Resiliency of Utah's Road Network:

a Logit-based Approach

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ABSTRACT

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In recent history, transportation network vulnerabilities have been increasingly scrutinized. Recent transportation disasters, such as the collapse of the I-35W bridge in Minneapolis, Minnesota, and the I-85 / Piedmont Road fire and bridge collapse in Atlanta, Georgia, have brought the need to easily identify network vulnerability to the forefront of the Utah Department of Transportation's (UDOT) planning efforts. UDOT manages and maintains a complex statewide network of highways, made up of facilities which include bridges, mountain passes, and canyon roads. To help with transportation planning efforts, UDOT has developed the Utah Statewide Transportation Model (USTM), which is a trip-based model. However, UDOT does not currently possess a model capable of quickly identifying network vulnerabilities, and the potential costs associated with link loss. Subsequently, this study seeks to develop a trip-based choice model using the USTM network, combined with socioeconomic data from the Utah Household Travel Survey (UHTS) taken in 2017, to estimate the dis-benefit experienced by road users if a link becomes damaged. Home-based Work (HBW), Home-based Other (HBO), and Non-home Based (NHB) trips were primarily considered in the development of what has been named the Resiliency Model. User mode choice, with options for automobile, non-motorized, and transit modes, was first found using a logsum calculation. Logit-based calculations are advantageous for two reasons: first, they capture the total value of user choice, and second, logsums are able to easily calculate total accessibility based on the value of choice. Thus, logsum calculations were then used as the main input into a destination choice model which also uses a logsum to determine a user's final destination choice. Adapting a trip-based model, such as USTM, to a logit-based destination choice model was the primary goal of this thesis. The ability of logit calculation to incorporate user choice along with multiple other data types, makes these modeling calculations advantageous when compared with traditional modeling methods. The other goal of this thesis is to determine the dis-benefit experienced by road users as a result of link loss on the USTM network. In this study, transit trips were held fixed, as they are outside the scope of the project.

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 critical to smooth operation of the system.

In 2017, AEM (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 and 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, Interstate 70, Interstate 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. Resiliency must therefore be considered a function of network, mode, and destination alternatives which comprise systemic redundancy. 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 research is to develop a methodology and tool to evaluate the network resiliency of critical UDOT assets across the state. We base this tool on data collected for 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 41 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 roughly 8500 Transportation Analysis Zones (TAZ), with a population of about 3.2 million people. Developing a choice model (aptly named the Resiliency Model) 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 Resiliency 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. Creating a choice model which uses the same network as USTM, and incorporates multiple datatypes is advantageous to UDOT moving forward because of the alternative estimates a choice model can provide.

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 the Model Application, description and comparison of model results, from the model developed in Chapter 3, to the highway links identified 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. There are three basic definitions that researchers have used include:

- 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 this 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). 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 is the primary consideration.

To begin, a basic understanding of what resiliency is – or is not – needs to be developed. Professionals, including those at UDOT, have adopted use of the Four R's as a means to predict some form of resilience on a highway network. The Four R's include: rapidity, redundancy, robustness, and resourcefulness. In the Four R's, rapidity is inversely related to the closure time and is heavily used to measure how quickly a road can recover from a setback such as a minor accident or temporary closure. Redundancy is measured by the additional time or distance a user has to travel when a route is broken. Ideally, a highly redundant system has many alternative routes built into itself such that a user could easily alter their route with little or no increased travel time or travel distance. Greater amounts of time or distance lower the overall redundancy. Robustness is the inverse of risk and represents the overall strength of the system as a whole. Resourcefulness, the last of the Four R's, is the ability to find quick solutions in a network.

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 worked with UDOT to develop an I-15 Corridor Risk and Resilience Pilot (AEM, 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 steps and assessments, AEM was able to provide a number of recommendations to UDOT that had the potential to improve resilience along the evaluated corridors (mainly sections of I-15) based on the criticality rating (a combination measure of the information listed above) 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 each year. Other threats such as terrorism affect important infrastructure as well. Thus, for the purpose of this thesis, it is important to understand which threats exist, and which threats AEM decided to analyze.

AEM identified a number of threats which should be considered in Utah, based on a number of different types of data which was available for use. AEM was also able to rule out certain types of threats based on the relevance of these threats in Utah. Ultimately, AEM considered nine physical threats which include: earthquake, flood (scour), flood (overtopping/debris), fire (wildland), 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 (roadway, bridge, etc.).

Once these threat layers were determined and the location of the threat- asset pairs along I-15 were found, AEM 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

Table 2.1: AEM Criticality Score

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 (Mi)	< 70	71-84	85-102	103-124	> 124

each asset (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 published report.

The AEM Risk and Resilience report provides a good template going forward for identifying links at risk, following the first definition of a resilient transportation network. 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 the some of the complications involved in attempting to identify critical roads. For example, a road may have a low AADT, but the majority of that AADT, which would show that 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 that in the previous example exist. What would happen in the case that a minor arterial became inundated, however, there was a redundant arterial just a few blocks or miles away? One other observation made from the 2.1 is that AEM does not take alternate routes into account. AEM does not include a way for their developed risk analysis methodology to anticipate what a user would actually do if faced with a real disaster scenario. AEM does not answer simple questions such as how many valid alternative routes exist? What is the new travel time or travel distance? Identifying the systemic resiliency of highway facilities – as implied by the third definition of resiliency, resilience through operability in crises – requires considering these alternate routes (AEM, 2017).

2.3 Lessons Learned from Crisis Events

Two major crisis events in the last fifteen years have given researchers an important opportunity to 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, Georgia.

