

Resiliency of Utah's Road Network:
a Logit-based Approach

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ABSTRACT

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The objective of this thesis is to evaluate the relative systemic criticality of highway links on a statewide network using a logit-based model sensitive to changes in route path, destination choice, and mode choice. In recent history, transportation network vulnerabilities have been increasingly scrutinized. Transportation disasters, such as the collapse of the I-35W bridge in Minneapolis, Minnesota, and the I-85/Piedmont Road fire and subsequent bridge collapse in Atlanta, Georgia, have brought identification of vulnerabilities to the forefront of transportation planning efforts. The Utah Department of Transportation (UDOT) manages and maintains a complex statewide network of highways. Currently, UDOT does not possess a method capable of quickly identifying network vulnerabilities, or potential costs associated with extended road closure. To aid planning efforts, UDOT has developed the Utah Statewide Transportation Model (USTM), which is a trip-based gravity model. USTM estimates the number of trips on Utah's highway network, however, USTM does not incorporate user mode or destination choice. Consequently, USTMs results are inflexible, meaning that trips cannot change mode or destination. Incorporating choice flexibility into USTM will allow human behavior to be represented. Subsequently, this thesis seeks to evaluate the relative systemic criticality of highway links on a statewide network using a logit-based model sensitive to changes in route path, destination choice, and mode choice. Logit-based calculations are advantageous in transportation modeling for two reasons: first, logsums capture the total value of user choice, and second, logsums are able to calculate total accessibility based on the value of the available choice set. The logsum model measures the overall dis-benefit experienced on an altered network, and this change is then converted into a measure of cost in dollars per day associated with road closure. Additionally, a travel time model was built to compare the logsum results to the results from traditional modeling methods. The travel time model calculates the total change in travel time by trip purpose, and converts into a measure of cost in dollars per day associated with road closure. The results of this thesis show that the logsum and travel time models provide different cost estimates, where the logsum results are typically lower than travel time estimates. Freight trips, which are included in only the travel time model, return estimated costs which far exceed the estimated costs for any other trip purpose or purposes combined. The development of the presented logsum model is important for two reasons: first, the model provides different estimates when compared with traditional methods, and second, the model accounts for route change and user mode and destination choice on a statewide network. Incorporating a logsum model into USTM allows UDOT to better identify vulnerabilities and estimate costs associated with road closure while considering user choice.

Keywords: resilience, logsum, logit model, choice model, mode choice, destination choice, transportation model, transportation planning

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CHAPTER 1. INTRODUCTION

1.1 Problem Statement

The Utah Department of Transportation (UDOT) is responsible for maintaining a transportation system to promote public welfare and economic activity throughout the state of Utah. UDOT is also responsible to maintain key components of the national highway transportation system. Given the importance of this system, UDOT has sought a way to identify those facilities which are most critical to smooth operation of the system.

In 2017, AEM Corporation (2017) completed a risk and resilience analysis report for the I-15 corridor on behalf of UDOT. This analysis quantified risk as the probability of threats (earthquakes, floods, fires, etc.) multiplied by the criticality of the asset to the overall system. The AEM analysis has two primary limitations. First, the methods are proprietary to AEM Corporation (2017) such that UDOT cannot now apply the methods to study the criticality of other transportation corridors with regional and national significance (e.g., U.S. Route 6, I-70, I-80). But more importantly, the current index treats each UDOT asset – each bridge, highway segment, etc. – as an independent unit, when in fact UDOT operates a system of interrelated transportation facilities. The criticality of a single bridge to the overall system is not determined by the volume of traffic it supports directly, but by how inconvenient it would be for that traffic to find another path or destination, were the bridge to fail. Therefore, a resilient network must be considered a function of available mode and destination alternatives. Developing a model capable of accounting for the choices a user makes will help transportation planners to calculate sensitive estimates of the costs associated with link closure.

1.2 Objectives

The primary objective of this study is to develop a methodology and tool to evaluate the relative systemic criticality of highway links on a statewide network using a model sensitive to changes in route path, destination choice, and mode choice. This tool is based on data collected from the Utah Statewide Travel Model (USTM), with certain improvements and additional model features to more accurately capture the economic costs associated with an impaired state highway network. In particular, we develop a method that explicitly considers the availability of alternative destinations, modes, and routes to individuals traveling on the impaired network. A secondary objective of this research is to apply the model to evaluate the criticality of specific highway links in Utah, by comparing the change in accessibility, or dis-benefit, experienced by road users. This thesis presents the results of this evaluation applied on 40 individual highway links.

1.3 Scope

The purpose of this thesis is to provide a functional tool that can be used to evaluate the potential economic costs associated with highway link closure in Utah. USTM comprises the entire highway network in Utah, with about 75,000 links, 36,000 nodes and 8,500 Transportation Analysis Zones (TAZ). Additionally, USTM covers the geographic area in which about 3.2 million people live. Developing a choice model such as the one presented in this study can help to determine the effects of road closures or long term link loss for the entire State of Utah. To better determine these effects, the presented model is based on the theory of logit choice modeling and shortest path finding in a network. The specific choice utility equations in the model represent a plausible utility outcome, but the focus of this research has not been on developing robust utility equations or calibrated volume-delay functions. This model is therefore not designed to forecast traffic volumes nor is it designed for any purpose other than providing a comparative estimate of the effects of link loss by man-made or natural causes.

1.4 Outline of Report

This thesis is organized as follows:

Chapter 1 This introductory chapter.

Chapter 2 This chapter presents a literature review, summarizing previous attempts to model network resiliency using the choices and accessibility of individuals on the impacted network.

Chapter 3 This chapter presents a proposed model design and implementation of the model within the CUBE transportation planning software application. This chapter also describes model calibration efforts.

Chapter 4 This chapter presents an application of the model developed in Chapter 3, and a description and comparison of model results, on the highway links chosen for analysis in Chapter 4.

Chapter 5 This chapter presents the conclusions, summarizes the findings of the research, and suggests next steps for this research.

CHAPTER 2. LITERATURE REVIEW

2.1 Overview

The resilience and connectivity of transport networks are a long-studied topic within transportation engineering in both theoretical and practical contexts. Within this long history however, there is variability in how scholars define resiliency. These definitions could be classified into three categories:

Resilience through Resistance Resilient transportation networks have few and manageable vulnerabilities. This is typically addressed through robust facility-level engineering and risk management (Bradley, 2007; Peeta et al., 2010).

Resilience through Recovery Resilient transportation networks are able to be repaired and returned to normal service without inordinate delay. This is accomplished through effective resource allocation and incident management during both disaster or degraded operation (Zhang and Wang, 2016).

Resilience through Operability in Crisis Resilient transport networks are able to operate effectively with damaged or unusable links (Berdica, 2002; Ip and Wang, 2011).

It is the final definition that is most relevant in the context of this study.

These definitions are not entirely mutually exclusive, and many researchers apply more than one definition in their work. For example, knowing where systemically critical or vulnerable links are will help in allocating maintenance resources. At the same time, the approach to identifying critical facilities implied by one of these definitions is not always compatible with the other definitions, and making distinctions between them is important (Rogers et al., 2012). For example, a bridge highly vulnerable to failure may be located on a little-traveled and systemically unimportant side street. The motivation of this research is to identify systemically critical facilities, and literature using the third definition of resiliency as the primary consideration.

We begin this review first by examining a study conducted by AEM on behalf of UDOT to identify vulnerable sections on the I-15 corridor. Next, we consider observations learned from systemic changes to networks and populations under real-life crisis events. We then consider previous attempts in the academic literature to evaluate the resiliency of real and fabricated transportation networks.

2.2 Identifying Critical Links on I-15

AEM Corporation worked with UDOT to develop an I-15 Corridor Risk and Resilience Pilot report (AEM Corporation, 2017). This project had a seven-step plan to understand the impact of physical threats to the Utah transportation network, specifically looking at two sections along I-15. These steps included:

Asset characterization A method to divide physical road assets into groupings with similar characteristics (e.g., roads, bridges, culverts, etc.)

Threat characterization A method to determine threat types each asset is exposed to or could be affected by (e.g., rock fall, fire, flood, etc.)

Consequence analysis An analysis determining the consequences of link loss, primarily estimating the cost of replacement should a link become damaged or broken

Vulnerability assessment An assessment of the amount of vulnerability each link is exposed to when single or multiple threat types are present

Threat assessment A method to determine the realized threat level present at each link examined

Risk/Resilience assessment A measure of the risk level and an attempt at a measure of the importance of each link to the roadway as a whole

Risk/Resilience management A summary of steps that should be taken to mitigate immediate risk, and reduce future risk while increasing the resilience level of individual road assets

From these different characterizations and assessments, AEM Corporation was able to provide a number of recommendations to UDOT that had the potential to improve resilience for the

identified threat-asset pairs along the evaluated corridors (mainly sections of I-15) based on the assigned criticality rating determined for each segment at risk.

It is easy to understand just how many natural or man-made threats exist to current infrastructure. Natural disasters such as earthquakes, wildfire, landslides and flash-floods cause billions of dollars of damage to infrastructure each year. Other threats, such as terrorism, affect important infrastructure as well. AEM Corporation identified a number of threats, derived from different types of data available for use. AEM Corporation was also able to rule out certain types of threats based on the relevance of these threats in Utah. Ultimately, nine physical threat types were considered. These threats include: earthquake, flood (scour), flood (overtopping/debris), fire (wild-land), railway-proximity, oil/gas/water pipeline-proximity, and water canal/ditch-proximity. Data comprising historical disaster occurrences or geographic location about these threat types exist and was assembled into threat layers which were intersected with physical assets (e.g., roadway, bridge, etc.).

Once these threat layers were determined and the location of the threat- asset pairs along I-15 were found, AEM Corporation was able to begin their analysis of how at-risk a link or road segment might be to the nine identified threat types. This process consisted of gathering characteristic data for each asset (e.g., length, width, depth, condition, etc.), determining a replacement cost for each asset, establishing an estimated service life for each asset, estimating (if not known) the design standard for each asset, establishing which magnitudes of each threat were to be analyzed, and gathering information on the likelihood of occurrence of each magnitude of each threat. These steps are further described in the Risk and Resilience report published by (AEM Corporation, 2017).

The report also provides a good template moving into the future for identifying links at risk, following the first definition of a resilient transportation network used in Section 2.1. The report also attempts to identify which links are most critical, assessing a “criticality” score to the network based on the five data elements and categories given in Table 2.1. Table 2.1 provides insight into some of the complications involved in attempting to identify critical roads. AEM Corporation uses several classifications to group roads together, such as the American Association of State Highway and Transportation Officials (AASHTO) classification, and Average Annual Daily Traffic (AADT). For example, a road may have a low AADT, but the majority of that AADT, which would show that

Table 2.1: AEM Criticality Score AEM Corporation (2017)

| Criteria | Very Low Impact | Low Impact | Moderate Impact | High Impact | Very High Impact |
|------------------------------|------------------|------------------|-----------------|---------------------|-----------------------|
| AADT | $\leq 1,145$ | 1,146-3,275 | 3,276-8,285 | 8,286-17,455 | $>17,455$ |
| Truck AADT | 0 | 1-494 | 495-1,881 | 1,882-4,794 | $>4,794$ |
| AASHTO Classification | Minor Collectors | Minor Collectors | Minor Arterials | Principal Arterials | Interstate Expressway |
| Tourism Traffic (\$M) | < 19.89 | 19.90-39.66 | 39.67-101.13 | 101.14-505.32 | >505.32 |
| Maintenance Distance (Miles) | < 70 | 71-84 | 85-102 | 103-124 | > 124 |

there is a very low to low impact, however, if the majority of traffic on that road were truck traffic, then that road almost immediately has a moderate to high impact. Other nuances such as the one proposed in this example exist. Another interesting situation to consider, is the case where a minor arterial becomes inundated with traffic or other hazard, however, a redundant arterial just a few blocks or miles away is able to handle much of the diverted traffic. Situations such as this one likely occur often, due to the way highway networks are traditionally built. One other observation made from Table 2.1 is that AEM Corporation does not take alternate routes into account. Additionally, AEM Corporation does not include a way for their risk analysis methodology to anticipate what a user would actually do if faced with a real disaster scenario. The work of AEM Corporation does not answer simple questions such as how many valid alternative routes exist? Or what is the new travel time or distance? Identifying the systemic resiliency of highway facilities – as implied by the third definition of resiliency, resilience through operability in crisis in Section 2.1 – requires considering these alternate routes (AEM Corporation, 2017).

2.3 Lessons Learned from Crisis Events

Two major crisis events in the last 15 years have given researchers an important opportunity to observe and study what happens to transportation networks and user behavior when critical links are suddenly disabled for an extended period of time. These events are the I-35W bridge collapse in Minneapolis, Minnesota, and the I-85 / Piedmont Road fire and bridge collapse in Atlanta,

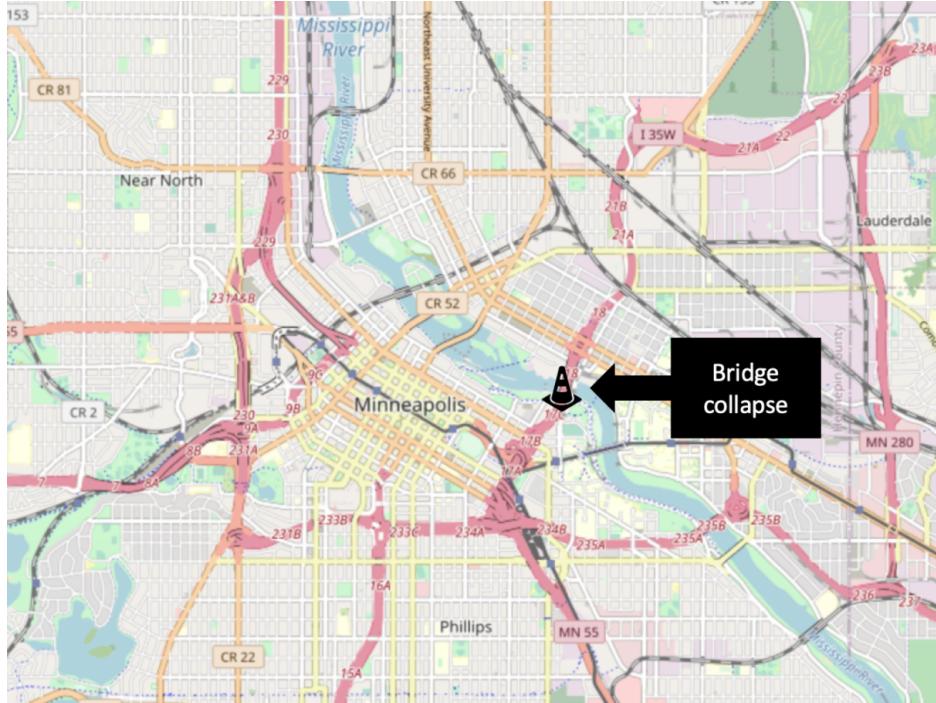


Figure 2.1: Approximate location of the I-35W bridge collapse.

