A utility-based approach to modeling systemic resilience of highway networks with an application in Utah

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ABSTRACT

The resilience of transportation networks is an important consideration in policy, management and planning, but practical techniques to identify systemically critical links are limited. Further, current practical techniques ignore that when transportation networks are damaged or degraded, people potentially change destinations and modes as well as travel routes. In this research, we develop a model to examine network highway resilience based on changes to mode and destination choice logsums, and apply this model to 41 scenarios representing the loss of links on the statewide highway network in Utah. The results of the analysis suggest a fundamentally different prioritization scheme than would be identified solely through a methodology based on increased travel times. Beyond this, the comparable user costs of the logsum method are generally lower than those considering only the value of increased travel times.

Keywords: Accessibility; Location Choice; Resiliency

INTRODUCTION

Systemic resiliency is an important consideration for transportation agencies, though specific definitions of "resiliency" might vary under different contexts. Some agencies and researchers see resiliency as facility-level design and engineering that hardens the system against failure (Bradley 2007; Peeta et al. 2010); others as an ability for maintenance staff to rapidly restore service following catastrophe (Zhang and Wang 2016); and others as an ability for a system to continue operating in degraded state (Berdica 2002; Ip and Wang 2011). Regardless of the definition used, assessing the resiliency of a transportation network — and addressing any potential shortfalls — requires a method to identify which links or facilities are most critical to the smooth operation of the network.

Identifying which links in a transportation network are most critical, however, is not trivial. State of the practice techniques typically rely on traffic volumes represented in terms of vehicles, trips, or freight value (e.g. AEM 2017). But these methods ignore the fact that some networks have alternate routes readily available, have multiple well developed modes of transportation, or have redundant destination locations. When a network link does break, routes, mode choice, and destination choice often change as well. These responses have been observed in real-world crisis events like the I-35 W bridge collapse in Minneapolis and the I-85 bridge fire and collapse in Atlanta (Hamedi et al. 2018; Xie and Levinson 2011; Zhu et al. 2010a; b).

In this research, we apply a destination choice accessibility model to identify critical highway links in a statewide highway context. This model is designed to capture the utility lost to individuals operating on a degraded network who may choose a longer route, a different travel mode, or a different destination. We then apply the model to a highway network representing the state of Utah. The model structure permits a more nuanced evaluation of link criticality than using traffic volume alone or in conjunction with an increased travel time measure.

The paper proceeds as follows. First, a literature review discusses previous attempts to analyze the resiliency of transportation networks. A methodology section presents the model developed for this research and describes the implementation process in Utah. A results section describes the model output in detail for one scenario and then compares and ranks the model outputs for an array of several dozen independent scenarios. The paper concludes with a discussion of limitations and associated avenues for future research.

LITERATURE

In a groundbreaking theoretical article, Berdica (Berdica 2002) attempted to identify, define and conceptualize network "vulnerability" — the complement of resiliency — by envisioning analyses conducted with several vulnerability performance measures including travel time, delay, congestion, serviceability, and accessibility. She then defined reliability as the level of reduced accessibility due to unfavorable operating conditions on the network. In particular, the author identifies a need for further research toward developing a framework capable of investigating reliability of transportation networks.

In this section we examine several attempts by numerous researchers to do precisely this using various measures of network performance. It is helpful to categorize the existing literature into three groups (summarized in Table 1) based on the overall technique applied in the study. These groups include:

- *Network connectivity*: How does damage to a network diminish the connectivity between network nodes?
- *Travel time analysis*: How much do shortest path travel times between origins and destinations increase on a damaged network?
- *Accessibility analysis* How easily can the population using the damaged network complete their daily activities?

The purpose of transportation networks is to connect locations to each other; presumably damage to a network would diminish the network's *connectivity*, or the number of paths between node pairs. It may even leave nodes or groups of nodes completely isolated. In studies using connectivity as the primary performance measure, researchers typically apply methods and concepts from graph theory. These measures may include elementary measures such as the isolation of nodes in a network

(Abdel-Rahim et al. 2007). More advanced measures have included heirarchical clustering of node paths (Agarwal et al. 2011; Zhang et al. 2015), a count of independent paths (Vodák et al. 2019), the reduction of total network capacity (Ip and Wang 2011), and special applications of the knapsack and traveling salesman problems (Guze 2014; Osei-Asamoah and Lownes 2014). Though useful from a theoretical perspective, many of these authors reported that their approaches tend to break down to some degree on large, real-world networks where the number of nodes and links numbers in the tens of thousands, and the degree of connectivity between any arbitrary node pair is high. They also do not typically account for how network users may react to the new topology or capacity constraints of the degraded network.