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 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 trips (ADT) over the bridge (Zhu et al., 2010b). 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. (2010b) conducts a travel survey to provide a more in-depth analysis of important data and traffic changes surrounding the I-35W bridge collapse in 2007. The article uses a methodology that attempts to identify mode-choice and other behavioral changes of survey respondents. The authors analyze data looking for variations in ADT, as well as origin-destination (OD) matrices. Importantly, they analyze loop detector data, bus ridership statistics, and survey response data in their work. The authors conduct a regression analysis of the collected data, which indicates 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. (2010a) explore traffic behavior and changes in the wake of major network disruptions such as those that occurred in Minnesota. The authors identify unique behavior, post disaster, using GPS tracking data, survey data from the post disaster phase, and other aggregate

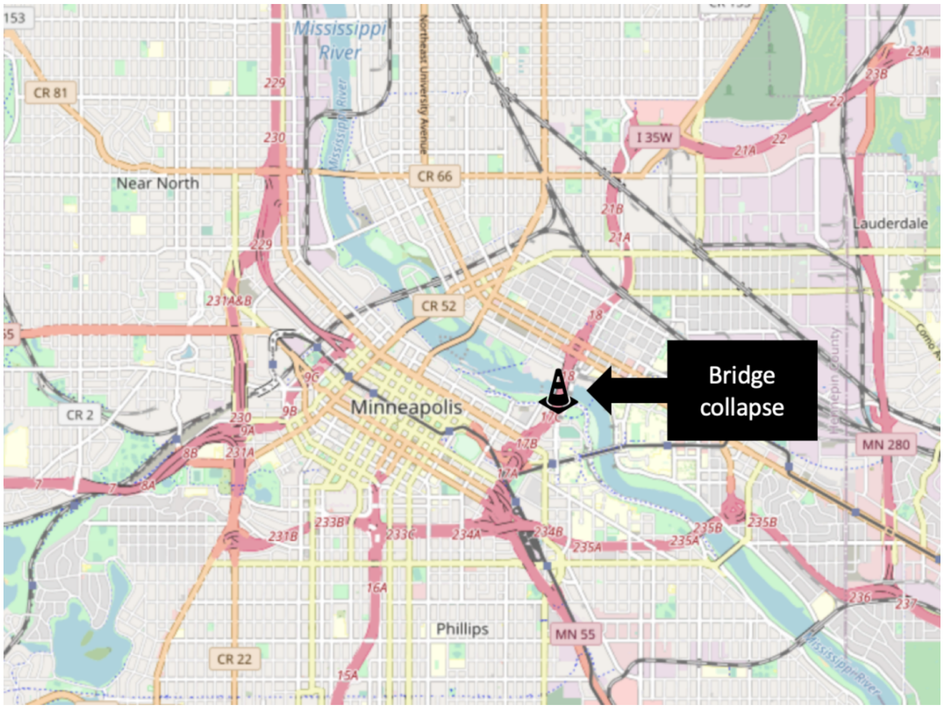

Figure 2.1: Approximate location of the I-35W bridge collapse.

data from surrounding freeways and traffic devices. This data is analyzed to track changes in ADT over bridges and alternative routes in the area after the disaster as well as after mitigation was complete. The authors provide increased understanding about how a network's operability changes during a post-crisis environment.

Xie and Levinson (2011) attempt 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 experienced a dramatic decrease on the crippled network.

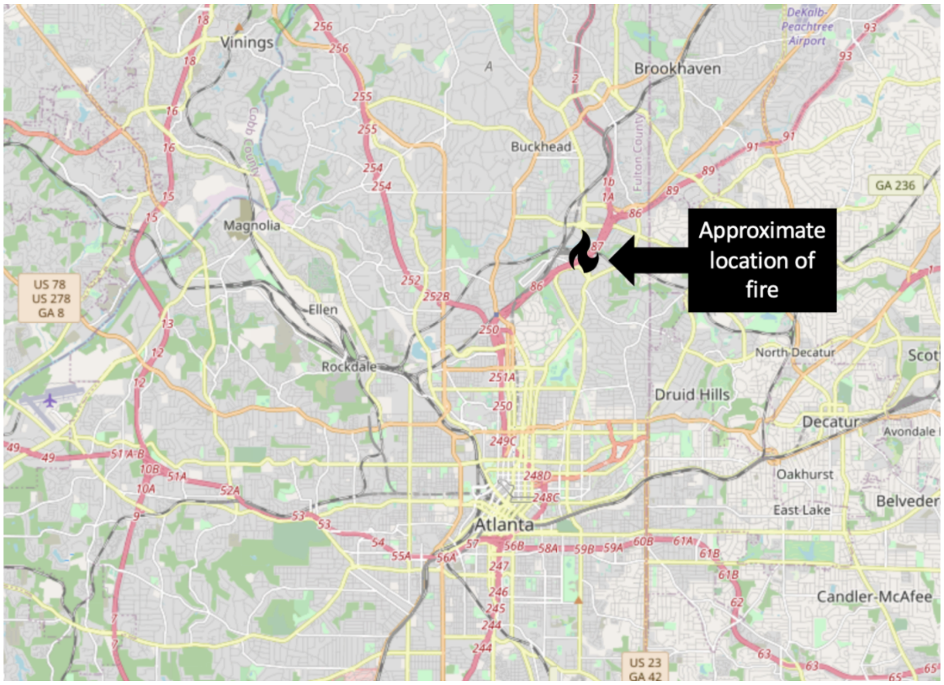

Figure 2.2: Approximate location of the I-85 / Piedmont Road bridge fire.

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 is 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 set 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 (GDOT, 2017). GDOT's efforts to open the bridge quickly after its collapse aided in abating negative user costs due to significant travel time delays that surfaced due to changes in route choice and assignment.

As a result of the fire, the highway, which had an average daily traffic count (ADT) of 243,000, was closed in both directions for a period of about two months. This closure led to a 30% increase in traffic volumes across the entire downtown network, with 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 able to extend service capacity by about 20 percent, 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 situation (MARTA, 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.

2.4 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 events that could happen in the real world. Thus, a number of researchers have conducted studies where real or fabricated transportation networks are constructed, damaged or degraded, and then the change to network metrics is evaluated. All of this is done to measure network performance without an actual disaster occurring beforehand. Berdica (2002) attempts 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 defines accessibility as the ability for users to travel between origins and destinations for any number of reasons. She then uses the performance measures to define vulnerability as the level of reduced accessibility due to unfavorable operating conditions on the network. In particular, Berdica identifies a need for further research toward developing a framework capable of investigating reliability of transportation networks.

In this section we will examine several attempts by numerous researchers to do precisely this, using different measures of network performance. A consolidation of this discussion is summarized in Table 2.2, namely the methods that different researchers have used in examining network performance under duress. The measures can be consolidated into three basic families:

- **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).

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). Within this discipline are the related concepts of network vulnerability and connectivity that have been accessed by researchers. In these studies, researchers tend to define critical links as those that connect to many other nodes (directly or indirectly), or as links whose loss isolates a number of nodes from the rest of the network.