Georgia. Both of these events were studied post-disaster, when the highway network was already operating in crisis, allowing researchers to examine how networks and road users operate or behave on a damaged network.

2.3.1 I-35W Bridge Collapse

On August 1, 2007, the I-35 bridge over the Mississippi River in downtown Minneapolis collapsed during rush hour. The bridge, which was undergoing maintenance, had been rated as structurally deficient and fracture critical, meaning that failure of one member would cause catastrophic structure failure (Schaper, 2017). The collapse occurred during rush hour traffic, and the bridge was additionally loaded with approximately 300 tons of maintenance equipment (Schaper, 2017). There were 13 fatalities, approximately 140 injuries, and abrupt disruption to roughly 140,000 average daily traffic (ADT) over the bridge (Zhu et al., 2010a). The complicated nature of the demolition and repair meant this systemically critical link would be missing for approximately 14 months. The approximate location of the bridge, one of two major routes over the Mississippi River, can be seen in Figure 2.1.

Zhu et al. (2010a) conducted a travel survey that provided a more in-depth analysis of important data and traffic changes surrounding the I-35W bridge collapse in 2007. The study attempted to identify mode-choice and other behavioral changes of survey respondents after the collapse. The authors analyzed data looking for variations in ADT, as well as changes in overall origin-destination (OD) matrices. Importantly, they analyzed loop detector data, bus ridership statistics, and survey response data in their work. The authors conducted a regression analysis of the collected data, which indicated that drivers are reluctant to make mode choice changes, rarely doing so in the real world. This is likely due to finances, time, or perceived difficulty of navigating a new mode of transport. At the same time, some drivers easily change destinations or routes when faced with increased travel times.

Zhu et al. (2010b) explored traffic behavior and changes in the wake of major network disruptions such as those that occurred in Minnesota. The authors identified unique behavior, post disaster, using GPS tracking data, survey data from the post disaster phase, and other aggregate data from surrounding freeways and traffic devices. These data were analyzed to track changes in ADT over bridges and alternate routes in the area after the disaster as well as after mitigation was complete. The authors provided increased understanding about how a network's operability changes in a post-crisis environment.

Xie and Levinson (2011) attempted to determine economic costs in the form of increased travel time of the 2007 I-35W bridge collapse using a scaled-down travel demand model. The authors used a simplified version of the SONG 2.0 travel demand model that had been developed for the Twin Cities area to determine vehicle hours traveled (VHT) and vehicle kilometers traveled (VKT). They also calculated the accessibility for each zone, from jobs to workers, and from workers to jobs, of the network using employment, residency, and transportation cost data. Using this simplified gravity-based travel demand model, the authors estimated that the bridge collapse cost the Twin Cities approximately \$75,000 per day in increased travel times. Interestingly, they are able to show that accessibility between workers and jobs was heavily affected by the loss of the bridge. The ease with which road users can access locations around the region experienced a dramatic decrease on the crippled network when compared to the whole, unbroken network.

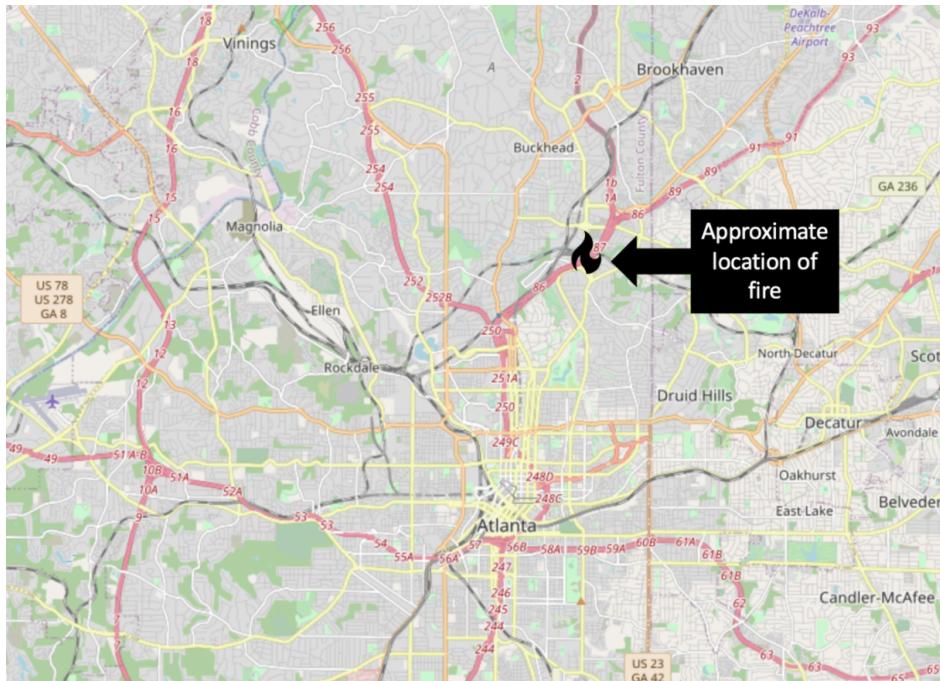


Figure 2.2: Approximate location of the I-85/Piedmont Road bridge fire.

2.3.2 I-85/Piedmont Road Bridge Fire

In Atlanta, Georgia, a section of bridge along I-85 near Piedmont Road collapsed due to a massive fire under the bridge on March 30, 2017. The fire grew quickly because of improperly stored construction materials under the bridge. The approximate location of the bridge collapse caused by the fire can be seen in Figure 2.2; the damaged link was at a critical point downstream of a merge point between two expressway facilities (GA-400 and I-85) bringing commuter traffic in from the suburbs of northern Fulton and Gwinnett Counties.

The section of I-85 that was closed impacted a large, upper income demographic in the greater Atlanta area who commuted across the bridge. As a result, the Georgia Department of Transportation (GDOT) along with the Governor created a \$3.1 million incentive program to help motivate project completion ahead of schedule. The bridge was originally scheduled to be closed for a period of 10 weeks, however, it re-opened after just 6 weeks, with construction being completed a month ahead of schedule. The accelerated finishing date was estimated to have saved approximately \$27 million in user and travel time costs (National Operations Center of Excellence, 2017). GDOT's efforts to reconstruct the bridge and quickly reopen the highway after the

bridge collapse and immediate highway closure aided in abating negative user costs (or dis-benefit) due to significant travel time delays that surfaced (in a post-disaster environment) due to changes in route choice and assignment.

As a result of the fire, the highway, which had an ADT of 243,000, was closed in both directions for a period of about six weeks. This closure led to a sudden 30% increase in traffic volumes across the entire downtown network, with notable increased congestion on side streets (Hamedi et al., 2018). Additionally, the Metropolitan Atlanta Rapid Transit Authority (MARTA) experienced a 20% increase in ridership, likely because many commuters made mode choice and route changes. To mitigate this, headways between buses and trains were decreased to allow greater passenger volume. MARTA was also able to extend service capacity by about 20%, adding 142,000 rail miles, 1,100 train hours, 8,202 bus miles, 512 bus hours, and 2,463 parking spaces in park and ride lots to help further mitigate the sudden increase in ridership (Metropolitan Atlanta Rapid Transit Authority, 2017, 2018). It is likely that MARTA's efforts to mitigate the rapid increase in passenger volumes greatly reduced any negative effects of the bridge fire on transit services, and helped alleviate other congestion generated by the disaster.

2.3.3 Observations: Change in Route, Mode, and Destination

Several lessons and key takeaways exist from both the I-35W bridge collapse and the I-85/Piedmont Road bridge fire and collapse. First, researchers observed that users quickly make route changes when faced with abruptly altered networks, but are reluctant to make mode choice changes (Zhu et al., 2010b). Second, researchers observed route and mode changes in the days and weeks following the Atlanta I-85 bridge fire. The effects of these changes were offset by efforts made by MARTA to extend transit services (Hamedi et al., 2018; Metropolitan Atlanta Rapid Transit Authority, 2017, 2018). These real world observations are invaluable because both route and mode choice changes do occur, and should therefore be considered in future transportation planning efforts.

2.4 Attempts to Evaluate Systemic Resiliency

Real world events do occur; however, and it is important for researchers to base efforts on both theoretical scenarios, and on actual events. Thus, a number of researchers have conducted studies where real or fabricated transportation networks are constructed, damaged or degraded, and then changes in performance measure are evaluated. All of this is done to measure network performance without an actual disaster occurring beforehand.

Berdica (2002) attempted to identify, define and conceptualize vulnerability by envisioning analyses conducted with several vulnerability performance measures, including travel time, delay, congestion, serviceability and accessibility. Here, Berdica defined accessibility as the ability for users to travel between OD pairs for any number of reasons. She then used the performance measures to define vulnerability as the level of reduced accessibility due to unfavorable operating conditions on the network. In particular, Berdica identified a need for further research toward developing a framework capable of investigating or measuring the overall systemic resiliency of transportation networks.

In the following section, the work of several researchers who have attempted to develop a framework capable of investigating or measuring the overall systemic resiliency of transportation networks will be examined. Many of the researchers use different methods to measure network performance while a network is operating under some kind of duress, and a consolidation of this discussion is summarized in Table 2.2. The measures can be consolidated into three basic species of study:

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? This in turn can be evaluated in a number of ways as explained by Dong et al. (2006).

Table 2.2: Attempts to Evaluate Systemic Resiliency

| Author | Year | Performance Metric |
|-------------------------|-------|--|
| Geurs and Van Wee | 2004 | Accessibility (isochrone, gravity, logsum) |
| Dong et al. | 2006 | Accessibility |
| Abdel-Rahim et al. | 2007 | Network Connectivity |
| Berdica and Mattson | 2007 | Network Connectivity |
| Taylor | 2008 | Accessibility (logsum) |
| Peeta et al. | 2010 | Travel time and cost |
| Geurs et al. | 2010 | Accessibility (logsum) |
| Jenelius | 2010 | Network Connectivity |
| Zhu et al. | 2010a | Travel time and cost |
| Zhu et al. | 2010b | Travel time and cost |
| Agarwal et al. | 2011 | Network Connectivity |
| Ip and Wang | 2011 | Network Connectivity |
| Serulle et al. | 2011 | Travel time and cost |
| Ibrahim et al. | 2011 | Travel time and cost |
| Xie and Levinson | 2011 | Accessibility (isochrone) |
| He and Liu | 2012 | Travel time and cost |
| Masiero and Maggi | 2012 | Accessibility |
| Omer et al. | 2013 | Travel time and cost |
| Osei-Asamoah and Lownes | 2014 | Network connectivity |
| Guze | 2014 | Network connectivity |
| Zhang et al. | 2015 | Network connectivity |
| Jaller et al. | 2015 | Travel time and cost |
| Xu et al. | 2015 | Network connectivity |
| Nassir et al. | 2016 | Accessibility |
| Winkler | 2016 | Accessibility (gravity) |
| Ganin et al. | 2017 | Accessibility (gravity) |
| Vodák et al. | 2019 | Network connectivity |

The following sections discuss relevant studies in each group; Table 2.2 consolidates these studies by year and labels them with an applicable group.

2.4.1 Network Connectivity

Graph theory is the mathematical study of networks of nodes connected by edges (links), and is useful for identifying shortest paths on a network. Concepts closely related to graph theory,

such as network vulnerability and network connectivity, have been studied by researchers who have considered resilience. In these studies, researchers tend to define critical links as those that are well connected to many other nodes (directly or indirectly), or as links whose loss easily isolates a number of nodes from the rest of the network (West et al., 2001).

Abdel-Rahim et al. (2007) developed a multi-layered graph approach to examine the resiliency of the traffic signal control system in Boise, Idaho. The researchers determined which traffic signals would be isolated by a failure to a particular power substation, and consequentially the percent of travel paths that would experience diminished levels of service. The research highlighted the degree to which interrelated infrastructure systems – power, telecommunications, and transportation – depend on each other, though the researchers did not attempt to look at the connective resiliency of the transportation network directly.

Agarwal et al. (2011) presented a method to represent a transportation network as a hierarchical, or cluster graph, that can be analyzed more directly for vulnerabilities. Clusters are formed as groups of links and nodes become isolated from each other. These clusters of links and nodes are then grouped together more tightly by including nearby clusters, which creates a “zoomed out” or less complex model where small clusters begin to act as nodes connected by links. In the study, links in the system are damaged, and the resulting connectedness of the network is evaluated. One scenario of importance noted by the authors, however, is that a maximal failure consideration where a node is entirely isolated from the network is unlikely in a real-world network with multiple paths of connectivity. The authors discussed the importance of having damaged networks with high levels of functionality.

Vodák et al. (2019) on the other hand, developed an approach to identify critical links in a network by searching for the shortest independent loops in the network. An independent loop is essentially a way to travel between an origin and a destination over any number of alternative routes. The algorithm progressively damaged one or more links between iterations to determine if nodes become isolated, or cut off from the network. If a node becomes easily isolated or has a higher likelihood of becoming isolated, then there is a higher degree of vulnerability present in the network. This method can both identify critical links in individual networks and provide a means to quantitatively compare networks.

Ip and Wang (2011) addressed the concept of friability, or the reduction of capacity caused by removing a link or node, in order to determine criticality of individual links. The methodology relied on the ability to determine the weighted sum of the resilience of all nodes based on the weighted average of connectedness with other city nodes in the network. The authors determined that the recovery of transportability between two cities largely depends on redundant links between nodes. The authors also commented that most traffic managers are more concerned with the friability of single links rather than the friability of multiple links or an entire system. This suggests that planners and managers may not consider the importance of understanding the impacts of widespread, all-inclusive disaster scenarios.

Guze (2014) conducted a review of the known uses of graph theory before reviewing several other multi-criteria optimization methods. Guze's methodology involved an analysis of the knapsack problem which focused on flow theory in transportation systems and identifying a method to find the best graph solution. Guze's greatest contribution to transportation research at the time was a simplified method for determining shortest path route options on simple networks.