Highway system network failures — in most imaginable cases — degrade the shortest or least cost path, but typically do not eliminate all paths. The degree to which travel time increases when a particular link is damaged, however, could provide an estimate of the criticality of that link or node. This general method has been used to evaluate potential choke points in various networks (Berdica and Mattsson 2007; Ganin et al. 2017; Jaller et al. 2015) as well as the allocation of emergency resources (Peeta et al. 2010). Though many applications only consider the increase in travel time, some authors consider how the users of the network will respond to the decreased capacity (Ibrahim et al. 2011; Serulle et al. 2011; Xu et al. 2015), and others attempt to model a shift in departure time or mode (Omer et al. 2013).

A primary limitation with increased travel time methodologies is that they ignore other possible ways a population might adapt its travel to a damaged network. Aside from shifting routes and modes, people may choose other destinations and it is possible that some previously planned trips might be canceled entirely. Travel time-based methods do not account for the costs of these changes in plans. But accessibility methods — in particular the accessibility calculations embedded within many existing regional transport models —- provide a framework for evaluating these costs (Ben-Akiva and Lerman 1985; Geurs and van Wee 2004).

Accessibility is an abstract concept with multiple methods of quantification (Handy and Niemeier

1997). Perhaps the most popular method is the cumulative opportunities measure: e.g., the number of jobs within a specified travel time threshold. This is the method employed by Xie and Levinson (Xie and Levinson 2011) in an analysis of the impact of the I-35 W bridge collapse in Minneapolis. But cumulative opportunities measures require the analyst to assert a travel time threshold, a mode, and an opportunity of interest. Some of these assumptions can be relaxed with a gravity-style access model, but the logsum of a destination choice model has several benefits as an accessibility term including its grounding in choice framework, ability to weigh multiple attributes of an alternative, and include travel impedances by all modes (Dong et al. 2006). These measures can even be weighted by a cost coefficient to translate the lost utility in monetary terms (Geurs et al. 2010; Geurs and van Wee 2004).

Logsum-derived accessibility meaures have been used before to evaluate network resiliency (Masiero and Maggi 2012; Taylor 2008; Winkler 2016). Where these previous efforts have been somewhat limited is in their theoretical nature. Though previous researchers have shown that logsum-derived accessibility measures are feasible and informative, their use in actual resilience analysis efforts by state departments of transportation and other relevant agencies appears limited.

METHODOLOGY

In this section we describe a model framework designed to evaluate resilience using a logit-based choice metric. This framework is heavily based on tools and methods in existing statewide travel models, with a few necessary extensions. We then describe the implementation of this model framework to a prioritization exercise on the Utah Statewide Travel Model (USTM).

3.1 Model Design

The overall model framework is presented in Fig. 1, and is designed to capture the utility-based accessibility for a particular origin zone i and trip purpose m. The model begins with a travel time skim procedure, to determine the congested travel time from zone i to zone j by auto as well as the shortest network distance for non-motorized modes. The transit travel time skim is fixed, assuming that transit infrastructure would not be affected by changes to the highway network. Throughout this section, lower-cased index variables k belong to a set of all indices described by the corresponding capital letter K.

With the travel time t_{ijk} for all modes $k \in K$, the model computes mode choice utility values. The multinomial logit mode choice model describes the probability of a person at origin i choosing mode k for a trip to destination j:

$$\mathcal{P}_{ijm}(k) = \frac{\exp(f(\beta_m, t_{ijk}))}{\sum_K \exp(f(\beta_m, t_{ijk}))} \tag{1}$$

The log of the denominator of the this equation is called the mode choice logsum, $MCLS_{ijm}$ and is a measure of the travel cost by all modes, weighted by utility parameters β_m that may vary by trip purpose.

The $MCLS$ is then used as a travel impedance term in the multinomial logit destination choice model, where the probability of a person at origin i choosing destination $j \in J$ is

$$\mathcal{P}_{im}(j) = \frac{\exp(f(\gamma_m, MCLS_{ijm}, A_j))}{\sum_J \exp(f(\gamma_m, MCLS_{ijm}, A_j))} \tag{2}$$

where A_j is the attractiveness — represented in terms of socioeconomic activity — of zone j. As with mode choice, the log of the denominator of this model is the destination choice logsum, $DCLS_{im}$. This quantity represents the value access to all destinations by all modes of travel, and varies by trip purpose.