Abdel-Rahim et al. (2007) developed a multi-layered graph 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 highlights 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) present 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. Clusters of links and nodes are then

Table 2.2: Attempts to Evaluate Systemic Resiliency

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

grouped together more tightly by including nearby clusters, which creates a "zoomed out" model where small clusters begin to act as nodes or 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 do discuss the importance of having damaged networks with high levels of functionality. Vodák et al. (2019) on the other hand, develop 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 damages 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, as well as provide a means to quantitatively compare networks.

Ip and Wang (2011) address this shortcoming through 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 relies 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 determine that the recovery of transportability between two cities largely depends on redundant links between nodes. The authors also comment 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 be considering the importance of understanding the impacts of widespread, all-inclusive disaster scenarios.

Guze (2014) conducts a review of the known uses of graph theory (a possible application of resiliency) before reviewing several other multi-criteria optimization methods. Graph theory is the study of pairwise objects, and is useful for identifying shortest path, network connectivity, and other methods of network optimization. Graph theory supports the idea of resilience through recovery as well as operability through crisis because of how it represents networks with links and nodes, and the theory's ability to identify next shortest paths in the case of disaster. Guze's methodology involves an analysis of the knapsack problem which is a combinatorial optimization problem. Specifically, Guze focuses on flow theory in transportation systems and identifying a method to find the best graph solution. Guze's greatest contribution to transportation research is a simplified method for determining shortest path route options on simple networks.

Osei-Asamoah and Lownes (2014) adopt a network analysis methodology that is able to analyze resilience of transportation networks. In this article, the authors evaluate 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 is given by:

$$\Phi = \frac{E'}{E} \tag{2.1}$$

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 are able to draw comparisons between two complex networks. Ultimately, the authors conclude that a denser, highly interconnected network will perform better if a link is cut due to a larger giant component value.

Zhang et al. (2015) investigates the role of network topology, or the physical layout of the network in a geographic location. The authors provide 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 determine that metrics such as throughput, connectivity and average reciprocal distance increase with greater lineage, however they decrease as networks become more widespread. This is likely because larger networks 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 though connectivity may not be an accurate representation of a node's importance.

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, or a node becomes isolated, 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. Thus, ensuring total isolation of a node or link does not occur becomes highly important to network resiliency in terms of graph theory.

Berdica and Mattsson (2007) attempt 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. 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. This method purely attempts 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.

Jenelius (2010) attempts to examine the importance of the link that becomes critical only after partial network degradation, or redundancy importance. This measure is primarily flow-based. In the presented context, flow-based measures aim to analyze and evaluate changes in the number of vehicles using a route given adverse circumstances on the network.

Peeta et al. (2010) construct 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.

Serulle et al. (2011) clarify variables related to resiliency of transportation networks including average delay and transport cost, adjusting interactions, and increasing metric transparency. The authors employ a methodology capable of quantifying resiliency using a fuzzy interference approach – an approach meant to use imprecise or vague data – that relates physical and performance characteristics. The used 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.

Ibrahim et al. (2011) provide 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 propose 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) proposes a methodology for assessing the resiliency of physical infrastructure during disruptions. To do this, the authors use a network model to build an origin-destination matrix that allows initial network loading and analysis. Omer's model uses 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 due to the way it analyzes networks experiencing suboptimal circumstances. The author's work identifies key parameters that should be measured to assess resiliency during disruptive events.

Jaller et al. (2015) seeks to identify critical infrastructure based on increased travel time or reduced capacity due to disaster. The proposed methodology utilizes user- equilibrium to determine proper initial network loading. Then the shortest path between one origin and one destination can be identified. To implement damage to the network, a link is cut, and then the next shortest path is 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 O-D pair, and the nodes with greatest change in travel time are determined to be the most critical. Jaller's methodology allows traffic managers to identify critical paths for mitigation purposes before the occurrence of disaster through careful analysis.

A primary limitation with increased travel time methodologies is that they ignore the 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 certain distance. This measure is often represented as a count, e.g., the number of jobs reachable from a particular location within thirty minutes travel time by a particular mode. Mathematically,

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

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., thirty 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 model,

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

where the function $f(d_{ij})$ is often a negative exponential with a calibrated impedance coefficient. An extension of the gravity model is to use the logsum term of a multinomial logit destination choice model,

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

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), and Geurs and Ritsema van Eck (2001), used isochrone type methods. Stewart (1947), Hansen (1959), Ingram (1971), Vickerman (1971), and Anas (1983) used gravity style models, and Neuburger (1971), Leonardi (1987), Williams and Senior (1978), Koenig (1980), Anas (1983), Ben-Akiva and Lerman (1985), Sweet (1997), Niemier (1997), Handy and Niemier (1997), Levine (1998), and Miller (1999) used or suggested logsums. They highlight the importance of using person-based measures such as these 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 captures five types of choice: activity, time period, trip-base, location, and mode choice, with key features being activity choice and trip-base (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 calculates an "inclusive value" (IV) and "consumer surplus" (CS) values.. 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 allow 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 investigates 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:

$$E(CS) = \frac{1}{\alpha}\log(\sum_{j=1}^{J}\exp(I_j)) + \beta \tag{2.5}$$

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 highlights the possibility for a comprehensive model capable of succinctly measuring the dis-benefit caused by a degraded network. Taylor continues by stating that traffic network simulation models could be considered for future research. Some of the key needs for future research specifically highlighted at the conclusion of Taylor's article include:

- efficient algorithm development
- improved vulnerability metrics
- use of network vulnerability indicators in studies of critical infrastructure and the implications of network degradation
- improved techniques for identifying network weaknesses

Several authors employ various types logit models in their research, or attempt to develop a methodology specifically for use analyzing disrupted networks.

Masiero and Maggi (2012) use logit-based calculations to determine the Value of Time (VOT) associated with the closure of a road in terms of cost, time, and punctuality for freight transport. In order to properly determine the VOT of route closure, the authors also use a method provided in Koppelman and Bhat (2006) which uses 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.

Nassir et al. (2016) applies 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 do 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 do not always choose the fastest route, nor do they always choose the route with the highest utility. He and Liu (2012) take 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 adjust their route choice to an altered network. The true implication here is that users do not automatically choose the best new route given an altered network, it takes users time to learn how the new network functions.