Osei-Asamoah and Lownes (2014) adopted a network analysis methodology that is able to analyze resilience of transportation networks. In this article, the authors evaluated resilience by comparing the biological network of a common mold with a rail network. The network for both the mold and the railway are complexly connected. The “giant component”, a construct of a graph representing its connectivity, is given by:

$$\Phi = \frac{E'}{E} \quad (2.1)$$

where Φ represents the giant component, E represents the level of connectivity before the network is damaged, and E' represents the level of network connectivity after the network is damaged. After the giant component is found, network efficiency is determined using the shortest path available. By combining both the ratio of link connections and network efficiency, the authors draw comparisons between two complex networks. Ultimately, the authors concluded that a denser, more highly interconnected network would perform better when a link is cut due to a larger giant component value.

Zhang et al. (2015) investigated the role of network topology, or the physical layout of the network in a geographic location. The authors provided several examples of network topology types including hub and spoke, grid, and ring networks. After computing resilience indexes, or general resilience levels of each type of network topology, the authors determined that metrics such as throughput, connectivity and average reciprocal distance increased with greater lineage, however these same measures decreased as networks became more widespread. This is likely because larger networks typically have fewer, less dense node connections, and therefore are less redundant.

Each of the graph theoretical approaches discussed in this section tend to break down in efficiency or connectivity as networks become larger. Real-world networks are typically extremely large, with nodes and links numbering in the hundreds, if not thousands. Thus, the connectivity of a node may be high, but may not be an accurate representation of a node's importance. Lack of node importance can be due to several factors, network efficiency Osei-Asamoah and Lownes (2014), network topology Zhang et al. (2015), friability Ip and Wang (2011), or other factors.

2.4.2 Changes in Travel Time

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 could provide an estimate of the criticality of that link or node. If a link or node becomes completely isolated, the travel time to that node or link would increase indefinitely.

Berdica and Mattsson (2007) attempted to examine what the effects of road degradation on Stockholm's transportation network would be if one or more chokepoints were to become damaged or all-together inundated. The authors sought to determine how interruptions affect the system, and how overall system performance was affected by the damaged or lost facility. Users in this method were only given the choice of an alternate route, and the authors acknowledge that this is not entirely reasonable in a real world situation because users would likely change departure or arrival time, mode, or even destination. This method purely attempted to quantify delay experienced by users compared to the original equilibrium state, but does make an attempt to determine a monetary value associated with closure or degradation.

Peeta et al. (2010) constructed a model to efficiently allocate highway maintenance and emergency response resources at locations throughout a network. Each link in the sample network was assigned a specific failure probability based on resource allocation; the model evaluated the increase in travel time resulting from a broken link. The authors applied a Monte Carlo simulation of multiple scenarios, which revealed resource allocation plans with the least network degradation, and thus which links were most critical to the network's operations.

Ibrahim et al. (2011) provided an approach for determining vulnerability of infrastructure by estimating the cost of single link failure based on the increase in shortest path travel time due to increased congestion levels. The authors proposed a hybrid heuristic approach that calculates the traditional user-equilibrium assignment for finding the first set of costs, and then fixes those costs for all following iterations to determine the effects of failure on overall travel time of the system.

Omer et al. (2013) proposed a methodology for assessing the resiliency of physical infrastructure during disruptions. To do this, the authors used a network model to build an origin-destination matrix which allows initial network loading and analysis. Omer's model used several metrics, but the main metric used to determine resiliency is the difference in travel time between a disturbed and undisturbed network. Omer's framework is applied to an actual network between New York City and Boston for analysis. Changes in demand, travel time, mode choice and route choice are tracked for analysis. Omer's framework supports operability of transportation networks (as seen in Section 2.1) due to the way it analyzes networks experiencing suboptimal circumstances. Omers's work identified key parameters that should be measured to assess resiliency during disruptive events including mode and route choice.

Jaller et al. (2015) sought to identify critical infrastructure based on increased travel time or reduced capacity due to disaster. The proposed methodology utilized user- equilibrium to determine proper initial network loading. Then the shortest path between one origin and one destination could be identified. To implement damage to the network, a link was cut, and then the next shortest path was found. This process is followed for all links in the system in order to determine a sense of the criticality of each link to network resiliency. The analysis is carried out for each OD pair, and the nodes which experience the greatest change in travel time are determined to be the most critical. Jaller's methodology allowed traffic managers to identify critical paths for mitigation purposes before the occurrence of disaster through careful analysis.

Ganin et al. (2017) attempted to investigate resiliency through a disruption of 5% of the roadways in 40 urban networks within the United States. The employed methodology determined that Salt Lake City had the most resilient transportation network while Washington D.C. had the least resilient. This determination is based on a comparison of simple gravity models of the identified networks after links are damaged versus before. The authors worked three factors into each model, which account for differences in car- truck ratios, average speed, and average vehicle length. Using a gravity model to determine commuting patterns, the authors were able to estimate the average annual delay per commuter. They used this to determine network efficiency. Ganin et al. noted that traffic delay times (or the travel time caused by a closure) increased significantly as road segments were broken.

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. Some people may choose other modes or destinations, and it is possible that some previously occurring trips might be canceled entirely. It may also be prudent to consider how access changes, and evaluate changes in user choice based purely upon accessibility.

2.4.3 Changes in Accessibility

In a travel modeling context, accessibility refers to the ease with which individuals can reach the destinations that matter to them; this is an abstract idea but one that has been quantified in numerous ways. Dong et al. (2006) provide a helpful framework for understanding various quantitative definitions of accessibility that we will simplify here. The most elementary definition of accessibility is whether a destination is within an isochrone, or destinations accessible within the same distance or time interval from an origin. This measure is often represented as a count (e.g., the number of jobs reachable from a particular location within 30 minutes travel time by a particular mode). Mathematically, accessibility is defined as:

$$A_i = \sum_j X_j I_{ij}; I_{ij} = \begin{cases} 1 & \text{if } d_{ij} \leq D \\ 0 & \text{if } d_{ij} > D \end{cases} \quad (2.2)$$

where the accessibility A at point i is the sum of the all the destinations X at other points j . I_{ij} is an indicator function equal to zero if the distance between the points d_{ij} is less than some asserted threshold (e.g., 30 minutes of travel time). By relaxing the assumption of a binary isochrone and instead using the distance directly, we can derive the so-called gravity accessibility model as

$$A_i = \sum_j X_j f(d_{ij}) \quad (2.3)$$

where the function $f(d_{ij})$ is an impedance function, often a negative exponential with a calibrated impedance coefficient. This gravity accessibility term is included in the gravity trip distribution model (i.e., the gravity model). An extension of the gravity model is to use the logsum term of a multinomial logit destination choice model,

$$A_i = \ln \sum_j \beta_d(d_{ij}) + X_j \beta \quad (2.4)$$

where the parameters β are estimated from choice surveys or calibrated to observed data. The logsum term has numerous benefits outlined by Handy and Niemeier (1997) and Geurs and van Wee (2004); namely, the measure is based in actual choice theory, and can include multiple destination types and travel times by multiple different modes.

Geurs and van Wee (2004) provide a review of accessibility measures such as those above, up to 2004 in a literature review done at the time. Of the papers they reviewed, Vickerman (1974), Ben-Akiva and Lerman (1979), Geurs and Ritsema van Eck (2001), used isochrone type methods. Stewart (1947), Hansen (1959), Ingram (1971), Vickerman (1974), Anas (1983), used gravity style models, and Neuburger (1971), Leonardi (1978), Williams (1978), Koenig (1980), Anas (1983), Ben-Akiva et al. (1985), Sweet (1997), Niemeier (1997), Handy and Niemeier (1997), Levine (1998), Miller (1999) used or suggested logsums. These researchers highlight the importance of using person-based measures such as logsums in evaluating network vulnerability and resiliency.

Taylor (2008) applied logsum-derived accessibility analysis to evaluate the consequences of a tunnel failure in Adelaide, Australia. An accessibility framework capable of evaluating the change in accessibility for a multimodal urban network was designed. The designed framework is capable of determining the ability of an individual to access an activity. Taylor's framework captured five types of choice, namely: activity, time period, trip-base, location, and mode choice,

with key features being activity choice and trip-base (e.g., the origin point of a trip). Each of these choice models use typical multinomial logit models (MNL), with the exception of the mode choice model, which uses a nested MNL model. The main choice considered in the framework is activity choice followed by trip choice. Taylor's proposed framework has been applied to an existing activity based choice model for the Adelaide region, however, the framework operates independently from the parent model.

Using the developed framework, Taylor calculated an “inclusive value” (IV) or logsum, and “consumer surplus” (CS) or utility value. Both the IV and CS values are vital to determining the benefit or dis-benefit associated with the change experienced by users in the individual model scenarios considered. Taylor's accessibility framework, applied as a separate or connected module to the Adelaide model, estimates the IV and CS values using a logsum. These values allowed Taylor to show that more disruption occurs near the failed link than occurs farther away. Additionally, Taylor is able to show that a greater cost (nearly 40 times greater) is experienced by those who live in a TAZ near the link than by those who live in a TAZ located farther away from the failed link. Taylor's framework primarily investigated accessibility on a network for a large city, but could easily be applied on a larger scale.

In the Adelaide model, Taylor breaks one link and then calculates the difference in IV and CS values using:

$$I_n = \log \sum_{r \in R} \exp(\cdot) V_{rn} \quad (2.5)$$

which represents the IV or logsum value, and estimates the CS value using:

$$E(CS) = \frac{1}{\alpha} \log \left(\sum_{j=1}^J \exp(I_j) \right) + \beta \quad (2.6)$$

where the α represents the negative of the coefficient of time or cost from the utility function, and β is an unknown constant that represents the difference between the actual value of CS and the estimated value. The I_j term represents the observable attributes of the possible utility.

Taylor's research highlighted the possibility for a comprehensive model capable of succinctly measuring the dis-benefit caused by a degraded network. Taylor continued by stating that

traffic network simulation models could be considered for future research. Four key needs for future research specifically highlighted at the conclusion of Taylor's article include:

- Development of an efficient algorithm
- Development of improved vulnerability metrics
- Improved techniques for identifying network weaknesses
- Use of network vulnerability indicators in studies of critical infrastructure and the implications of network degradation

Several other authors employed various types of logit models in their research, or attempted to develop a methodology specifically for use in analyzing disrupted networks. Geurs et al. (2010) compared the benefits attributed to various climate change-mitigation land use and transport policies under two different evaluation metrics. The authors directly compared a “rule of half (RoH)” calculation where the travel time reduction is distributed between existing and new travelers on a route with a mode choice logsum derived from utility theory. The authors argued that because the logsum is more comprehensive and inclusive of the full changes to travel demand (capturing the total value of the choice set), the additional benefits attributed to proposed projects are both more realistic and more economically favorable to climate change mitigation policies. They showed this by evaluating the accessibility and travel time changes resulting from land use densification strategies in the national travel demand model for the Netherlands.

Serulle et al. (2011) clarified variables related to resiliency of transportation networks including average delay and transport cost, adjusting interactions, and increasing metric transparency. The authors employed a methodology capable of quantifying resiliency using a fuzzy interference approach – an approach meant to analyze imprecise or vague data – that relates both physical and performance characteristics. The employed approach is able to determine a resiliency index that supports comparative and sensitivity analyses. Accessibility data, including available road capacity, road density, alternate route proximity, average delay, transport cost, and average speed reduction, are analyzed for importance to the integrity of the network.

Masiero and Maggi (2012) used logit-based calculations to determine the value of the indirect costs associated with the closure of a road in terms of economic consequences, including

punctuality for freight transport. In order to properly determine the cost of route closure, the authors also used a method discussed in Koppelman and Bhat (2006) which used model derived coefficients and values to determine the cost of an alternative. The authors implemented their model on a network consisting of a single travel corridor that has experienced long (1 week to 2 months or more) closures in the past in Southern Europe.

Xiangdong et al. (2015) developed network-based measures and computational methods to evaluate transportation network redundancy. This methodology used two dimensions in the analysis: travel alternative diversity and network spare capacity, meaning the number of effective connections available for each OD pair and the congestion effect/choice behavior of travelers. To create the analysis, the authors first constructed a sub-network which only looks at efficient routes. Next, the method counted the number of efficient routes from the origin to all nodes, and then estimates the multi-modal network spare capacity. Each dimension helps evaluate the capacity of the network based on different scenarios. Xiangdong's method supports operability (seen in Section 2.1) by evaluating the capacity of transportation networks using altered or damaged networks.

Nassir et al. (2016) applied a nested logit model to examine a transit network in Australia. The main contribution in Nassir et al. (2016) is an improved methodology for calculating accessibility measures related to transit, accomplished by developing a method to account for diversity information. The authors did note, however, that this measure is best applied to models with complex transit systems that serve large portions of the community. One important observation, however, is that users did not always choose the fastest route, nor did they always choose the route with the highest utility. He and Liu (2012) took another look at the after effects of the I-35W bridge collapse previously discussed. A key contribution of He and Liu (2012) is that people often initially base route choice on what they assume will be best based on past experience. So, over time, users adjusted their route choice to an altered network. The true implication here is that users did not automatically choose the best new route given an altered network, rather, it takes users time to learn how the new network functions.

Winkler (2016) proposed a travel demand model that is valid for all networks, especially those with more than one constraint, where a constraint is a limiting factor present in the model, such as the maximum number of trips produced at an origin, or the maximum number of receivable trips at a destination. A logsum approach fails when two or more sets of constraints exist. The

proposed method uses CS, a measure of benefit, to derive a method capable of analyzing a doubly constrained network. Traditionally, constraints are used for trip distribution, and the best known model is the doubly constrained gravity model. Winkler's methodology utilized a model that uses production, distribution, and mode choice as inputs. The methodology shows that models can be used to help determine outputs for multi-constraint MNLs. Winkler uses the change in CS as the logsum difference, which would allow utility to be estimated across the transportation network being modeled.

2.5 Summary

The lessons learned from the events in Minneapolis and Atlanta demonstrate that when transportation networks are damaged or degraded by link failure, multiple changes result. Traffic diverts to other facilities and other modes, and some people make fundamental changes to their daily activity patterns, choosing new destinations or eliminating trips entirely. Numerous other researchers have identified methodologies to capture the effects, or at least have made quality attempts to capture the costs of these potential changes to accessibility in modeled crisis events. From this extensive review of existing literature, we are able to see that no one has attempted evaluate the relative systemic criticality of highway links on a statewide network using a logit-based model sensitive to changes in route path, destination choice, and mode choice. Doing so would provide a method for determining network vulnerabilities using estimates of dis-benefit that consider the entire available choice set, and estimates which account for user choice.