The $DCLS_{im}$ measure is relative, but can be compared across scenarios. The difference between the measures of two scenarios

$$\Delta_{im} = DCLS_{im}^{\text{Base}} - DCLS_{im}^{\text{Scenario}} \tag{3}$$

provides an estimate of the accessibility lost when $t_{ij\text{drive}}$ changes due to a damaged highway link. This accessibility change is *per trip*, meaning that the total lost accessibility is $P_{im} * \Delta_{im}$ where P is the number of trip productions at zone i for purpose m. This measure is given in units of dimensionless utility, but the mode choice cost coefficient β_{cost} provides a conversion factor between utility and cost. The total financial cost of a damaged link for the entire region for all trip purposes is

$$\text{Cost} = \sum_{I}\sum_{M} -1/\beta_{\text{cost},m} * P_{im}\Delta_{im} \tag{4}$$

For comparison to a simpler resiliency method that only includes the increased travel time between origins and destinations, we compute the change in congested travel time between δt_{ij} and multiply the number of trips by this change and a value of time coefficient derived from the cost and vehicle time coefficients of the mode choice model,

$$\text{Cost}' = \sum_{I}\sum_{J}\sum_{M} \frac{\beta_{\text{time},m}}{\beta_{\text{cost},m}} T_{ijm}\delta t_{ijm} \tag{5}$$

3.2 Model Implementation in Utah

The Utah Department of Transportation (UDOT) manages an extensive highway network consisting of interstate freeways (I-15, I-80, I-70, and I-84), intraurban expressways along the Wasatch Front, and rural highways throughout the state. The rugged mountain and canyon topography throughout the state places severe constraints on possible redundant paths in the highway network. A landslide or rock fall in any single canyon may isolate a community or force a redirection of traffic that could be several hours longer than the preferred route; understanding which of these many possible choke points is most critical is a key and ongoing objective of the agency.

Several data elements for the model described above were obtained from the Utah Statewide Travel Model (USTM). USTM is a trip-based statewide model that is focused exclusively on long-distance and rural trips: intraurban trips within existing Metropolitan Planning Organization (MPO) model regions are pre-loaded onto the USTM highway network. This means that USTM as currently constituted can be used for infrastructure planning purposes, but would be inadequate to evaluate the systemic resiliency of the highway network given the disparate methodologies of the MPO models. USTM can, however, provide the following data elements

1. *Highway Network*: including free flow and congested travel speeds, link length, link capacity estimates, etc.
2. *Zonal Productions P_{im}*: available for all zones by purpose, including those in the MPO region areas.
3. *Zonal Socioeconomic Data*: the destination choice model described in Eq. 2 calculates attractions A_{jm} from the USTM zonal socioeconomic data based on the utility coefficients in Table 2.
4. *Calibration Targets*: USTM base scenario estimates of mode split and trip length were used to calibrate the utility coefficients as described below.

Among MPO models in Utah, only the model jointly operated by the Wasatch Front Regional Council (WFRC, Salt Lake area MPO) and the Mountainland Association of Governments (MAG, Provo area MPO) model includes a substantive transit forecasting component. The transit travel time skim from the WFRC / MAG model was used for the mode choice model in Eq. 1; the zonal travel time between the smaller WFRC / MAG model zones was averaged to the larger USTM zones, and the minimum time among the several modes available (commuter rail, light rail, bus rapid transit, local bus) was taken as the travel time for a single transit mode in this implementation.

The utility coefficients for the destination and mode choice models are presented in Table 2. The mode choice coefficients were adapted from USTM and supplemented with coefficients from the Roanoke (Virginia) Valley Transportation Planning Organization (RVTPO) travel model. This model was selected for its simplicity and analogous data elements to the proposed model. The alternative-specific constants were calibrated to regional mode choice targets developed from the 2015 Utah Household Travel Survey (UHTS) using methods described by Koppelman and Bhat (2006).

The destination choice utility equation consists of three parts: a size term, a travel impedance term, and a calibration polynomial. Coefficients for the size term and travel impedance terms were adapted from the Oregon Statewide Integrated Model for all purposes except HBW. Instead, these coefficients were adapted from the RVTPO model. The distance polynomial coefficients were calibrated to targets developed from the 2012 Utah household travel survey.

3.2.1 Vulnerable Link Identification

To develop evaluation scenarios on which to apply the model, we used information contained in the UDOT Risk Priority Analysis online map Transportation (2020). This map considers the probability of various events that could impact road performance including rock falls, avalanches, landslides, and other similar occurrences. Using this tool, combined with information gathered from the research team and UDOT officials, 41 locations of interest were identified for analysis. Each link was identified due to its location in relation to population centers, remote geographic location, and proximity to other highway facilities, or because the link was known to be at risk due to geologic or geographic features, or because it was a suspected choke point in the network.

RESULTS

In this section we apply the model to scenarios where critical highway links are removed from the model network. This includes first a detailed analysis of a single scenario, where I-80 between Salt Lake and Tooele Counties is severed. We compare the model output to an alternative method that measures only the change in travel time and does not allow for mode or destination choice. The model was then applied to 40 additional link closure scenarios throughout the state.