Winkler (2016) proposes a travel demand model that is valid for all networks, especially those with more than one constraint. Winkler's methodology utilizes 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 Multinomial Logit Models (MNL). Logsums like Winkler's also allow for consumer surplus calculations, or utility, to be estimated across the transportation network being modeled.

Ganin et al. (2017) attempt to investigate resiliency through a disruption of 5% of the roadways in 40 urban networks within the United States. The employed methodology determines that Salt Lake City has the most resilient transportation network while Washington D.C. has 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 work 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. (2017) noted that traffic delay times (or the travel time caused by a closure) increase significantly as road segments are broken.

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. Some researchers have even applied logit-based models to small scale activity-based models. From this extensive review of existing literature, we are able to see that no one has attempted to apply a logit-based choice model on a statewide level.

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 model sensitive to changes in route path, destination choice, and mode choice.

In this chapter, we describe the existing Utah Statewide Travel Model (USTM) and why it is not entirely suitable for this study. We then present a new model framework designed to evaluate resilience using a logit-based choice model on USTM's network and it's implementation within the CUBE travel demand modeling software.

3.2 Utah Statewide Travel Model

The Utah Department of Transportation (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. 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 (CMPO), and the Dixie Metropolitan Planning Organization (DMPO). Additionally, the Summit/Wasatch Travel Demand Model is incorporated into USTM (Utah Department of Transportation, 2021). 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:

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

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) between two zones can be represented in a number of ways, such as with a negative exponential function:

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

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. Destinations are fixed, and trips calculated using the gravity model must have a proportional number of users assigned to each destination based on its size or level of attraction (i.e. in and ideal scenarios, if there are 100 productions, there should be 100 attractions).

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 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.

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:

$$\mathscr{P}_{ij} = \frac{e^{u_{ij}}}{\sum_{j \in J} e^{u_{ij}}} \tag{3.3}$$

Where $\mathscr{P}_{ij}$ represents the probability of trips made between an origin i and a destination j among all destinations J, and u represents the utility. The probabilities calculated are then used to calculate the mode or destination choice probability, which allow trips by purpose and trips by mode to be calculated. These Equations are shown in Equations 3.17 and 3.18 later in this chapter. Then we have the logsum calculation, which is the denominator of the probability function. 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.

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

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 3.3.2.

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 model framework was developed to ensure a robust logit-based model could be created. The model framework used to create the Resiliency 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 Logsum** - The mode choice logsum is a function of the travel impedances and serves as an accessibility term in the destination choice model. The mode choice logsum contains utility functions that determine the probability and logsum associated with travel between each OD pair. The mode choice 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 mode choice logsum) and the attraction size term of each destination zone. This is the key evaluation metric of the model because of the ability to incorporate multiple data types into the model structure. 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 by 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 model begins with a travel time skim procedure, to determine the congested travel time from zone i to zone j by auto, as well as the shortest network distance for non motorized modes. The transit travel time skim is fixed, assuming that transit infrastructure would not be affected by changes to the highway network. Throughout this section, lower-cased index variables k belong to a set of all indices described by the corresponding capital letter K.

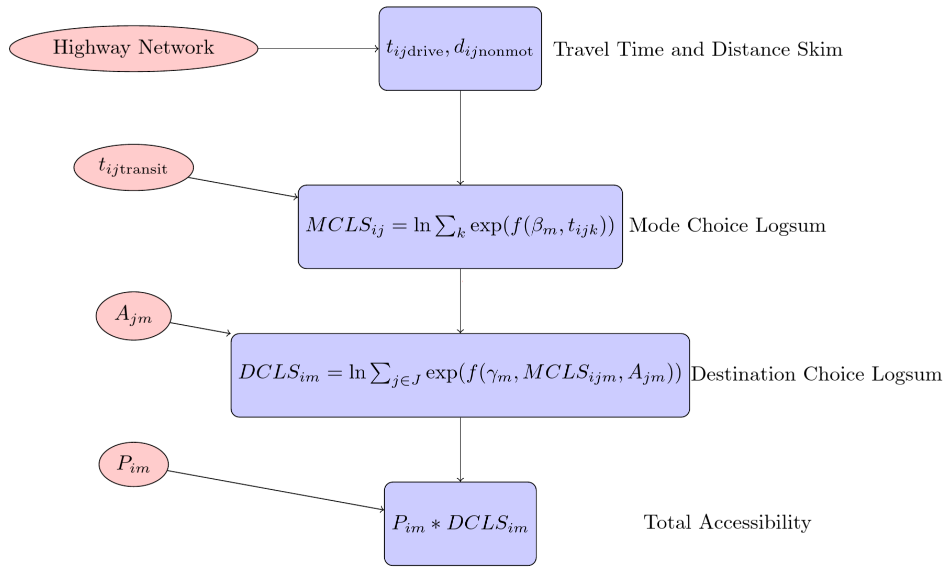

Figure 3.1: Resiliency Model framework.

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

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

The log of the denominator of the this equation is called the mode choice logsum, $MCLS_{ijm}$ and is a measure of the travel cost by all modes, 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

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

where A_j is the attractiveness — represented in terms of socioeconomic activity — of zone j. As with mode choice, the log of the denominator of this model is the choice logsum, $DCLS_{im}$. 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,

$$\Delta_{im} = DCLS_{im}{}^{\text{Base}} - DCLS_{im}{}^{\text{Scenario}} \tag{3.7}$$

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 mode choice 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:

$$\text{Cost} = \sum_{I}\sum_{M} -1/\beta_{\text{cost},m} * P_{im}\Delta_{im} \tag{3.8}$$

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

$$\text{Cost}' = \sum_{I}\sum_{J}\sum_{K} \frac{\beta_{\text{time},k}}{\beta_{\text{cost},k}} T_{ijm_{auto}} t_{ij_{auto}} \tag{3.9}$$

Deriving a simpler way to calculate resilience was necessary for two reasons. First, data was 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 Resiliency Model was needed. Calculating dis-benefit based solely on increased travel time provides valuable insight and tools for further analysis of the Resiliency Model results.

Transportation Networks

The Resiliency Model requires an understanding of the 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 was 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, transportation analysis zone number (TAZ ID), 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 (or 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.