CHAPTER 3. MODEL DESIGN AND IMPLEMENTATION

3.1 Overview

The objective of this study is to evaluate the relative systemic criticality of highway links on a statewide network using a logit-based model sensitive to changes in route path, destination choice, and mode choice.

In this chapter, some of USTM's properties are described, and additional detail is given as to why USTM is not entirely suitable for this study as presently constituted. A new model framework designed to evaluate resilience using a logit-based choice model on USTM's network is then presented. Implementation of this new model within the CUBE travel demand modeling software is also described.

3.2 Utah Statewide Travel Model

UDOT manages an extensive highway network consisting of interstate highways (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 places severe constraints on possible redundant paths in the highway network outside and between external access points. 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.

USTM is developed and maintained by the travel demand modeling group at UDOT, and focuses exclusively on long-distance trips. Within Utah, there are five travel demand models developed for urban centers under the purview of Metropolitan Planning Organizations (MPOs). USTM incorporates these other models as inputs and covers the rural areas lying outside of the MPO model regions. Consequently, USTM covers the highway facilities across the entire state,

and incorporates the MPO models developed by the Wasatch Front Regional Council (WFRC), Mountainland Association of Governments (MAG), Cache Metropolitan Planning Organization, and the Dixie Metropolitan Planning Organization. Additionally, the Summit/Wasatch Travel Demand Model is incorporated into USTM (Utah Department of Transportation, 2021a). 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 incorporated. USTM can, however, provide the following data elements:

Highway Network including free flow and congested travel speeds, link length, link capacity estimates, etc.

Zonal Productions available for all zones by purpose, including those in the MPO region areas

Calibration Targets USTM base scenario estimates of mode split and trip length that could be used to calibrate the utility coefficients of a new model

Each of the local travel demand models and USTM employ a gravity-based trip distribution model. The gravity model assumes that trips between OD pairs are proportional to total productions P and attractions A throughout the state. That is, all productions will be attracted to a location based on the size of a location (i.e., a location's attractiveness) and the impedance (or friction) factor between the OD pair. A mathematical representation of the gravity model is given by:

$$T_{ij} = \frac{P_i * (A_j F_{ij})}{\sum_{j \in J} (A_j F_{ij})} \quad (3.1)$$

where T_{ij} represents the trips made between an origin i and a destination j among all destinations J , P_i represents the productions at origin i , A_j represents the attractions and destination j , and F_{ij} is the impedance factor between an *OD* pair. The friction factor (also known as the impedance, or resistance to movement) between two zones can be represented in a number of ways, such as with a negative exponential function:

$$F_{ij} = \alpha \exp(-\beta * d_{ij}) \quad (3.2)$$

where d_{ij} is the distance or cost between zones i and j , and α and β are calibrated parameters. In the gravity model, as the distance between an OD pair increases, users become less likely to make trips between that OD pair.

A primary weakness of gravity-based distribution models is their inability to consider multimodal impedances or other attributes of a destination other than a destination's size (as represented by A_j in Equation 3.1). The impedance factor in Equation 3.2 asks an implicit question with its distance or cost variable d_{ij} : which mode is used for the trip? In almost all cases, automobile distances or costs are asserted as the only option, but if a destination happens to be close by rail and far by highway, the gravity model will not be able to incorporate this unless a mode split function is carried out first.

Alternatively to gravity models, logit-based models are becoming increasingly more popular for trip distribution. Logit-based destination choice models improve model sensitivity compared with gravity models, and are advantageous because they possess an increased ability to introduce additional variables and reflect other statistical assumptions into a model (Travel Forecasting Resource, 2021). A typical choice model is made up of a combination of utility and probability values in the following equations:

$$\mathcal{P}_{ij} = \frac{e^{u_{ij}}}{\sum_{j \in J} e^{u_{ij}}} \quad (3.3)$$

where \mathcal{P}_{ij} represents the probability of trips made between an origin i and a destination j among all destinations J , and u represents the utility. Next, the logsum calculation is used. The logsum is similar to the denominator of the probability function, however the logsum captures the total value of the choice set, and is interpreted as the benefit — or dis-benefit — experienced by users in a choice model,

$$Logsum_i = \ln \sum_{j \in J} \exp(f(\beta, u_{ij}, A_j, \gamma, t_{ij})) \quad (3.4)$$

Where β represents a mode choice coefficient, u_{ij} represents the utility, A_j represents the attraction at zone j , γ represents a DC parameter, and t_{ij} represents the travel time between an OD pair.

The ability to incorporate multiple types of data, as in Equation 3.4, as well as improved methods for determining trip distribution, mode choice, and destination choice all allow logit-based models to add an additional layer of sensitivity into estimations of trips between OD pairs on a road network. Consequently, logit-based travel demand models are better equipped to estimate the choice-based effects caused by major changes to a road network, such as link loss or major link degradation caused by adverse natural or man-made events.

Destination choice models explicitly consider multimodal accessibility, such as accessibility by automobile, non-motorized trip, or transit. The ability to consider accessibility from a multimodal perspective gives a user the ability to choose the location of their destination based on a variety of factors including mode accessibility (i.e. ease of access to a mode of transport). The information derived from the socioeconomic data primarily comprises the size term, which is a measure of the appeal or attractiveness of one destination when compared with another destination. The DC size term is discussed in further detail in Section 3.6.

A critical feature of logit-based choice models – described briefly in Section 2.4.3 – is that they are more versatile than traditional modeling methods, with the ability to incorporate different types of data — *and* account for user choice. Additionally, logit-based choice models are better able to measure the changes in accessibility of a destination due to network changes than other models because of their adaptive nature. As such, logit-based models are typically used in new or more advanced travel models.

Logit-based destination choice models are becoming increasingly common in four-step and other modern travel models. However, no logit-based destination choice models have been implemented within an MPO model in Utah or within USTM except for some home-based work trips in the WFRC/MAG model. As a result, the local MPO models, and therefore USTM, are not sufficient to analyze accessibility on their own as proposed by this thesis. Therefore, a new standalone model must be developed to examine choice-based resiliency in Utah.

3.3 Model Design

An initial framework was developed to model the impact of link loss on the USTM network. The model framework used to create the presented model consists of the following steps:

Skim Network In this step, the model determines the shortest path by AM peak travel time on the USTM network between each origin and destination. The model also determines the distance of the shortest time path. Transit times are given by an external data source.

Mode Choice (MC) Logsum The MC logsum is a function of the travel impedances and serves as an impedance term in the destination choice model. The MC logsum contains utility functions that determine the probability and logsum associated with travel between each OD

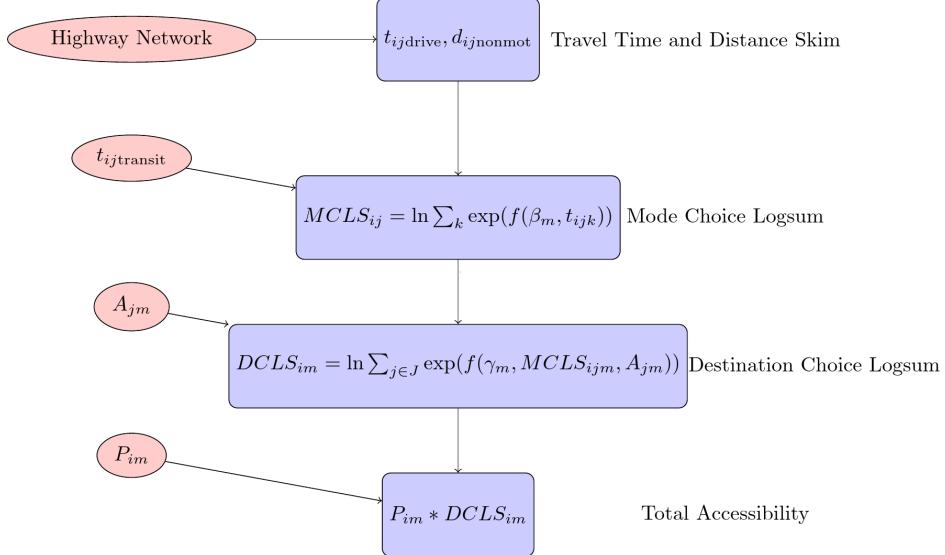


Figure 3.1: Model framework.

pair. The MC model also contains constants and coefficients that can be used to calibrate and adjust the utility equations, determining the mode choice probabilities.

Destination Choice (DC) Logsum The destination choice logsum is a function of the travel impedances (represented by the MC logsum) and the attraction size term of each destination zone. This is the key evaluation metric of the model. The attraction size term is determined using socioeconomic data for each destination zone given by USTM.

The model framework as used is presented in Figure 3.1, where inputs are denoted with red ovals, and functions are denoted with purple rectangles. The model framework is designed to capture the utility-based accessibility for a particular origin zone i and trip purpose m . The trip purposes considered in the presented model include Home-based work (HBW), Home-based other (HBO), and non-home based (NHB) trips are primarily considered. Other trips purposes, such as recreation (REC) trips and Freight trips were not included because they either have fixed OD pairs, or do not generate a significant number of trips. The model begins with a travel time skim procedure, to determine the congested travel time from zone i to zone j by auto (i.e., t_{ijauto}), as well as the shortest network distance (i.e., d_{ijnmot}) for non motorized modes using the USTM network. The transit travel time skim is fixed, assuming that transit infrastructure would not be affected by changes to the highway network, thus $t_{ijtransit}$ is held fixed. Throughout this section, acronyms

from the model framework will be described and 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} and distance for all modes $k \in K$, the model computes MC utility values. The multinomial logit MC model describes the probability of a person at origin i choosing mode k for a trip to destination j :

$$\mathcal{P}_{ijm}(k) = \frac{\exp(f(\beta_m * t_{ijk}))}{\sum_K \exp(f(\beta_m * t_{ijk}))} \quad (3.5)$$

The log of the denominator of this equation is called the MC logsum, $MCLS_{ijm}$ or $MCLS$ and is a measure of the travel cost by all modes, k , weighted by MC utility parameters β that may vary by trip purpose m . The parameter values are described in greater detail in Table 3.1.

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

$$\mathcal{P}_{im}(j) = \frac{\exp(f(\gamma_m, MCLS_{ijm}, A_{jm}))}{\sum_J \exp(f(\gamma, MCLS_{ijm}, A_j))} \quad (3.6)$$

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

The $DCLS$ measure is relative, but can be compared across scenarios. The difference between the measures of two scenarios,

$$\Delta_{im} = DCLS_{im}^{\text{Base}} - DCLS_{im}^{\text{Scenario}} \quad (3.7)$$

provides an estimate of the accessibility lost when $t_{ij,\text{auto}}$ changes due to a damaged highway link. This accessibility change is *per trip*, meaning that the total lost accessibility is $P_{im} * \Delta_{DCLS}$ where P is the number of trip productions at zone i for purpose k . This measure is given in units of dimensionless utility, but the MC cost coefficient β 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:

$$\text{Cost} = \sum_I \sum_M -1/\beta_{\text{cost},m} * P_{im} \Delta_{im} \quad (3.8)$$

For comparison to a simpler resilience method that only includes the increased travel time between an OD pair, we compute the change in travel time, Δt_{ij} , between two scenarios, and multiply the increase in time by the number of trips in USTM. This is converted to a cost by a value of time directly from USTM and UDOT (Utah Department of Transportation, 2020). These values can be seen in Table 3.2 at the end of this chapter. Converting to a cost gives an estimate with units in dollars per day. This conversion is accomplished with

$$\text{Cost}' = \sum_I \sum_J \sum_K VOT_m * T_{ijmkt_{ijk}} \quad (3.9)$$

Deriving a simpler way to calculate resilience was necessary for two reasons. First, data were not readily available for trips that do not have flexible OD pairs, such as freight trips. Other purposes included in USTM, such as recreation trips (REC) and trips that occur between external nodes (i.e., inter-state trips that do not originate or terminate within the state), make up very small percentage of total trips. Second, a method capable of creating data that could be compared with the results of the presented logsum model was needed. Calculating dis-benefit based solely on increased travel time provides valuable insight and tools for further analysis of the model results.

3.4 Model Inputs

Several inputs derived from various sources are needed for the presented model to properly function. First, a highway network is needed which contains attribute data needed to extract information about travel times and distances between transportation analysis zones (TAZ). Additionally, a transit network is needed because USTM does not explicitly consider transit. Non-motorized distances are considered in the following sections.

3.4.1 Transportation Network

The presented logsum model requires an understanding of the travel time and distance between zones by multiple modes, and how these distances change when a link in the network is damaged or destroyed. To measure the automobile, transit, and non-motorized trip times, initial data were needed for each trip mode.

The highway network is made up of both the urban and rural highway networks for the whole state of Utah. The highway network contains many link- and node-attribute data including street name, link distance, lanes, functional classification, TAZ, county name, as well as speed limits and travel time data for five different times of day. Of particular interest from the available information was the *AM_TIME* which contains the travel time in minutes for the AM time period along a link and the *DISTANCE*, which contained the linear distance between nodes along a link. The *AM_TIME* was used to determine the travel time between an origin and destination. The *DISTANCE* was used to measure the network distance between the shortest OD pair based on AM travel time.

The highway skim module creates an output matrix (i.e., the highway skim) of travel times and distances between OD pairs and must be created before automobile (AUTO) and non-motorized (NMOT) trips can be incorporated into the model. We used the *AM_TIME* and *DISTANCE* variables available in the highway network file to create a matrix of distances and shortest travel times between all OD pairs in the USTM network. The output matrix forms the basis for further analysis by providing the needed automobile and non-motorized information for the other modules in the model.

3.4.2 Transit Network

Transit network resiliency is outside the scope of this project. Accordingly, transit services are fixed, meaning that changes to the network do not influence transit availability on the network. However, transit is an important mode to include in the model because of ample availability in Salt Lake City, and should be considered in future model development if applicable for more robust analysis. Among MPO models in Utah, only the model jointly operated by the WFRC and MAG model include a substantive transit forecasting component. The transit travel time skim

from the WFRC/MAG model was used for the MC model in Equation 3.5; the zonal travel time between the smaller WFRC/MAG model zones was averaged to the larger USTM zones using a crosswalk, or matrix transformation function, 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 non-motorized trip distances are held fixed, similarly to the transit distances. It was determined that the longest distance a pedestrian would commute via a non-motorized mode is 2.5 miles or less. The decision to hold non-motorized trips constant was made for several reasons, mainly because pedestrians can usually access routes that are not available to vehicles, such as neighborhood walkways/bikeways or other shortcuts available only to pedestrians and cyclists. Additionally, pedestrians are often also able to cut through or traverse the perimeter of an area where a highway may be degraded or damaged. non-motorized trips also typically have higher accessibility to smaller roads or side-streets that would not be included with the USTM network.