4.1 Detailed Scenario Analysis

To illustrate how the logsum-based model framework captures the costs of losing a link, we conducted a scenario where I-80 between Tooele and Salt Lake Counties west of the Salt Lake City International Airport becomes unavailable. Tooele is a largely rural county with increasing numbers of residents who commute to jobs in the Salt Lake Valley. I-80 is the only realistic path between the two counties, as alternate routes involve mountain canyons and many additional miles of travel.

The costs obtained by the logsum and travel time based methods for this scenario are shown in Table 3. In both analyses, we separate the costs spatially, though the definitions of the two are slightly different. In the logsum-based method, “Inside Tooele” are costs associated with decreased accessibility for trips produced in Tooele County. The increased costs in this case capture the loss in utility by measuring increased multi-model travel impedances to destinations with high attractiveness. In the travel-time method, by contrast, the “Inside Tooele” costs are those for trips with an origin in Tooele County and a destination in Salt Lake County, and are the increase in travel time multiplied by a value of time and the number of vehicles making the trip. The difference in definition is required by the difference in framework construction.

In general, the logsum-based method arrives at cost estimates that are less than half of the comparable estimates of the travel time-based method. This is not unexpected, as the travel time-based method assumes that all the preexisting trips would still occur, but on a longer path. The logsum-based method on the other hand attempts to capture the fact that when a path changes, people may shift their destination or their mode of travel. To be clear, the framework we have developed for this exercise does not explicitly model the selection of a new alternative destination; rather, we calculate instead the value of a destination choice set before and after the link is removed. But the implication is that the availability of alternative destinations still provide some benefit to the choice maker, a proposition that the travel time method ignores.

Another key element of Table 3 is that the largest single element of costs in the scenario is associated with through freight, as well as contributions from other purposes for which the logsum model developed in this study did not include a corresponding methodology. This was due to data limitations and the modeling approach of the existing USTM, but it is obvious that a choice-based framework for examining the costs of through and inbound / outbound traffic is an important limitation in this scenario and potentially many others.

4.2 Prioritization Scenario Results

We now apply the model to compare 40 additional scenarios where individual highway facilities are removed from the model highway network. Table 4 presents the logsum and travel time results for all 41 scenarios, ordered by decreasing logsum costs. In other words, I-15 at the boundary between

Utah and Salt Lake Counties is the most "vulnerable" or "critical" link analyzed in this exercise. Were this link to be cut, the people of Utah would have the highest costs per day in lost destination and travel access of any other link. Each of the highest-ranking roads in this analysis is an interstate facility in northern Utah, which is more heavily populated than the remote areas in the south. A map showing the locations of these scenarios is given in Fig. 2. The concentration of the highest cost links in the Salt Lake City metropolitan area is obvious, though the links with the highest cost are not *in* Salt Lake City where multiple parallel routes exist. Rather, they are in mountain canyons surrounding the main urban area.

Perhaps strangely, many scenarios in the analysis show a *benefit* from loss of the link. Investigating these scenarios showed that for many paths, the shortest automobile travel time in the complete network is *not* the shortest path by distance. When the shortest time path is disrupted, the new shortest time path may be only a few minutes longer by time but dozens of miles shorter (on a slower road). Because the automobile operating costs are calculated per mile and not per minute, this means that the new path actually produces a benefit. This challenge is exacerbated by the apparent agency practice of placing artificial time penalties on the network links in some canyons during calibration. This exercise reveals one reason why such a practice should be discouraged, and also highlights the importance of using consistent functions for impedance calculation at all stages of the model.

The remaining columns of Table 4 present the costs associated with link closure based on the travel time method. Many of the most costly scenarios in the logsum model also appear to be costly in the comparable elements of the travel time method. That is, the scenario breaking the interstate link between Salt Lake and Utah counties is the most costly scenario in both methods, and underscores the significance of this link to Utah's economy and people. But while many of the largest and most impactful scenarios have similar rankings and scales, there are also drastic differences between the two methods down the line. To put it simply, the choice of analysis method would change the priority that UDOT places on its roads in terms of preparing for incidents and hardening assets.

4.3 Sensitivity Analysis

A primary limitation of the model framework presented to this point is that the input parameters used for the mode and destination choice utilities were gathered from several different sources including a statewide trip-based model, a statewide activity-based model, and an urban model for a small region. How much would the findings presented to this point change if the parameters in Table 2 were to change modestly?

To examine this possibility, we construct 25 independent draws of the parameter coefficients using Latin Hypercube Sampling (Helton and Davis 2003). The coefficient of variation for each parameter was assumed to be 0.1; originally, a value of 0.3 was selected (Zhao and Kockelman 2002), but this resulted in an unreasonable range of implied values of time. Using each of the 25 draws, we ran the base scenario and three large-impact scenarios and calculated the logsum-based costs.