Transit network resiliency is outside the scope of this project. Accordingly, the Resiliency Model assumes that 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 Resiliency Model, 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 Wasatch Front Regional Council (WFRC, Salt Lake area MPO) and the Mountainland Association of Governments (MAG, Provo area MPO) model include a substantive transit forecasting component. The transit travel time skim from the WFRC / MAG model was used for the mode choice 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 NMOT trip distances are held fixed, similarly to transit distances. We determined that the longest distance a pedestrian would commute via a NMOT mode is 2.5 miles or less. The decision to hold NMOT 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. NMOT trips also typically have higher accessibility to smaller roads or side-streets that would not be included with the USTM network.

Trip Productions and Socioeconomic Data

The Resiliency Model uses socioeconomic data to estimate the productions at each zone. The socioeconomic data, which is adapted from the Utah Household Travel Survey (UHTS) conducted in 2015, 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. More importantly perhaps, is that the size term denotes the significance of a TAZ in attracting trips. 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).

3.3.1 Mode Choice Model

The mode choice (MC) module calculates the mode choice logsum (MCLS) between each OD pair in the network for each trip purpose. The trip purposes considered in the model are home-based work (HBW), home-based other (HBO) and non-home-based (NHB). The MC module includes the highway skim, the transit skim, and the MC coefficients and constants as inputs.

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

The MC constants and coefficients used in the Resiliency Model were extracted from USTM where , or adapted from SWIM. The travel time represented with tt_ij, travel cost represented as a variable C_{ij}, walk distance (less than 1 mile) represented as $D_{<1MILE}$, and walk distance (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 Roanoke (Virginia) Valley Transportation Planning Organization (RVTPO) travel model where USTM had gaps in the data. This model was selected as a source for these coefficients due to its simplicity and analogous data elements to the purpose of the proposed resilience 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 2015 Utah Household Travel Survey (UHTS) using methods described by Koppelman and Bhat (2006). Mode constants typically represent the effects of all factors on MC, but are not limited to those values included in the utility equations (Koppelman and Bhat, 2006). The utility coefficients for the destination model are also presented in Table 3.1.

The following are sample utility equations for each of the modes considered in the Resiliency Model. α denotes mode choice constants, β denotes mode choice coefficients, γ denotes destination choice parameters, and C will denote other variables which are typically zonally related. Additionally, the equation used to calculate the MC logsum will be shown.

$$U_{ijm\text{AUTO}} = \beta_{tt} * tt_{ij\text{AUTO}} + \beta_{cost} * cost_{ij\text{AUTO}} \tag{3.10}$$

$$U_{TRANSIT_{ij}} = \alpha_{TRANSIT} + \beta_{tt} * tt_{ij} + \beta_{cost} * cost_{ij\text{TRANSIT}} \tag{3.11}$$

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

$$Logsum_{ijm} = \ln(\sum_{K} \exp(U_{ijmk})) \tag{3.13}$$

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 variable in the Resiliency Model. Second, both the $AUTO$ and $NMOT$ equations account for a distance variable, and last, 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. Once the logsum was calculated, it was necessary to calculate the probability associated with a users decision to use each mode of travel for an OD pair, such that the total probability added up to 1. The equation used to accomplish this is shown:

$$\mathscr{P}_{ijk} = \frac{\exp U_{ij}}{\sum \exp U_{ijk}} \tag{3.14}$$

3.3.2 Destination Choice Model

The DC module includes the highway skim, the socioeconomic data extracted from USTM, and DC parameters as inputs. The destination choice utility equation consists of three parts: a size term (A_j, a travel impedance term (MCLS value), and a calibration polynomial. Coefficients for the size term and travel impedance terms were adapted from the Oregon Statewide Integrated Model (SWIM) for all purposes except HBW. Instead, these coefficients were adapted from the RVTPO model. This was done because SWIM does not account for work trips in the same way as it does the other purposes. The distance polynomial coefficients were calibrated to targets developed from UHTS.

The DC utility equation, seen in Equation 3.15, is made up of the MCLS calculated in the previous module, the size term, and several distance and cubic polynomial coefficients and their corresponding values. The terms in this equation follow the same conventions as mentioned above, however, D is used to represent the distance variable in the calibration polynomial:

$$U_{ijm} = \gamma_{MCLS} * MCLS_{ijm} + \log(A_{jm}) + f(d_{ij}) \tag{3.15}$$

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

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 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 choice in the model. The size term is made up of statistical data about a zone. This data was published in 2015 as part of the UHTS and made available via UDOT. The size term equation can be seen below:

$$A_{jm} = \gamma_{m_{off}} * \text{office}_j + \gamma_{m_{oth}} * \text{other}_j + \gamma_{m_{hh}} * \text{hh}_j + \gamma_{m_{ret}} * \text{retail}_j \tag{3.16}$$

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

The DC logsums are calculated by summing each row in the DC utility matrix, and then exponentiating that value. The process used to accomplish this can be seen in Equation 3.15. 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.

3.4 Model Calibration and Validation

To ensure the Resiliency Model is accurately reflecting the distribution of trips and MC in the USTM model, it must be calibrated accordingly. To do this, target values were extracted from the USTM for each trip purpose.

3.4.1 Trips by Purpose and Mode

In order to calibrate the model, trip totals needed to be broken up by purpose ($Trips_{ijm}$) and by mode ($Trips_{ijmk}$), as shown in Equations 3.17 and 3.18. To find the trips by purpose ($Trips_{ijm}$), the probability of a trip occurring between an OD pair needed to be determined. Likewise, to find the trips by purpose and mode ($Trips_{ijkm}$), we multiplied the $Trips_{ijm}$ by the MC probabilities calculated during the MC module. A mathematical representation of this can be seen in the equations below:

$$Trips_{ijm} = P_{im} * \mathscr{P}_{ijm} \tag{3.17}$$

Where P_i is the productions at zone i, and,

$$Trips_{ijkm} = Trips_{ijm} * \mathscr{P}_{ijk} \tag{3.18}$$

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.

3.4.2 Calibrating Choice Constants

The utility functions in Equations 3.15 and 3.16 contain calibration constants which are necessary to calibrate the model. Model calibration is completed by iteratively adjusting the MC constants and DC constants to ensure accurate output estimation. The nature of the Resiliency 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.