3.4.3 Socioeconomic Data

The model uses socioeconomic data to estimate the trip productions at each zone. The socioeconomic data, which is adapted from the Utah Travel Survey (UTS) conducted in 2013, contains TAZ related information such as county name, total households, household population, total employment, and a breakdown of employment by job category, among other data. This information is useful when determining the DC attractions, or size term because they can be used to describe population density of residential zones, or business density and type of commercial zones in a network.

3.5 Mode Choice Model

The MC module calculates the MCLS between each OD pair in the network for each trip purpose. The trip purposes considered in the model are HBW, HBO and NHB. The MC module includes the highway skim, the transit skim, and the MC coefficients and constants as inputs.

The MC constants and coefficients used in the model were extracted from USTM where possible, or adapted from the Roanoke (Virginia) Valley Transportation Planning Organization

Table 3.1: Choice Model Coefficients

| Variable | HBW | HBO | NHB |
|---|---------|---------|---------|
| Destination Choice | | | |
| γ_{hh} Households | 0.0000 | 1.0187 | 0.2077 |
| γ_{off} Office Employment | 0.4568 | 0.4032 | 0.2816 |
| γ_{oth} Other Employment | 1.6827 | 0.4032 | 0.2816 |
| γ_{ret} Retail Employment | 0.6087 | 3.8138 | 5.1186 |
| γ_{MCLS} Mode Choice Logsum | 1 | 1 | 1 |
| κ_1 Distance | -0.0801 | -0.1728 | -0.1157 |
| κ_2 Distance squared | 0.0026 | 0.0034 | 0.0035 |
| κ_3 Distance cubed | 0.0000 | 0.0000 | 0.0000 |
| Mode Choice | | | |
| $\alpha_{TRANSIT}$ Transit constant | -0.3903 | -1.9811 | -2.2714 |
| α_{NMOT} Non-Motorized | -1.2258 | -0.3834 | -0.8655 |
| β_{tt} Travel Time [minutes] | -0.0450 | -0.0350 | -0.0400 |
| β_{cost} Travel Cost [dollars] | -0.0016 | -0.0016 | -0.0016 |
| β_{d1} Walk Distance (less than 1 mile) [miles] | -0.0900 | -0.0700 | -0.0800 |
| β_{d2} Walk Distance (1 mile or more) [miles] | -0.1350 | -0.1050 | -0.1200 |

Note: The data in this table were extracted from the USTM, RVTPO, and SWIM models.

(RVTPO) or SWIM models. The travel time represented with t_{ij} , travel cost represented as a variable C_{ij} , walk distance (i.e., less than 1 mile) represented as $d_{<1MILE}$, and walk distance (i.e., 1 mile or more) represented as $d_{>1MILE}$ are the coefficients for the HBW, HBO, and NHB purposes. The MC coefficients were adapted from USTM and supplemented with coefficients from the RVTPO travel model where USTM had gaps in the data (Roanoke Valley Transportation Planning Organization, 2017; Oregon Department of Transportation, 2017). This model was selected as a source for these coefficients due to its simplicity and analogous data elements to the purpose of the presented model. The values for each of the coefficients are in Table 3.1. The alternative-specific constants in the model were calibrated to regional MC targets developed from the UTS using methods described by Koppelman and Bhat (2006).

The following are sample utility equations for each of the modes considered in the model, where α denotes MC constants, β denotes MC coefficients, γ denotes destination choice parameters, and C will denote other variables which are typically zonally related. Additionally, the

equations used to calculate the MCLS are shown:

$$U_{AUTO_{ij}} = \beta_{tt} * tt_{ij}^{AUTO} + \beta_{cost} * cost_{ij}^{AUTO} \quad (3.10)$$

$$U_{TRANSIT_{ij}} = \alpha_{TRANSIT} + \beta_{tt} * tt_{ij} + \beta_{cost} * cost_{ij}^{TRANSIT} \quad (3.11)$$

$$U_{NMOT_{ij}} = \alpha_{NMOT} + 20 * (\beta_{tt} * tt_{ij} + \beta_{cost} * cost_{ij}^{NMOT}) \quad (3.12)$$

$$Logsum_{ijm} = \ln\left(\sum_K \exp(U_{ijmk})\right) \quad (3.13)$$

From the equations above, several aspects between the three MC utility equations are apparent. First, the transit and *NMOT* utility equations both have a constant, denoted by a α , included. The *AUTO* equation does not have a constant because auto serves as the reference alternative in the presented model. Second, both the *AUTO* and *NMOT* equations account for a distance variable. Finally, each of the three utility equations account for travel time, either in the form of an in-vehicle travel time coefficient, or another modified factor. The *NMOT* utility equation is not calculated using a specific coefficient for time. Instead, the *NMOT* distances are multiplied by an assumed walking speed of 20 minutes per mile. This is common practice in other choice models for *NMOT* trips. After the MC utilities were calculated, it was necessary to calculate the logsum for each trip purpose m , as seen in Equation 3.13.

3.6 Destination Choice Model

The DC module includes the MCLS, the socioeconomic data extracted from USTM, and DC parameters as inputs, all of which are needed to estimate the DC utility value. The DC utility equation consists of three parts: a size term A_j , a travel impedance term (MCLS value), and a several distance and cubic calibration polynomial coefficients and their corresponding values.

The terms in the DC utility equation follow the same conventions mentioned previously, however, d_{ij} is used to represent the distance variable in the calibration polynomial:

$$U_{ijm} = \gamma_{MCLS} * MCLS_{ijm} + \log(A_{jm}) + f(d_{ij}) \quad (3.14)$$

where $f(d_{ij})$ is a calibration function discussed later in this section.

Coefficients for the size term and travel impedance terms were adapted from SWIM Oregon Department of Transportation (2017) for all purposes except HBW. Instead, these coefficients were adapted from the RVTPO model Roanoke Valley Transportation Planning Organization (2017). This was done because SWIM does not account for work trips in the same way as it does other trip purposes. The distance polynomial coefficients were calibrated to targets developed from UTS.

The MCLS value is applied to the DC model utility equation as the impedance term, or a measure of a user's resistance to using the specified path or mode. This is like the impedance factor in the gravity model discussed in Section 2.4.3. Feeding the MCLS value into the DC module is what allows users to choose a destination while considering accessibility from all modes. In these equations, the log terms serve to create the logsum values needed to find the DC logsum values later on. The size term, which will be discussed in greater detail later in this chapter, helps to determine the attractiveness of a destination zone compared to another destination. The cubic polynomial terms serve as a method to calibrate the DC module outputs and will also be discussed in greater detail later in this chapter.

The socioeconomic data is used in the DC model to compute the size term, or the attractiveness of a destination in the model. The size term is made up of statistical data about a zone. The size term is created using various DC parameters combined with corresponding socioeconomic data to determine the size or attractiveness of a zone. The size term equation was partially adapted from the Oregon Statewide Integration Model (SWIM) (Oregon Department of Transportation, 2017).

This data was published in 2013 as part of the UTS and made available via UDOT (Resource Systems Group, Inc., 2013). The size term equation can be seen below:

$$A_{jm} = \gamma_{m_{off}} * \text{office}_j + \gamma_{m_{oth}} * \text{other}_j + \gamma_{m_{hh}} * \text{hh}_j + \gamma_{m_{ret}} * \text{retail}_j \quad (3.15)$$

where each different zonal socioeconomic element in the UTS data influences utility through a corresponding γ parameter.

The DC logsums are calculated by summing the exponentiated values in each row in the DC utility matrix, together. The process used to accomplish this can be seen in Equation 3.14. The purpose of taking the log of the entire row is to measure the logsum between a zone and all the

other zones at the same time. By doing this, we can determine the overall change in accessibility between scenarios by TAZ, which is the measurement of interest. The logsum tells us the value of a zone based on a user's ability to choose a mode and destination.

3.7 Model Calibration and Validation

Modeling efforts can produce a wide range of estimates, and it is important to check that model outputs are estimating trips accurately according to available trip data. To ensure the model was accurately reflecting trips by MC in the USTM model, the presented model must be calibrated accordingly. To do this, target values were extracted from USTM for each trip purpose.

3.7.1 Trips by Purpose and Mode

In order to calibrate the model, trip totals needed to be calculated by purpose (T_{ijm}) and by mode (T_{ijmk}). To find the trips by purpose (T_{ijm}), the probability of a trip occurring between an OD pair needed to be determined. Likewise, to find the trips by purpose and mode (T_{ijkm}), we multiplied the T_{ijm} by the MC probabilities calculated during the MC module. A mathematical representation of this can be seen in the equations below:

$$T_{ijm} = P_i * \mathcal{P}_{ijm} \quad (3.16)$$

Where P_i is the productions at zone i, and,

$$T_{ijkm} = T_{ijm} * \mathcal{P}_{ijk} \quad (3.17)$$

The ability to account for trips by purpose and by mode allows us to determine information about how well the model is calibrated, and the utility values can also be used to determine the logsum calculations, which are capable of accounting for more than one type of data.

3.7.2 Calibrating Choice Constants

The utility functions in Equations 3.14 and 3.15 contain calibration constants which are adjusted to calibrate the model. Model calibration is completed by iteratively adjusting the MC

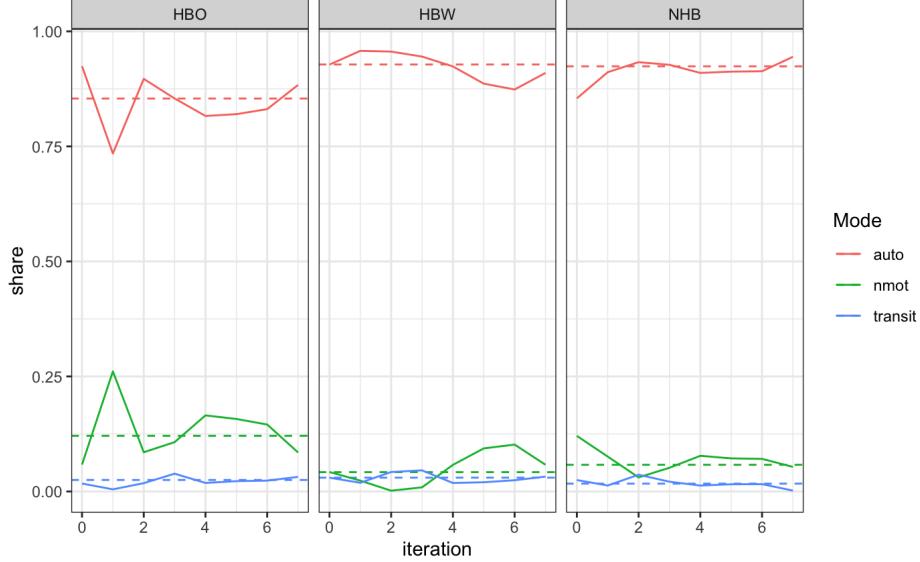


Figure 3.2: Mode choice splits by trip purpose.

constants and DC constants to match extracted target values. The nature of the presented model causes the MC and DC portions to interact. As such, the best method for calibration was to iteratively run the model, changing the MC constants and DC parameters after each new iteration was complete.

To calibrate the MC constants, the alternative specific constants must be adjusted so that the mode split target extracted from USTM closely matches the model mode split values. A multinomial logit model will use alternative-specific constants to match a particular sample share. By adjusting these constants, it is possible to match a MC model to target values. Figure 3.2 shows the target values for each mode represented as a dotted line, and shows the change of the MC calibration constants (and the target shares for each purpose) over the five iterations; the first iterations moved the calibration the most, with some adjustment over the following iterations. Overall the fit is fairly good.

The DC parameters were also calibrated, however this process differed slightly from the MC constant calibration process. A destination choice model is also a multinomial logit model, but this model cannot have alternative-specific constants because of the high numbers of alternatives (one alternative for every zone). Instead, the destination choice utility equation can include a calibration polynomial that adjusts the implied utility to match a trip length frequency distribution

(TLFD) extracted from USTM. In this model, a cubic polynomial is included as the destination choice calibration term seen below:

$$f(d_{ij}) = \kappa_1 d_{ij} + \kappa_2 d_{ij}^2 + \kappa_3 d_{ij}^3 \quad (3.18)$$

where d_{ij} represents the distance from i to j and each of the $\kappa_1, \kappa_2, \kappa_3$, are calibrated to minimize the difference between the model and target trip length frequency distribution. The target values for calibration are derived from USTM. The cubic polynomial in Equation 3.18 — which is part of the DC utility in Equation 3.14 — was applied and calibrated to match the target TLFD values from USTM. The final calibration values are presented in Table 3.1.

3.7.3 Calibration Results

To ensure that calibration efforts were successful, it was necessary to compare the TLFD results from USTM and the presented model. A TLFD script that could divide trips into distance bins was created. Dividing the trips into distance bins allows for the breakdown of resiliency trip frequencies by destination, which can then be compared to the original USTM values. Initial target values for total trips by purpose were extracted from USTM to ensure that trips in the presented model were being conserved. Trip totals were compared using the TLFD outputs to ensure trips of similar lengths were being estimated, and to the total trips by purpose and mode to ensure trip conservation.

Final trip length distributions for each purpose are similar to the extracted USTM target values for both the TLFD comparison and the overall total value comparison. Additionally, Figure 3.3 shows the original versus the final TLFD for the USTM and resilience models. The fit for both is similar, though there is some variation present between each trip purpose considered.