Fig. 3 presents the estimated monetary costs for each of these three scenarios under each of the 25 parameter draws. The results are ordered in the figure by the estimated cost for the highest-impact scenario. Two observations can be made from this figure. First, different parameter values do not affect the scenarios uniformly. The second observation is that despite the within-scenario variation, the overall scale of the three scenarios is maintained regardless of the drawn parameter values. Indeed, the three scenarios remain in their priority ranking across all 25 draws of the choice model parameters. We therefore do not expect that the selection of parameters is a major element in the relative ranking of scenarios.

LIMITATIONS AND DISCUSSION

The issue of systemic resilience to natural and other hazards is an important question for transportation agencies in the United States and around the world, given the precarious situation of many of its transportation assets. Flash floods, rockfalls, avalanches, earthquakes, and other incidents pose threats to the network of independent transportation facilities. This research did not consider risk assessment directly at any level, but rather took as a given that 41 facilities were at some level of risk and played a potentially large systemic role. A well-conceived approach to systemic resilience should involve all three elements of resilience: hardening assets from failure through high-quality engineering and construction; locating maintenance resources in areas where they can most quickly resolve issues and return facilities to optimal conditions; and understanding how the system could work effectively in a damaged or degraded state for medium to long periods of time if necessary.

This research focused on the systemic criticality of 41 facilities that were assumed to fail independently. Some of the disaster scenarios most likely to affect highway facilities – especially a major earthquake – are likely to damage multiple highway assets simultaneously. This research might be extended to consider what would happen if a set of highway facilities failed; is there a facility that is not critical were it to fail by itself, but ends up being a critical component of several combinations of failures? Taking the question further, agencies might consider scenarios where emergency services or evacuations must operate on a degraded network, an element of the emerging research area of functional recovery (Zhan et al. 2022). Of course, it is also an open question as to whether destination and mode choices will follow the same behavioral patterns in such a scenario.

This research developed a trip-based statewide transportation planning model using common model design practices including a destination choice trip distribution model and a complete —- if rudimentary —- logit-based mode choice model. The model presented in this particular research should not be used for infrastructure policy or forecasting analyses, but is instead an illustrative tool. Many statewide models, on the other hand, use a trip-based statewide transportation planning model with a basic gravity-type trip distribution model and no mode choice component. Using logit-based choice frameworks for trip distribution and mode choice allows the model to incorporate greater sensitivity to influencing variables and other benefits, in addition to providing data to support this type of resiliency analysis.

The flexibility and sensitivity afforded by choice models can introduce some additional challenges, however. The results of the logsum-based choice analysis highlight one such risk, in that using different cost functions for network skimming and destination choice can lead to inconsistent model behavior. In this research and in the USTM highway assignment — and common to many agency modeling practices — vehicle trips between origins and destinations are loaded onto the shortest time path, but their destinations are chosen by a combination of travel time and path distance. Though this issue does not always arise during calibration and typical volume forecasting efforts, it represents a serious inconsistency in the travel model framework. Along the same lines, this research included only a single feedback iteration; understanding how many iterations are necessary for a travel model to successfully converge – where the destinations chosen are no longer changing based on changes to travel times between origins and destinations – is an important model design decision that was not explored here.

A potential limitation in the model developed for this research is that all HBW trips are flexible in destination choice. This implies that a user could choose to work in a different place when the path to their previously-chosen work location is disrupted. This might not be entirely logical for short-term or even medium-term highway closures, considering that most people will not switch jobs so quickly. With the recent increase in telecommuting instigated by the COVID-19 pandemic, workplace location is likely even more flexible now than it has been in the past. This increased flexibility has already called into question how HBW trips are handled in travel behavior modeling (Salon et al. 2021). A more nuanced method for estimating HBW trips that accounts for both flexibility and inflexibility of workplace location might be developed, or the use of activity-based models that consider journeys to work or telecommuting as a function of trip distance could be employed.

Another limitation in this research surrounds the daily trip assignment procedure, which introduces two related issues. The first is that the analysis does not consider incidents which close a facility for a time shorter than 24 hours. Though the target of this research was an understanding of incidents of longer duration (allowing for a shift in destination choice), the impacts of shorter incidents on user costs is an important topic. A departure time choice model might allow users to shift trips to periods with a less compromised network. Addressing this issue, however, would introduce challenges related to long-distance trips that would stretch across time periods. A dynamic traffic assignment or mesoscopic network simulation may be a better strategy to address this issue (e.g., Kaddoura and Nagel 2018).

Policies that result in a clear and certain outcome are rare, though travel demand models are sometimes misinterpreted, misused, or even mis-designed to imply a single policy prediction. Along the same lines, agencies should take a proactive role in helping travel modelers and transportation planners incorporate uncertainty in their analysis and convey this uncertainty responsibly in communications with transportation decision-makers and the general public. The sensitivity test supplied in this research is a modest step in this direction.