Mode Choice Calibration

To calibrate the MC constants, the alternative specific constants must be adjusted so that the mode split target extracted from USTM closely matches the Resiliency 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 mode choice model to target values. Table **??** presents the original statewide mode split targets from the UHTS, and the final calibrated mode splits in the Resiliency Model. Figure 3.2 shows the change of the mode choice 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.

Destination Choice Calibration

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

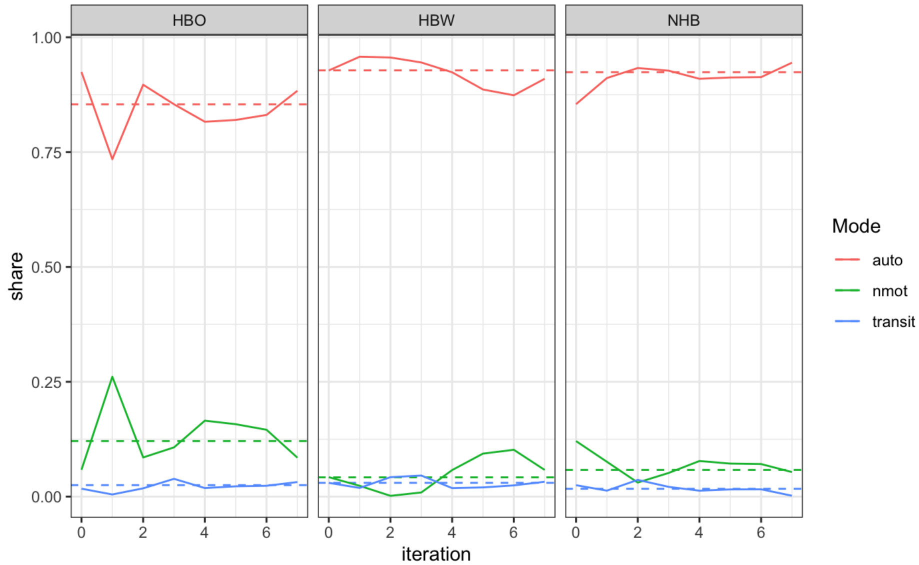

Figure 3.2: Mode choice splits by trip purpose.

(TLFD) extracted from USTM. In this model, we include a cubic polynomial as the destination choice calibration term seen in the equation below:

$$f(d_{ij}) = \kappa_1 d_{ij} + \kappa_2 d_{ij}^2 + \kappa_3 d_{ij}^3 \tag{3.19}$$

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 3.19 — which is part of the DC utility in Equation 3.15 — was applied and calibrated to match the target TLFD values from USTM. The final calibration values were presented in Table 3.1.

3.4.3 Calibration Results

To ensure that calibration efforts were successful, it was necessary to compare the TLFD results from USTM and the Resiliency Model. We created a TLFD script that could divide trips into distance bins. 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 so that we could ensure trips in the Resiliency Model were being conserved. Trip totals were compared using the TLFD outputs to

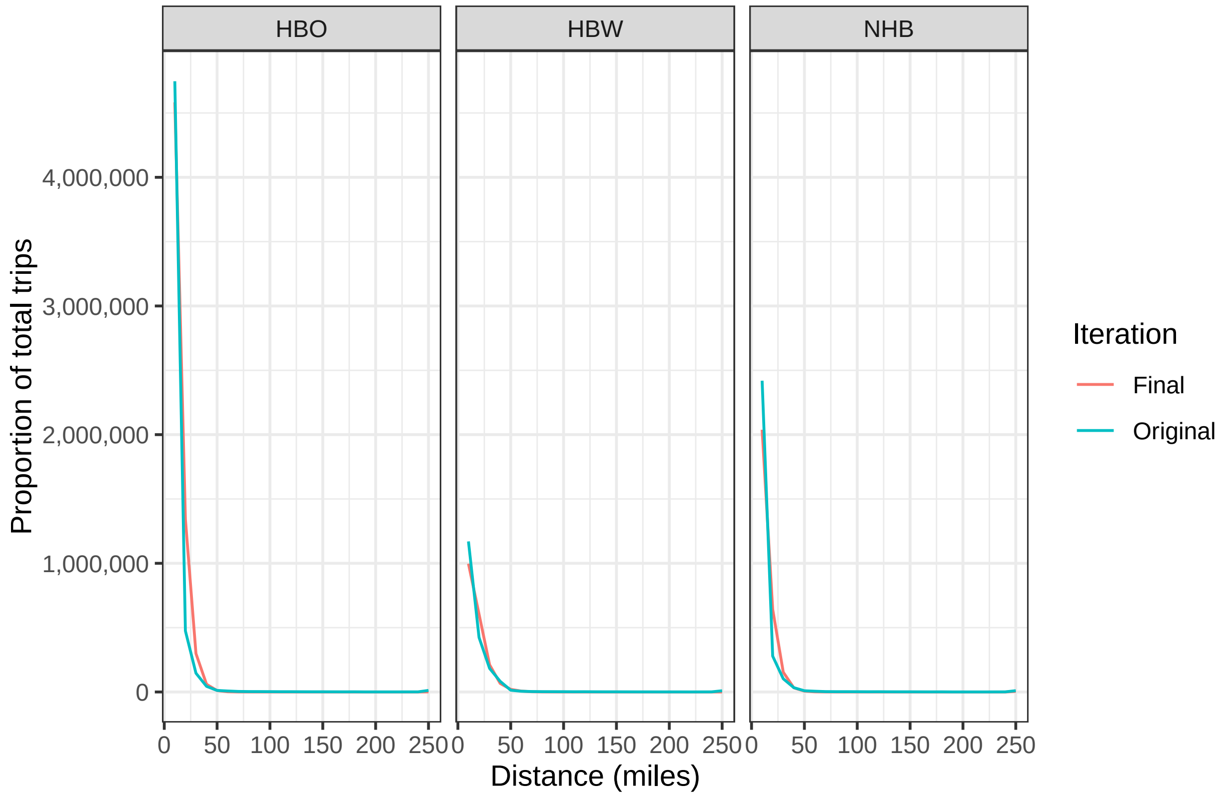

Figure 3.3: Original and final trip length frequency distribution.

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.

3.5 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 Resiliency 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 each link could be calculated, especially for those purposes not primarily included in the Resiliency Model and for comparison purposes.