3.8 Method to Calculate Costs for Non-model Purposes

Some trip purposes contained in USTM did not have enough available data to include in the logsum portion of the model or did not have significant impacts and were left out of the logit-based model calculation. This section will discuss other methods by which costs associated with

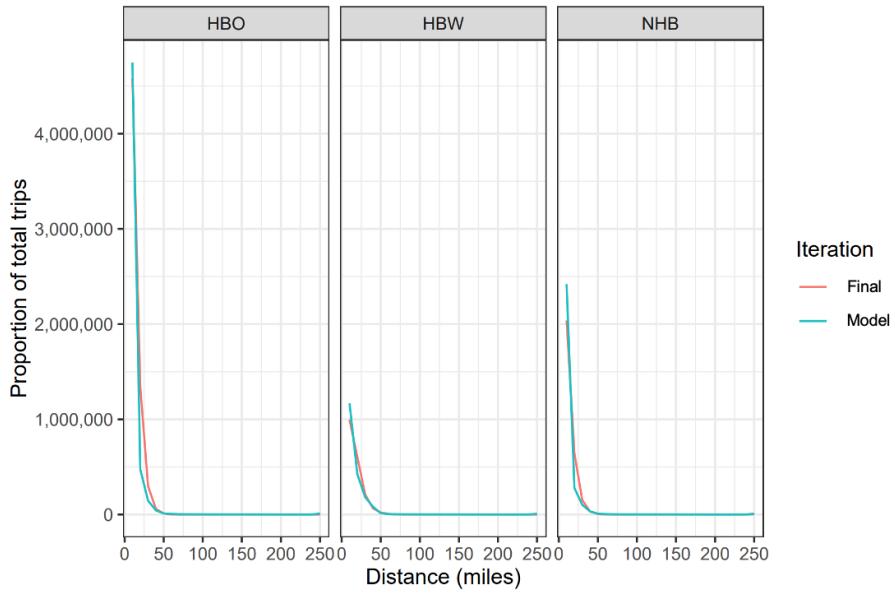


Figure 3.3: USTM target and final iteration trip length frequency distributions.

each link could be calculated, especially for those purposes not primarily included in the presented model and for comparison purposes.

Purposes including freight, recreation (REC), and home-based college (HBC) trips were evaluated using overall travel time change. These purposes are either rigid in their origins and destinations, as is the case with most freight trips, or have much smaller frequencies than do the three main trip purposes HBW, HBO, NHB included in the model. At the same time, the data needed to create logsum calculations for these excluded purposes was not readily available. As a result, the costs associated with these trip purposes was computed based on the increase, or change, in travel time between the base scenario and an alternative scenario.

The travel time difference is calculated by comparing the change in travel time between the base scenario and any alternative scenario. The base scenario highway skim module chooses a route between an OD pair based on the shortest travel time, not the shortest distance. Thus, the difference in travel times always remained the same, or increased. The distances, however, could become shorter, as the shortest distance between an OD pair was not always the fastest by time.

Table 3.2: Values of Time for Time Difference Calculations

| Freight | Auto | Logsum | |
|---------|-------|--------|------------|
| 94.04 | 17.67 | 16.87 | Dollars/Hr |
| 156.73 | 29.45 | 28.11 | Cents/Min |

Equation 3.19 shows a representation of how differences in travel time were calculated:

$$\Delta tt_{ij} = ScenarioTime_{ij} - BaseTime_{ij} \quad (3.19)$$

Finding the difference in travel time for each scenario allows for additional costs to be incorporated that are not included in the logsum calculation performed on the HBW, HBO, and NHB purposes.

Applying a VOT evaluation, the cost associated with link closure per day can be measured for each of the purposes not included in the main logsum analysis. Freight trips and auto trips have different values of time in USTM, thus the calculated travel time change was multiplied by different VOTs for each purpose. For passenger vehicle trips, a VOT of \$17.67 was used, while for freight trips, a VOT of \$94.04 per hour was used. These values were extracted from USTM and verified by UDOT's Asset Risk Management Guide (Utah Department of Transportation, 2020). Additionally, the VOT for the logsum method equates to \$16.87 per hour as seen in Table 3.2. The method for deriving this value is shown in ???. The auto VOT for the logsum and travel time methods are similar, with a difference of about \$0.80. The difference in these values would not make an appreciable difference in the cost estimates between the two methods.

The conversion between the measured DCLS and the actual cost for the logsum method differs from the conversion for the travel time method. In Table 3.1, the coefficient β_{cost} is equal to -0.0016. To convert between the change in DCLS, or dis-benefit, and the monetary cost to a single user for each purpose, Equation ?? must be used. This gives an estimate of the cost experienced by the whole network as a result of the closure of a single link.

3.9 Summary

The creation of a logit-based model, which is sensitive to mode and destination choice, allows for more sensitive and robust estimations of accessibility because of the ease with which additional data types can be incorporated into the model. The model also accounts for modes that are not flexible in the case of link closure. The presented model is capable of analyzing the effects of road closure on mode and destination choice, and it can estimate overall dis-benefit (in dollars) experienced by road users per day.

CHAPTER 4. MODEL APPLICATION

4.1 Overview

In this chapter, model described in Chapter 3 is applied to evaluate the relative systemic criticality of highway links on a statewide network using a logit-based model sensitive to changes in route path, destination choice, and mode choice. To do this, the model is applied to scenarios where critical highway links have been removed from the USTM network. This chapter includes first, a detailed analysis of a single scenario, where I-80 between Salt Lake and Tooele Counties is severed. Then, the model output is compared 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 41 individual scenarios, with 40 of those scenarios involving link closure scenarios throughout the state.

4.2 Vulnerable Link Identification

In order to determine which links on the USTM network might be most critical, a method must be developed to identify links of interest for analysis. Currently, UDOT uses an online Risk Priority Analysis GIS toolkit created by both BIO-WEST and UDOT, which grades highway links based on several criteria, including:

- Threat (e.g., rock fall/flood, etc.)
- Probability of threat
- Cost to replace
- User Costs (e.g., AADT and Truck Volume)

This tool, combined with information gathered from the research team and UDOT officials, 40 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.

After identifying locations of interest on the network, the model is applied to each of the selected scenarios. In each scenario, an individual highway link is removed from the model highway network. Some of the links identified by AEM Corporation, the Utah Department of Transportation, or the research team are also examined. The locations of each of the 40 selected links are shown in Figure 4.5, and are then analyzed one by one. The final results of each scenario are presented in the following sections. First, a detailed analysis of a single scenario are presented, however.

4.3 Analysis of I-80 at Tooele / Salt Lake County Line

This section outlines an in-depth analysis that was conducted to ensure the presented model was accurately describing trips likely behavior with OD pairs in the targeted area around a severed link. This analysis was done on a link between Tooele and Salt Lake City, Utah, which is located close to the county line. A map, with the approximate location of road closure can be seen in Figure 4.1.

This detailed analysis is useful because it provides a closer look at the way the model works, capturing trips between two population centers. Scenario 50, which is located along I-80 between Tooele and Salt Lake Counties was examined here. The localized analysis shows that the majority of trips affected by damage to this link either originate or terminate in one of the two counties, as expected. These results can be seen in Table 4.1. Another method used to compare results is the travel time method, which serves to capture trips that have fixed OD pairs such as freight and recreational trips. This localized analysis also looks at this method.

Table 4.1 compares the overall cost estimates between the logsum and travel time methods, and the specific cost for trips originating in Tooele County. We can see that the logsum method captures \$123,042.44 of expenses experienced by road users due to the closure of the link across the whole network. Specifically, for trips originating in Tooele County, the logsum analysis using the Resiliency Model captures \$118,766.19 of expense, which is approximately 96.52% of the total

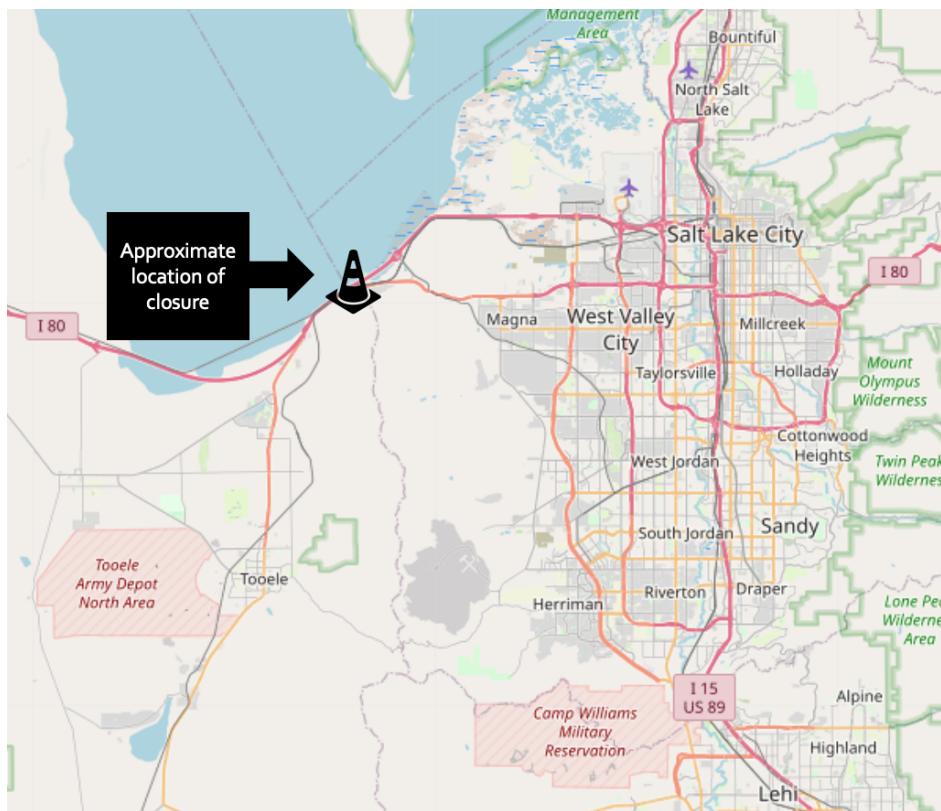


Figure 4.1: Approximate location of the I-80 closure on the Tooele/SL County line.

expense experienced statewide. A further breakdown of expenses experienced at the local level for trips originating in Tooele County can be seen Table 4.1.

The data supports the conclusion that the model is effectively capturing trips originating in Tooele based on the amount of cost captured, shown in Table 4.2 as a percent capture rate. Additionally, when the travel time method of analysis is examined, it can be seen that the cost estimated is equal to \$11,377,504.92 for the whole network, and \$781,015.04 for only those trips originating in Tooele County. These two estimates include Freight trips, which have much higher cost estimates than do any of the other trip purposes. Though some Freight trips do originate in Tooele County, many more Freight trips traverse I-80, which cause the cost estimate to increase greatly when the travel time method is used.

In order to better visualize the change in DCLS experienced in Tooele and Salt Lake Counties, several choropleth maps were generated. Each of the three maps depicts the change in DCLS

using a different method of analysis. First, the total change in DCLS is calculated using,

$$DCLS_{HBW\ Original} - DCLS_{HBW\ Broken} \quad (4.1)$$

is shown in Figure 4.2. Second, the percent change in DCLS is calculated using,

$$\frac{DCLS_{HBW\ Original} - DCLS_{HBW\ Broken}}{DCLS_{HBW\ Original}} \quad (4.2)$$

is shown in Figure 4.3. Finally, The total change in DCLS weighted by the number of households located within a TAZ is calculated using,

$$HH * DCLS_{HBW\ Original} - DCLS_{HBW\ Broken} \quad (4.3)$$

is shown in Figure 4.4. In each of these choropleths, darker red zones represent zones with greater change when compared with lighter zones.

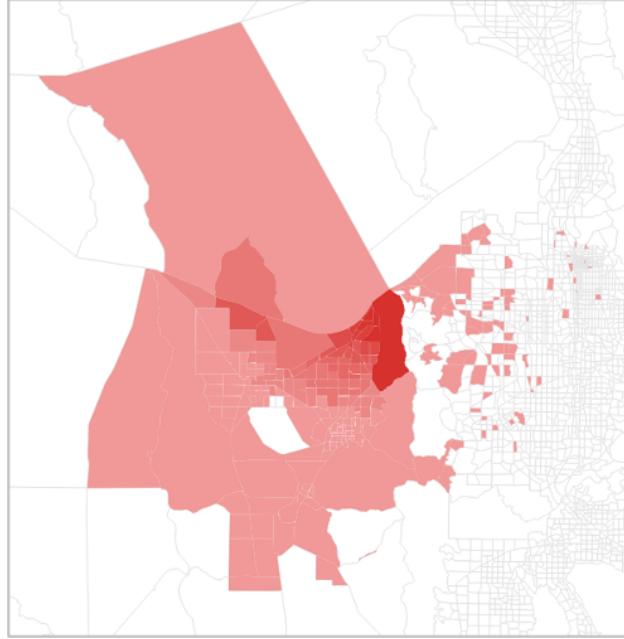


Figure 4.2: Total change in DCLS by TAZ in Tooele and Salt Lake Counties.

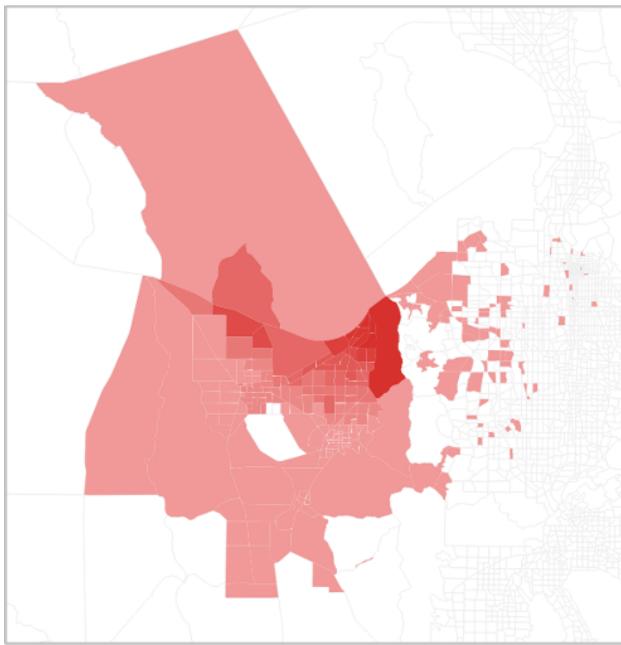


Figure 4.3: Percent change in DCLS by TAZ in Tooele and Salt Lake Counties.