CONCLUSIONS

The question of systemic resilience of highway assets is an increasing concern to agencies that must maintain critical infrastructure as it ages in the face of a changing climate and economy. The basic tools of travel forecasting — based on coherent representations of human behavior — provide compelling tools for evaluating the criticality of individual highway assets. These tools may require different expertise than more traditional agency engineers are usually equipped with, but simplified or simplistic methods can lead to fundamentally different evaluations of what may happen when the network changes. Demand modelers must first equip their models with the tools to be useful outside of simple volume forecasting, and then communicate with their stakeholders and peers the purpose of the model and its powerful potential for helpful analysis.

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AUTHOR CONTRIBUTION STATEMENT

Gregory S. Macfarlane: Conceptualization, Methodology, Writing - review & editing, Supervision **Max Barnes:** Methodology, Software, Formal Analysis, Investigation, Data curation, Writing - original draft **Natalie Gray:** Formal Analysis, Investigation, Data curation, Writing - original draft, Visualization

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List of Tables

Table 1. Attempts to Evaluate Systemic Resiliency

Year	Author	Performance Metric
2004	Geurs and van Wee	Accessibility (isochrone, gravity, logsum)
2007	Abdel-Rahim et al.	Network Connectivity
2008	Taylor, M	Accessibility (logsum)
2010	Peeta et al.	Travel time and cost
2010	Geurs et al.	Accessibility (logsum)
2010	Levinson and Zhu	Travel time and cost
2010	Zhu et al.	Travel time and cost
2011	Agarwal et al.	Network connectivity
2011	Ip and Wang	Network connectivity
2011	Serulle et al.	Travel time and cost
2011	Ibrahim, S	Travel time and cost
2011	Xie and Levinson	Accessibility (isochrone)
2013	Omer et al.	Travel time and cost
2014	Osei-Asamoah and Lownes	Network connectivity
2015	Zhang et al.	Network connectivity
2015	Guze	Network connectivity
2015	Jaller et al.	Travel time and cost
2015	Xu et al.	Network connectivity
2016	Winkler, C.	Accessibility (gravity)
2017	Ganin et al.	Accessibility (gravity)
2019	Vodak et al.	Network connectivity
2019	Hackl and Adey	Network connectivity

Table 2. Choice Model Coefficients

Variable	HBW	HBO	NHB
Destination Choice			
Households	0.0000	1.0187	0.2077
Office Employment	0.4568	0.4032	0.2816
Other Employment	1.6827	0.4032	0.2816
Retail Employment	0.6087	3.8138	5.1186
Distance	-0.0801	-0.1728	-0.1157
Distance^2	0.0026	0.0034	0.0035
Distance^3	0.0000	0.0000	0.0000
Mode Choice			
Shared	-1.1703	0.0164	-0.0336
Transit	-0.3903	-1.9811	-2.2714
Non-Motorized	-1.2258	-0.3834	-0.8655
Travel Time [minutes]	-0.0450	-0.0350	-0.0400
Travel Cost [dollars]	-0.0016	-0.0016	-0.0016
Walk Distance (less than 1 mile) [miles]	-0.0900	-0.0700	-0.0800
Walk Distance (1 mile or more) [miles]	-0.1350	-0.1050	-0.1200

Table 3. Comparison of Logsum-based and Time-based costs for I-80 at Tooele

	Utility Logsum			Travel Time		
Purpose	Other Counties	Inside Tooele	Total	Other Counties	Inside Tooele	Total
Passenger						
HBO	$2,637	$28,290	$30,927	$8,595	$75,862	$84,457
HBW	$4,039	$113,660	$117,699	$7,868	$234,009	$241,877
NHB	$2,141	$44,911	$47,051	$5,875	$100,245	$106,120
External / Freight						
Internal Freight				$24,617	$26,083	$50,700
Inbound / Outbound Freight				$59,758	$1,190	$60,948
Recreation				$176	$190	$366
Through Freight				$251,508		$251,508
Through Passenger				$56,103		$56,103
Comparable Total	$8,817	$186,860	$195,677	$22,338	$410,116	$432,454
Total	$8,817	$186,860	$195,677	$414,499	$437,580	$852,079