Purposes including freight, recreation *REC*, and home-based school *HBSC* trips were evaluating 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 Resiliency Model. At the same time, the data needed to create logsum calculations for these excluded purposes was not readily available. We chose to simply compute the costs associated with these trip purposes 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. Equation 3.20 shows a representation of how differences in travel time were calculated:

$$\Delta tt_{ij} = ScenarioTime_{ij} - BaseTimeij \tag{3.20}$$

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 value of time (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).

3.6 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

Table 3.2: Values of Time for Time Difference Calculations

Freight	Auto	
94.04	17.67	$/hr
156.73	29.45	cents/min

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 Resiliency 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, we apply the Resiliency Model to evaluate the effects of link loss or degradation on the USTM network. We do this by applying the model 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. We then compare the model output to an alternative method that measures only the change in travel time and does not allow for mode or destination choice. The model was then applied to 41 individual scenarios, with 40 of those scenarios involving link closure scenarios throughout the state.

4.2 Vulnerable Link Identification

The methodology developed to identify vulnerable links in Utah uses an online Risk Priority Analysis map created by UDOT to identify points of interest based on existing risk analysis data. Additional points of interest were identified by the research team or by UDOT officials, who have a familiar working knowledge of the USTM network. Using this method, links were identified due to their location in relation to population centers, remote geographic location, proximity to other highway facilities, were known to be at risk due to geologic or geographic features, or because they were suspected choke points in the network.

After identifying locations of interest, we now apply the model to compare the results of 40 scenarios. In each scenario, an individual highway facility is removed from the model highway network. Each of these scenario locations is shown in Figure 4.1, and some are identified in a report by AEM (2017) or the research team using the methodology described. A detailed analysis of the results of a single scenario will be done, followed by a more general analysis for all 40 scenarios considered in the Resiliency Model.

4.3 Localized Scenario Analysis

This section outlines an in-depth, localized analysis that was conducted to ensure the Resiliency 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. This detailed analysis is useful because it provides a closer look at the way the Resiliency 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 we used to compare results against 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 trips and the overall costs 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 about $123,000 of expenses experienced by road users due to the closure of the link. Specifically, for trips originating in Tooele County, the logsum based analysis using the Resiliency Model captures $1,700 of expense, which is approximately 1.5% of the total 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 Resiliency Model is effectively capturing trips originating in Tooele based on the percent capture rates in of cost in Table 4.2. Additionally, when we look at the travel time method of analysis, we can see that the costs at both the local and statewide levels are much greater with about $382,000 and $437,000 respectively estimated as the costs due to just the increase in travel time, not using the logit-based model.

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 Resiliency 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

Table 4.1: Localized Analysis Results

Trip Purpose	Whole Network Cost (Dollars per Day)		Tooele - SLC Cost (Dollars per Day)	
	Logsum Method	Travel Time Method	Logsum Method	Travel Time Method
HBW	$65,655.13	$244,275.72	$359.94	$12,143.11
HBO	$49,851.54	$108,412.94	$910.05	$3,577.62
NHB	$7,535.78	$84,712.36	$441.73	$5,025.24
REC	$ -	$398.72	$ -	$29.72
XXP	$ -	$55,870.17	$ -	$ -
Freight	$ -	$10,883,835.01	$ -	$360,899.92
HBW, HBO, NHB Total	$123,042.44	$437,401.02	$1,711.72	$20,745.97
Total	$123,042.44	$11,377,504.92	$1,711.72	$381,675.61

Table 4.2: Localized Analysis Cost Capture Rates

	Logsum	Travel Time
HBW	0.0055	0.0497
HBO	0.0183	0.0330
NHB	0.0586	0.0593

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 who are included in the Resiliency Model.

The HBW, HBO, and NHB purposes are estimated using the logsum portion of the Resiliency 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 Resiliency 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 Resiliency Model, an estimate can be made that represents all traffic on the USTM network.

4.4 Resiliency Model Results

The following sections will present the results of the 40 scenarios analyzed. First, 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 as follows 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 Resiliency 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 Resiliency Model. Each of the roads in these 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. 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. In the results, we see that the first a few of the first 10 scenarios differ from the logsum ranking when considering only HBW, HBO, and NHB as a trip purpose. Scenarios 17, 42,