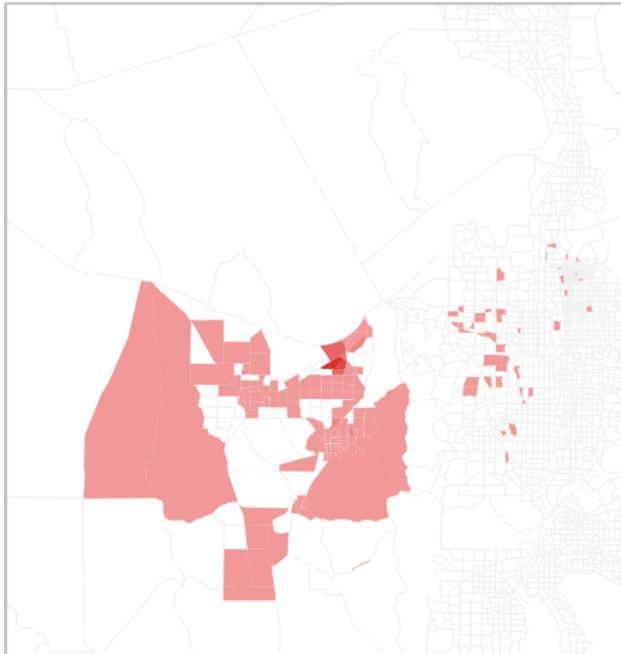


Figure 4.4: Change in DCLS weighted by households located in a TAZ in Tooele and Salt Lake Counties

Table 4.1: Localized Analysis Results

| Trip Purpose | Whole Network Cost (Dollars per Day) | | Tooele Cost (Dollars per Day) | |
|---------------------|---|-----------------------|----------------------------------|-----------------------|
| | Logsum Method | Travel Time Method | Logsum Method | Travel Time Method |
| HBW | \$65,655.13 | \$244,275.72 | \$64,555.39 | \$240,181.80 |
| HBO | \$49,851.54 | \$108,412.94 | \$46,793.14 | \$102,699.90 |
| NHB | \$7,535.78 | \$84,712.36 | \$7,417.66 | \$77,025.58 |
| REC | \$ - | \$398.72 | \$ - | \$208.74 |
| XXP | \$ - | \$55,870.17 | \$ - | \$ - |
| Freight | \$ - | \$10,883,835.01 | \$ - | \$360,899.92 |
| HBW, HBO, NHB Total | \$123,042.44 | \$437,401.02 | \$118,776.19 | \$419,907.28 |
| Total | | \$11,377,504.92 | | \$781,015.04 |

Table 4.2: Localized Analysis Cost Capture Percentage Rates

| | Logsum | Travel Time |
|-----|--------|-------------|
| HBW | 98.32% | 98.32% |
| HBO | 93.86% | 94.73% |
| NHB | 98.43% | 90.93% |

Overall, two key findings are drawn from this localized analysis of the changes caused by link loss at the Tooele/Salt Lake County Line:

Finding 1 Cost estimates are different by trip purpose and overall depending on which estimation method is used

Finding 2 The majority of cost for this link is generated by Freight trips

The logsum and travel time methods can be broken down into the overall costs and the comparable costs. The comparable costs are made up of those purposes which are included in both the presented model and in the travel time method for determining cost. HBW, HBO, and NHB trip purposes can be compared because all three trip purposes are represented by each method of cost estimation.

The travel time method measures the difference in travel time between the base scenario and any other scenario caused by link closure, and then multiplies that difference by the VOT

for each trip purpose and the number of trips estimated for each trip purpose. For external trips, freight trips, and REC trips, these were all extracted directly from USTM. Attempting to include a calculation of the costs associated with increased travel time for freight trips, external trips, and REC trips allows a better estimation of the true cost experienced by all road users, not just those that are included in the model.

The HBW, HBO, and NHB purposes are estimated using the logsum portion of the model. Calculating the costs associated with the change in logsum provides estimations of the costs experienced by road users due to link loss that account for user choice of mode and destination. The logit-based model employed in the presented model ultimately provides lower estimates of the total dis-benefit, and therefore cost, experienced by road users due to link degradation or loss for the purposes included for analysis. However, the logsum calculation is only used for three purposes in the USTM model. A way to account for freight trips, REC trips, and trips that occur between external nodes must also be found. These trip purposes typically have fixed origins and destinations. As such, a way to account for all purposes must be developed. Thus, by combining elements from the travel time method and the logsum model, an estimate can be made that represents all traffic on the USTM network.

4.4 Model Results

The following section presents the results of the 40 scenarios analyzed. First, Figure 4.5 shows the geographic location of each of the 40 links analyzed, where the links are numbered starting with 10. Then, Table 4.3 shows each of the scenarios we examined, labeled simply as “10” for Scenario 10, and “11” for Scenario 11, along with the change in accessibility, Δ_{Logsum} , and the Cost Value in dollars per day associated with link closure. Other identifying information, such as route numbers or street names and geographic or other identifying descriptions about the locations where the link was cut, are also provided.

The logsum method results are shown in Table 4.3. The results are ranked from the road with the largest (most positive cost) to the road with the smallest cost. We can see that Scenario 27, which corresponds to I-84 between Ogden and Morgan, experiences the largest cost per day according to the model. Following Scenario 27, Scenarios 50, 37, 30, and 17 make up the five most critical roads according to the cost estimation provided by the model. Each of the roads in these

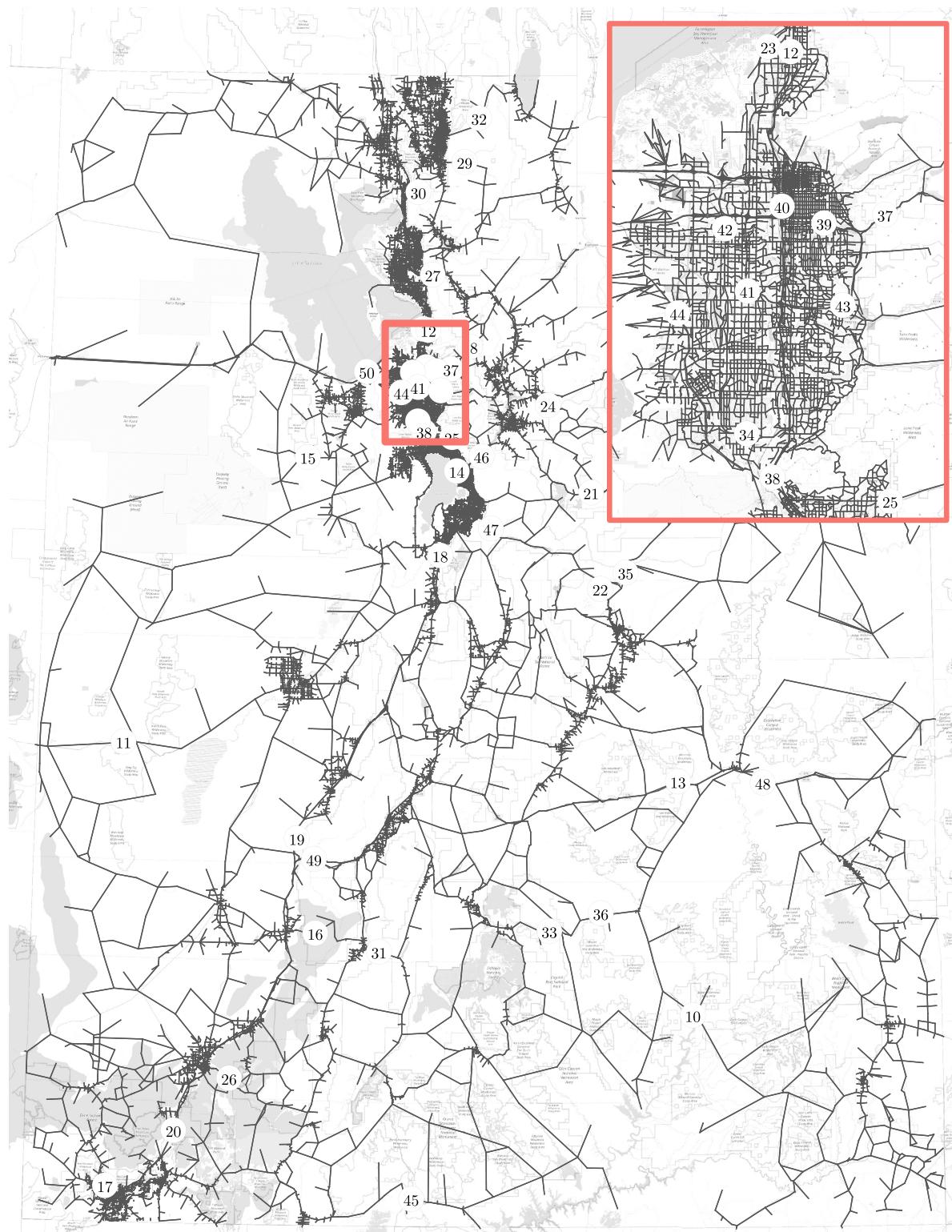


Figure 4.5: Links Identified for Analysis.

scenarios — with the exception of SR-18 in St. George — is an interstate or state highway facility in northern Utah, which is heavily populated. Following these five scenarios, are Scenarios 46, 38, 18, 42, and 41. Each of these facilities are located in northern Utah as well. Some scenarios, such as Scenario 10, Scenario 11, or Scenario 33, are roads that are located in remote parts of the state, and experience no measurable change to HBW, HBO, or NHB traffic. This is likely due to the remoteness of the geographic location of the highway link that was cut. Additionally, a few scenarios returned positive benefits, which is not entirely intuitive. These results will be discussed in greater depth later in this chapter. A ranking is provided for all of the scenarios examined using the logsum method in Table 4.3.

4.4.1 Scenario Comparison

Table 4.4 contains a comparison of the results of the logsum and travel time methods of cost estimation for all 40 scenarios. In the results, it can be seen that first 10 scenarios differ from the logsum ranking when considering only HBW, HBO, and NHB as a trip purpose. Scenarios 17, 42, and 46 , which correspond to SR-18 near St. George, Bangerter Highway near West Valley, and SR-189 in Provo Canyon, are among the most critical facilities in the logsum ranking, but not in the travel time method for the same trip purposes. The other roads that make up the most critical facilities for the travel time analysis include Scenarios 18, 27, 30, 37, 38, 41, and 50. Nearly all of these scenarios are located in Northern Utah, and are facilities located on interstate or state highways.

When we consider just those purposes that are a part of the travel time analysis, but which are not included in the logsum ranking, a few interesting changes occur. First, Scenario 48 becomes the most critical road due to increased travel time. Scenario 48 is a facility on I-70 near Green River, Utah. The other scenarios that comprise the top 10 most critical road segments in this analysis are Scenarios 13, 18, 19, 20, 27, 37, 47, 49, and 50. Some of these scenarios appear in the logsum ranking, and in the travel time method analysis which only considers HBW, HBO, and NHB trip purposes.

A scenario appearing in more than one result comparison is not unexpected, because the facilities considered in the model are typically main arterials in the region where they are located, or are interstate highway facilities which large amounts of private passenger vehicles and freight.

Table 4.3: Logsum Analysis Results

| Scenario | Δ Logsum | Cost (per Day) | Route | Location |
|----------|-----------------|-------------------|-----------|---|
| 27 | -23830.208 | \$148,938.80 | I-84 | between Ogden and Morgan |
| 50 | -19686.788 | \$123,042.42 | I-80 | between SLC and Tooele |
| 37 | -8932.691 | \$55,829.31 | I-80 | in Parley's Canyon |
| 30 | -7511.948 | \$46,949.67 | US-91 | between Brigham City & Mantua |
| 17 | -5243.828 | \$32,773.92 | SR-18 | just North of St. George |
| 46 | -4911.457 | \$30,696.60 | SR-189 | up Provo Canyon near Vivian Park |
| 38 | -4422.194 | \$27,638.71 | I-15 | at the Point of the Mount |
| 18 | -3186.967 | \$19,918.54 | I-15 | in Rocky Ridge (between Payson & Nephi) |
| 42 | -2657.614 | \$16,610.08 | Bangerter | near West Valley City |
| 41 | -1700.167 | \$10,626.04 | I-215 | near Taylorsville |
| 25 | -1139.020 | \$7,118.87 | Timp Hwy | at the mouth of AF Canyon |
| 24 | -387.467 | \$2,421.66 | UT-35 | outside of Francis |
| 23 | -297.882 | \$1,861.76 | Legacy | near West Bountiful |
| 20 | -253.712 | \$1,585.70 | I-15 | near New Harmony |
| 47 | -142.671 | \$891.69 | US-6 | Spanish Fork Canyon at Diamond Fork Rd |
| 26 | -125.740 | \$785.87 | SR-14 | in Cedar Canyon |
| 15 | -67.634 | \$422.71 | SR-199 | near Rush Valley |
| 32 | -60.883 | \$380.51 | US-89 | between Logan and Bear Lake |
| 14 | -45.386 | \$283.66 | I-15 | in Orem between Univ. Ave & Center St |
| 29 | -41.595 | \$259.96 | SR-101 | East of Hyrum |
| 31 | -40.108 | \$250.67 | SR-62 | East of Kingston |
| 22 | -30.394 | \$189.96 | US-6 | in Carbon County North of Helper |
| 49 | -17.768 | \$111.05 | I-70 | near Richfield & Fillmore |
| 45 | -17.029 | \$106.43 | US-89 | near Arizona Border |
| 21 | -11.267 | \$70.41 | US-40 | East of Strawberry Reservoir |
| 36 | -10.170 | \$63.56 | SR-24 | near Steamboat Point |
| 16 | -9.724 | \$60.77 | SR-153 | between Beaver & Junction |
| 48 | -9.717 | \$60.73 | I-70 | near Green River (NW of Moab) |
| 19 | -7.623 | \$47.64 | I-15 | near I-70 & Fillmore |
| 35 | -3.762 | \$23.51 | SR-191 | between Helper & Duchesne |
| 13 | -0.135 | \$8.40 | I-70 | at Dragon Point (W of Green River) |
| 28 | -0.103 | \$0.64 | SR-65 | border of Salt Lake & Morgan Counties |
| 10 | 0.000 | \$0.00 | SR-95 | near Hite |
| 11 | 0.000 | \$0.00 | US-6 | near King Top |
| 33 | 0.000 | \$0.00 | SR-24 | in Capitol Reef National Park |
| 12 | 894.999 | -\$5,593.74 | I-15 | in Bountiful |
| 44 | 2149.291 | -\$13,433.06 | UT-85 | West of West Jordan |
| 43 | 4043.132 | -\$25,269.57 | I-215 | near Cottonwood Heights |
| 40 | 5576.276 | -\$34,851.72 | I-15 | in SLC between 2100 S & 1300 S |
| 39 | 7434.744 | -\$46,467.15 | I-80 | in SLC near Sugar House and 1300 E |
| 34 | 9362.283 | -\$58,514.26 | Bangerter | near Bluffdale |

Here again, several of the roads that are most critical are located in Northern Utah. From the travel time method, it is important to note that the main driving factor as to why a road is important or not closely corresponds closely with the amount of freight and external traffic that road experiences along that route. Including freight trips in the analysis changes the rankings drastically because of the significantly higher value of time associated with freight trips.