Table 4. Scenario Results of Both Methodologies

		Logsum	Travel Time		
Route	Location	HBW, HBO, NHB	HBW, HBO, NHB	Freight, External, etc.	Total
I-15	Utah / Salt Lake county line	$587,126	$827,014	$387,138	$1,214,152
I-80	Salt Lake / Tooele county line	$195,677	$432,454	$419,625	$852,079
I-84	Weber Canyon	$133,705	$100,415	$87,561	$187,976
I-80	Parley's Canyon	$96,614	$77,320	$164,493	$241,813
I-15	Orem	$68,707	$137,034	$105,174	$242,208
I-215	Taylorsville	$51,327	$79,619	$2,750	$82,370
US-91	Box Elder Canyon	$39,676	$55,515	$106,704	$162,219
SR-189	Provo Canyon	$39,088	$43,095	$13,098	$56,193
I-15	SLC 2100 S	$32,508	$98,707	$43,222	$141,929
I-15	Bountiful	$28,787	$56,806	$53,575	$110,381
I-15	Utah / Juab county line	$28,531	$49,815	$578,167	$627,982
Bangerter	West Valley City	$27,150	$27,009	$503	$27,512
SR-18	Snow Canyon	$21,857	$12,131	$199	$12,330
I-15	North of Zion	$13,164	$14,793	$646,271	$661,064
I-15	North of Cove Fort	$6,313	$1,378	$393,559	$394,937
Timp Highway	American Fork Canyon	$1,015	$2,566	$71	$2,637
Legacy Parkway	West Bountiful	$464	$242	$42	$284
UT-35	Francis	-$4,311	$2,846	$219	$3,064
SR-14	Cedar Canyon	-$5,407	$479	$136	$615
US-89	Logan Canyon	-$5,515	$1,245	$5,382	$6,626
SR-199	Rush Valley	-$5,688	$335	$77	$413
SR-62	Kingston	-$5,900	$779	$72	$850
US-6	Price Canyon	-$5,966	-$152	$62,556	$62,404
SR-101	Hyrum	-$6,020	-$3	$67	$65
US-40	East of Strawberry Reservoir	-$6,036	-$197	$56,200	$56,003
I-70	Colorado state line	-$6,056	$516	$1,603,381	$1,603,896
I-70	East of Cove Fort	-$6,099	-$13	$118,387	$118,374
US-89	Arizona state line	-$6,112	$315	$98,484	$98,798
SR-153	Beaver Canyon	-$6,124	-$120	$2,665	$2,545
SR-24	West of Hanksville	-$6,141	-$127	$227	$100
I-70	West of Green River	-$6,157	-$166	$320,401	$320,235
SR-24	in Capitol Reef National Park	-$6,172	-$179	$328	$149
SR-95	Hite	-$6,173	-$187	$859	$672
US-6	King Top	-$6,173	-$184	$423	$239
SR-65	Emigration Canyon	-$6,173	-$186	$82	-$104
US-6	Spanish Fork Canyon	-$7,472	$2,213	$178,115	$180,328
MVC (UT-85)	West Jordan	-$8,406	$10,854	$329	$11,184
I-215	Cottonwood Heights	-$8,901	$34,851	$1,917	$36,768
SR-191	between Helper & Duchesne	-$9,487	$31	$17,093	$17,124
Bangerter	near Bluffdale	-$27,720	$42,503	$1,026	$43,529
I-80	SLC 1300 E	-$42,433	$50,471	$41,831	$92,302