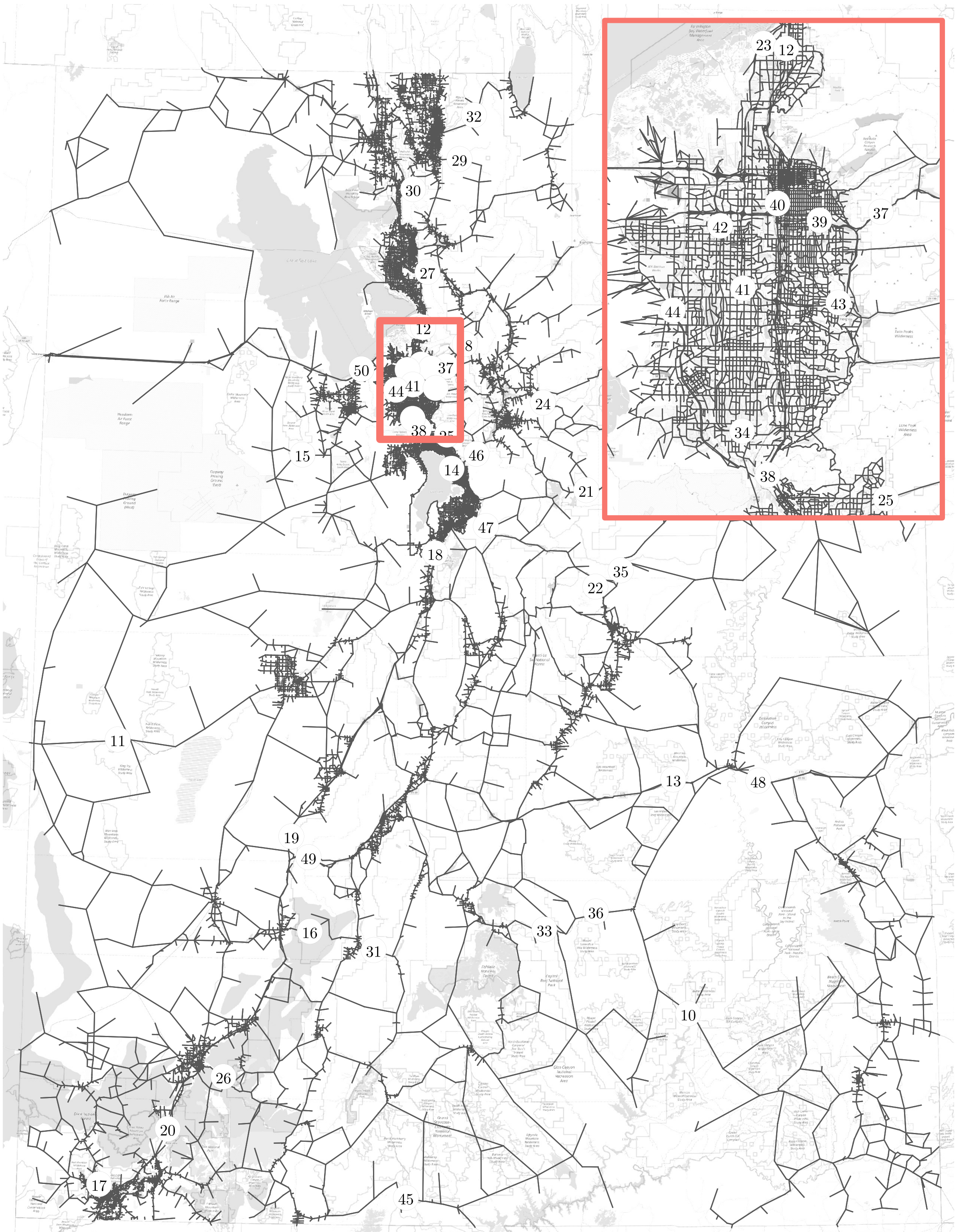

Figure 4.1: Links Identified for Analysis.

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

and 46 , which correspond to SR-18 near St. George, Bangerter Highway near West Valley, and SR-189 near Vivian Park, 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 theses 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 the 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 Resiliency 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. H ere 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.

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

Scenario	HBW, HBO, NHB Logsum Method	HBW, HBO, NHB Travel Time Method	Freight, XX Pass, 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

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.

A discovery made while troubleshooting some calculations is that when a highway link is broken, the new shortest path by time is 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. The automobile accessibility is determined by the AM congested travel time in the Utah Statewide Travel Model (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 us to understand 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:

- The presence of high-speed expressways and parallel local roads means that alternate paths with shorter distances but longer vehicle times are more likely.
- 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 Resiliency Model is less sensitive to network changes than the travel time comparison. This is likely because other behaviors are accounted for in the Resiliency Model. The ability for a user to choose both a mode and destination (or alternate destination) cause the logsum results to often estimate a smaller cost than the travel time results would. However, when the travel time results are factored in, the overall rankings of the 41 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 **??** 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 Recommendations

The USTM model is a gravity-based travel demand model, while the Resiliency Model is logit-based. The logit-based nature of the Resiliency Model allows for greater sensitivity in user mode and destination choice, which causes the estimated costs associated with link closure to be lower using the Resiliency Model. The Resiliency 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 value of a link in the network. This is a highly important adaptation to USTM because more accurate and efficient estimation allows UDOT to better understand the monetary importance of highway links throughout Utah. 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.

5.3 Limitations and Next Steps

Implementation of a logit-based travel demand model is highly important for resource allocation moving into the future. Updating USTM to include a logit-based trip distribution model instead of a gravity-based model would improve the flexibility of travel demand estimates moving forward.

The decision to not include a feedback loop, which iteratively runs the model until a the specifications of a convergence factor are met. Incorporating a feedback loop would have allowed for more accurate estimation of increased travel times and more accurate route choices between OD pairs in the final iteration of the Resiliency model compared with the first iteration. This decision introduces limitations on the ability of the model to accurately estimate the effects of link closure on travel time. This limits the ability of the model to estimate accurate changes in response to increased travel time due to congestion because cannot be accurately measured after one iteration.

Adding a congestion feedback loop to the Resiliency Model would allow more accurate cost estimations to be made. 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 loop would allow for better estimates of the change in travel time due to both route change and resulting congestion. The loop also allows for more accurate route choice, mode choice, and destination choice to be made when the true effects of congestions are accounted for. In June 2020, the UDOT Technical Advisory Committee decided to not include a feedback loop to save time on model development for this study. A feedback loop and sensitivity analysis should be included as part of future work.

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 Resiliency 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. Developing a fully functioning transit oriented logit model would be highly advantageous to the Utah Transit Authority as well. The capability is already incorporated into the structure of the resiliency 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 Resiliency Model because freight trips do not typically have a mode or destination choice option, so it would be more prudent to be able to account for other choices such as travel time, distance or even elevation change on a given route. One option is to use the national freight network, which would allow freight trips to divert through other Interstate facilites.

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 reflects all trips on the network.

5.4 Summary

The development of a logit-based travel demand model can improve the way UDOT estimates costs associated with link loss experienced by Utahns when compared with traditional modeling methods. The Resiliency Model provides a different cost estimate than does the travel time methodology created as a method of comparison in this thesis. Logit-based models possess unique properties which allow modelers to incorporate multiple types of data. With this ability in mind, the Resiliency Model includes several types of available data deemed pertinent to constructing a working logit-based model in Utah. The Resiliency Model's logsum estimations, which account for user choice were calculated, and can help professionals better evaluate risk to Utah's infrastructure by identifying critical facilities. User choice is a highly important consideration in modern modern modeling practice because it accounts for user choice while estimating network trips. The Resiliency Model generates valuable results that should be used to prioritize link importance to the overall functionality of Utah's highway network. There are several important implications that follow the results. First, purely using change in travel time or travel time delay as the main disbenefit measure may not be entirely accurate in most situations. This is due to the difficulty of finding available data for all trip purposes included in USTM. Second, allowing users in the model to choose both a mode and destination increases the resemblance of a real life decision making process, especially given adverse circumstance on Utah's highway network. Importantly, the Resiliency Model is able to provide results measured using two different methods of cost estimation, first the logsum and second the travel time difference, allowing different priorities to be evaluated from the Resiliency Model's results. It is evident that the Resiliency Model brings several modeling estimation advantages to the forefront, something which must be explored further in future research.

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