Some other interesting findings are that in the top 10 most critical scenarios of each analysis method, three scenarios appear in each of the rankings or comparison rankings. Scenario 18, which is located on I-15 between Payson and Nephi, Scenario 27 which corresponds to I- 84 in Weber Canyon, and Scenario 37 which corresponds to I-80 in Parley's Canyon, are included in the top 10 scenarios for each of the comparison methods of analysis. This is likely due to the number of passenger trips along these routes, combined with the number of freight trips that occur along these routes as well. Interestingly, several of these routes are the only way through mountain ranges in Utah.

One scenario, Scenario 10, which corresponds to SR-95 near Hite, shows a dis-benefit equal to \$0.00. This link is located in a remote part of Utah and likely does not carry a significant amount of traffic belonging any of the trip purposes considered in the logsum model. When the results of the travel time method are examined, however, a cost equal to \$1,126.41 is estimated. This indicates that either freight, REC, or external passenger trips occur on the link. There is wide variation present between the results of each of the scenarios considered in this thesis. Some links are more systemically important to network functionality based on the cost associated with link loss.

4.4.2 Positive Benefit Scenarios

Five of the scenarios indicated a benefit resulting from highway link closure, which is an unintuitive result. A network should not experience a benefit due to degradation. As a result, these scenarios were examined more closely to determine what possible causes could exist behind these atypical and unexpected results. The affected links are all located in the Salt Lake Valley area at the following locations: Bangerter Highway near Bluffdale, I-80 near 1300 E, I-15 between 2100 S and 1300 S, I-215 near Cottonwood Heights, Mountain View Corridor near West Jordan and I-15 near Bountiful.

Table 4.4: Result Comparison: Logsum vs. Travel Time Method

| Scenario | HBW, HBO, NHB Logsum Method | HBW, HBO, NHB Travel Time Method | Freight, External Passenger, REC, Travel Time Method |
|----------|--------------------------------|-------------------------------------|---|
| 10 | \$0.00 | \$0.00 | \$1,126.41 |
| 11 | \$0.00 | \$2.83 | \$7,577.46 |
| 12 | \$(5,593.74) | \$34,668.13 | \$381,210.38 |
| 13 | \$0.84 | \$3.25 | \$25,310,152.43 |
| 14 | \$283.66 | \$105,735.73 | \$963,048.78 |
| 15 | \$422.71 | \$546.85 | \$214.16 |
| 16 | \$60.77 | \$67.07 | \$30,651.68 |
| 17 | \$32,773.92 | \$12,151.12 | \$2,086.96 |
| 18 | \$19,918.54 | \$56,962.31 | \$5,942,067.87 |
| 19 | \$47.64 | \$150.50 | \$3,478,861.17 |
| 20 | \$1,585.70 | \$6,722.35 | \$19,531,654.45 |
| 21 | \$70.41 | \$154.68 | \$541,664.03 |
| 22 | \$189.96 | \$49.60 | \$688,612.02 |
| 23 | \$1,861.76 | \$261.55 | \$168.24 |
| 24 | \$2,421.66 | \$2,952.39 | \$1,885.03 |
| 25 | \$7,118.87 | \$2,641.43 | \$56.56 |
| 26 | \$785.87 | \$665.40 | \$751.68 |
| 27 | \$148,938.80 | \$109,218.22 | \$4,555,377.53 |
| 28 | \$6.43 | \$0.14 | \$18.65 |
| 29 | \$259.96 | \$185.03 | \$1.93 |
| 30 | \$46,949.67 | \$53,897.87 | \$915,569.50 |
| 31 | \$250.67 | \$965.35 | \$260.08 |
| 32 | \$380.51 | \$1,457.39 | \$48,530.21 |
| 33 | \$0.00 | \$7.51 | \$4,113.02 |
| 34 | \$(58,514.26) | \$34,461.91 | \$19,568.64 |
| 35 | \$23.51 | \$87.66 | \$184,332.87 |
| 36 | \$63.56 | \$59.19 | \$1,938.05 |
| 37 | \$55,829.31 | \$120,030.03 | \$2,066,635.37 |
| 38 | \$27,638.71 | \$249,676.74 | \$1,752,537.58 |
| 39 | \$(46,467.15) | \$50,316.65 | \$833,831.51 |
| 40 | \$(34,851.72) | \$58,824.15 | \$373,714.76 |
| 41 | \$10,626.04 | \$51,461.48 | \$15,198.52 |
| 42 | \$16,610.08 | \$15,291.76 | \$4,321.63 |
| 43 | \$(25,269.57) | \$30,170.94 | \$5,014.80 |
| 44 | \$(13,433.06) | \$10,701.45 | \$3,498.34 |
| 45 | \$106.43 | \$495.15 | \$592,294.39 |
| 46 | \$30,696.60 | \$48,805.90 | \$82,831.00 |
| 47 | \$891.69 | \$2,473.30 | \$2,044,690.24 |
| 48 | \$60.73 | \$481.41 | \$85,971,156.40 |
| 49 | \$111.05 | \$154.96 | \$8,148,497.64 |
| 50 | \$123,042.42 | \$437,401.02 | \$10,940,103.91 |

When a highway link is broken, the new shortest path by time is always longer than in the base scenario with the broken link available. However, the new path may actually be shorter by distance. This causes an increase in the utility of accessing destinations by non-motorized modes, potentially overwhelming the decrease in automobile utility. It also results in increased auto costs, which are measured per mile of distance travelled. The automobile accessibility is determined by the AM congested travel time in USTM. The travel distance – used to determine the accessibility of destinations by driving or walking – is the distance of that path, and not the actual shortest distance path. Additionally, supporting evidence of this theory was found when it was discovered that for the alternative route between Grouse Creek, Utah, and Salt Lake City, was nearly twice as long in the case where I-80 was closed between Tooele and Salt Lake Counties. This discovery led to the understanding that not all route choices become logical when made using only the model data. In reality, it is possible that a user would find a shorter route which consists of roads that are not all in the state highway system. This occurrence is only observed in heavily urbanized regions for two reasons:

Reason 1 The presence of high-speed expressways and parallel local roads means that alternate paths with shorter distances but longer vehicle times are more likely.

Reason 2 The increased availability of destinations within the non-motorized distance threshold (2.5 miles) means that alternative destinations exist.

Overall, the results of the analysis indicate that the likely cause of a positive cost being estimated for these five scenarios is that there are easily accessible alternate routes in the area, or extremely different alternate routes along with competing TAZ of similar size in the DC size term equation.

4.5 Summary

The overall results show that the logsum model estimates lower costs than the travel time comparison due to network changes. These lower, more conservative estimates are likely due to how the logsum model accounts for a user's ability to choose a new mode or destination. Thus, the logsum ranking provides more conservative, lower cost estimates. However, when the travel time results are included, the overall rankings of the 40 scenarios considered change dramatically. This

is due to the large expenses experienced by freight traffic, which has a much higher VOT than other passenger trips do. In summary, Table 4.3 and Table 4.4 show the rankings for both the logsum and travel time analysis methods respectively. The logsum suggests that I-84 between Ogden and Morgan is the most critical road, while the travel time method, or total priority, indicates that I-70 near Green River is the most critical road due to cost associated with closure.

CHAPTER 5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Overview

This chapter summarizes the recommendations resulting from the resiliency model application, it also contains information about obtaining the model and outlines next steps.

5.2 Problem and Objective

UDOT is responsible for maintaining a transportation system to promote public welfare and economic activity throughout the state of Utah. UDOT is also responsible to maintain key components of the national highway transportation system. Given the importance of this system, UDOT has sought a way to identify those facilities which are most critical to overall systemic function. Therefore, the objective of this study is to evaluate the relative systemic criticality of highway links on a statewide network using a logit-based model sensitive to changes in route path, destination choice, and mode choice.

The development of the presented model directly addresses the objective of this study. The model is logit-based, incorporating a user's ability to choose a new mode and destination, while still being sensitive to route path in terms of time and distance. Using the logsum, which captures the total value of the available choice set, different estimates were provided compared to the travel time method, which is more traditional than the logsum method. The ability that the presented model gives UDOT to quickly analyze any highway link on USTM, and return a cost estimate, is highly advantageous. The model allows UDOT to determine the relative systemic criticality of highway links on the network.

5.3 Recommendations

The USTM model is a gravity-based travel demand model, while the presented model is logit-based. The logit-based nature of the model allows greater sensitivity towards user mode and destination choice to exist, which causes the estimated costs associated with link closure to be different using the presented model. The model's incorporation of both the logsum for HBW, HBO, and NHB purposes, as well as the travel time calculation for the other purposes included in USTM, provide important functionality towards estimating more realistic, conservative costs associated with long term highway closure.

Logit-based modeling returns more conservative estimations of the criticality of a link to a network than the travel time method. Adapting USTM to use a logsum is important because UDOT can better estimate and therefore understand the monetary and thus systemic importance of individual highway links. Additionally, the model's design allows for further analysis of additional link closure, eased identification of critical points on Utah's highway network, and even multi-link closure in the future. Thus, it is recommended that USTM include a logit-based mode and destination choice model in the future. This is standard practice in other states, and enables better understanding of human behavior. Additionally, UDOT should consider behavior in its resiliency analysis. Road users do change modes, destinations, and routes when a network suddenly becomes altered, as has been observed in both the I-35W and I-85 disasters. These decisions do result in different criticality priority rankings as shown through the logsum and travel time rankings in this study. UDOT should also consider development of a better regional freight model.

5.4 Limitations and Next Steps

Trip forecasting and estimation, such as that done in USTM and in the logsum model can be prone to over or underestimation. Equilibrium feedback loops are used to iterate through the trip distribution, mode and destination choice modules until the impedance value, which is a measure largely based on congestion, stabilizes. Trip assignment and a subsequent feedback loop was not included in the development of the logsum model. Incorporating a feedback loop would have allowed more accurate estimation network impedance and increased travel times to be made. Accurate estimations would have allowed for more precise route changes between OD pairs to be

made considering congestion levels on the model network. The decision to not include a feedback loop introduces limitations to the ability of the model to accurately estimate the effects of link closure on travel time and route choice due to congestion.

Inclusion of a feedback loop would cause the travel time and logsum information to be fed back into the beginning of the model and rerun continuously until the specifications of a convergence parameter were met. The feedback loop also allows for more accurate route choice, mode choice, and destination choice to be made when the true effects of congestion are accounted for. In June 2020, the UDOT Technical Advisory Committee decided to not include a feedback loop to in order to save time on model development for this study. A feedback loop and sensitivity analysis should be included as part of future work.

Another limitation in the logsum model is that all HBW trips are flexible in destination choice. This implies that a user could choose to work in a different TAZ than that in which their actual place of employment is located. This might not be entirely logical for short-term highway closures, considering that most workplace locations are fixed. With the recent turn towards telecommuting, workplace location flexibility is likely more prevalent now than it has been in the past. This increased flexibility would likely have a large impact on how HBW trips are estimated in travel demand modeling. Thus, a more nuanced method for estimating HBW trips that accounts for both flexibility and inflexibility of workplace location should be developed. Additional data could be collected in future travel studies about workplace location could be gathered and analyzed into a HBW model designed to model different types of trip – both flexible and inflexible.

It is not unreasonable to assume that in the event of an earthquake or similar widespread disaster event, that multiple links could become damaged. An important use of the presented model in future research would be to analyze the results of simultaneous multiple link loss. This will allow for greater understanding of the effects that adverse events can have on Utah's highway network, and help UDOT to better prepare for the development and maintenance needs of the future. The capability is already incorporated into the structure of the model, however, a few modifications need to be made in order for it to become fully functioning. Additionally, the development of logsum calculations for trips with fixed origins and destinations should also be considered. This model, however, would be very different than the presented model because freight trips do not typically have a mode or destination choice option, so it would be more prudent to incorporate a method to

account for other choices such as travel time, distance or even elevation change on a given route. Driver awareness of physical conditions of the highway network – including knowledge about current weather conditions, road construction, or existing road closure – would also play a role in how a freight trip is routed on a highway network. One option to overcome this limitation, is to use the national freight network, which would allow freight trips to divert through other Interstate facilities.

Another limitation present in the travel time method of analysis is that passenger trips occurring between internal-external or external-internal nodes were not included. These trips likely do not make up a large portion of trips on the network, however, this may still affect the ability of the travel time method of comparison to make estimations that reflect all trips on the network. Additionally

5.5 Summary

The development of a logit-based travel demand model can improve the way UDOT estimates costs associated with link loss when compared with traditional modeling methods. The presented logsum model provides a different cost estimate than the travel time method. This is due to the ability of the logsum model to account for user mode and destination choice. Additionally, logit-based models possess unique properties which allow modelers to incorporate multiple types of data. With this ability in mind, the presented logsum model includes several types of available data deemed pertinent to constructing a working logit-based model in Utah.

The logsum cost estimations account for user behavior which can help professionals better evaluate systemic criticality of Utah's infrastructure. Logsums are becoming an increasingly important consideration in modern modeling practice because of their unique ability to account for user choice while estimating network trips. The presented logsum model generates valuable results that should be used to prioritize link criticality to the overall functionality of Utah's highway network. There are several important implications that follow the results. First, consideration of only the change in travel time as the main measure of dis-benefit may not accurately represent some situations. HBW, NHB, and HBO trips, can be better estimated using the logsum because these trip purposes have more flexible mode and destination choices than REC or freight trips do. However, both REC and freight trips were only considered by the travel time method because they typically have fixed OD pairs. Availability of data which could be used to better determine how

REC or freight trips might change mode or destination choice could be used to better estimate costs for these purposes. Second, allowing users in the model to choose both a new mode and destination increases the resemblance of a real life decision making process. Incorporating a method to better represent human behavior can only help a model to more accurately reflect what researchers have observed after the I-35W and I-85 incidents. Importantly, the presented model is able to provide results produced using two different methods of cost estimation, which can help UDOT to understand how different modeling methods provide more or less conservative estimates of criticality. However, combining estimation methods into a single model may be effective because trip purposes which are flexible or inflexible can be estimated at the same time.

It is evident that the presented model brings several modeling estimation advantages to the forefront of current research, something which must be explored in the future. The biggest contribution of this thesis to the field of transportation modeling is the incorporation of a logit-based model into a statewide highway network. Applying a logsum to a network as large as USTM, and estimating the dis-benefit associated with link closure, provide the basis for both UDOT and other state transportation agencies to be able to quickly estimate the criticality of any single link or combination of links to overall systemic resiliency of a highway network while accounting for route change, mode choice, and destination choice.

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