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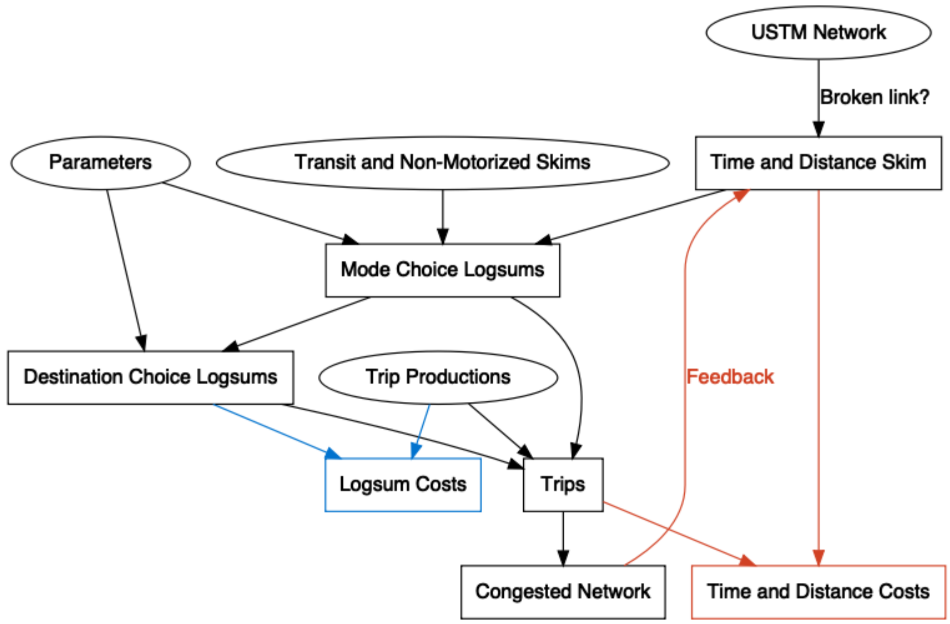
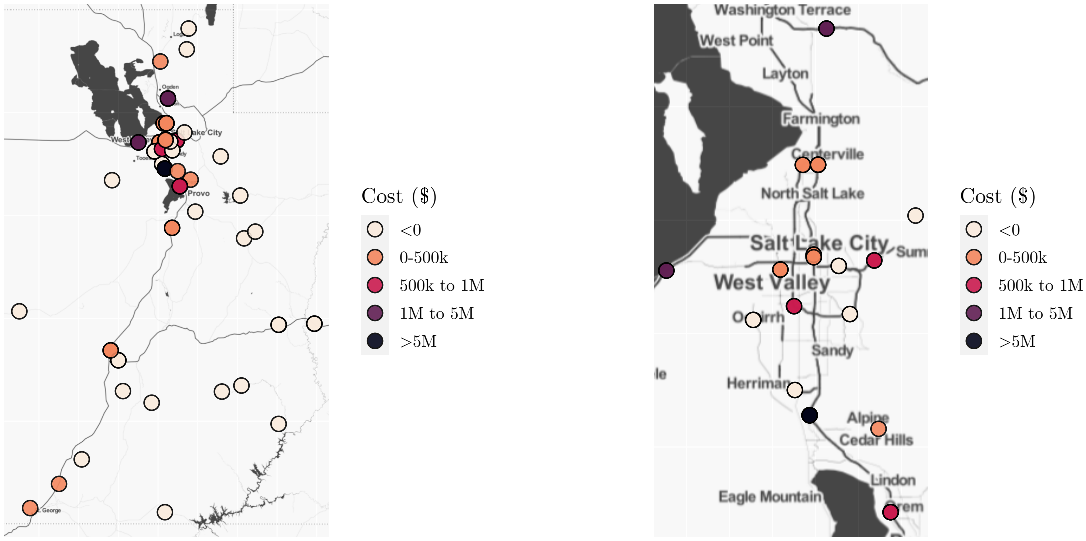


Fig. 1. Model framework with feedback cycle. Blue boxes are calculated after the second feedback loop.



(a) Statewide

(b) Wasatch Front

Fig. 2. Total cost of link closure for each scenario by the logsum method.

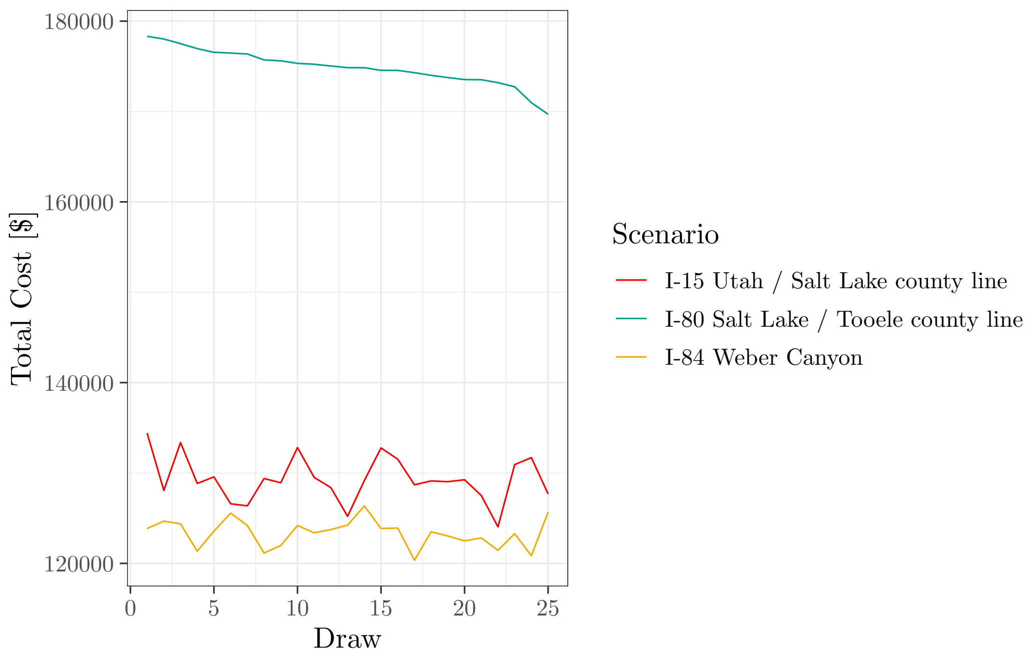


Fig. 3. Estimated logsum-based scenario costs in 25 different draws of the choice model parameters.