is noteworthy that the least-cost extra-cost exceeds the combined cost difference of the robust assignment. This final outcome indicates that a robust strategy can accommodate both the initial extra-cost and the incurred delays. The benefits of such a strategy are observed not only on a single route plan but across the entire transportation network.

In this section, we have demonstrated that achieving robustness carries a cost. To attain a robust outcome, passengers may need to tolerate a longer travel time. This presents a dilemma for passengers seeking a robust trip. Nevertheless,

the results indicated that robustness can be advantageous if taken into consideration (by as little as 10%).

5 Conclusion

The objective of this study is to reduce the negative impact of disruptions on passenger journeys. We introduce a novel passenger-oriented model that measures a route's robustness to complete roadway closures, based on the number of alternate routes available along the way. Enhancing robustness increases a route's travel time. When a disruption occurs, even a route with low robustness can absorb both the initial excessive travel time and the resulting delay.

When a roadway becomes suddenly closed, a route passing through it must be replanned, causing delays for passengers. The extent of this delay is contingent on the quality of the alternative routes available. The metric developed in this study seeks to quantify this delay by assessing the existence of alternative routes and determining their quality.

This model can assist passengers in making informed decisions when choosing a route. Robust routes ensure a dependable journey with fewer unexpected delays, resulting in less stress for passengers. Additionally, passengers can save time by avoiding frequent detours and closures.

This paper presents a new contribution to vulnerability analysis theory through our purely topological model. While previous works have taken a network-oriented approach, we adopt a passenger-focused perspective. Their focus is on identifying critical elements within a transportation network. In contrast, we are focused on identifying critical trips. Our work captures a new aspect of vulnerability and represents a completion to what has been previously done on the network side.

The presented model is currently static. Our next step is to expand it into a more realistic dynamic version. Additionally, we aim to incorporate this model into a dynamic traffic assignment tool to analyze various disruption scenarios.

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