# Resiliency of Utah's Road Network:

# a Logit-based Approach

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A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

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ABSTRACT

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The abstract is a summary of the dissertation, thesis, or selected project with emphasis on the findings of the study. The abstract must not exceed 1 page in length. It should be printed in the same font and size as the rest of the work. The abstract precedes the acknowledgments page and the body of the work.

Keywords: resilience, logsum, logit, modechoice, destination choice, CUBE

## ACKNOWLEDGMENTS

Students may use the acknowledgments page to express appreciation for the committee members, friends, or family who provided assistance in research, writing, or technical aspects of the dissertation, thesis, or selected project. Acknowledgments should be simple and in good taste.

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## NOMENCLATURE

| | |
|---|---|
| $B$ | Barrier to extract information about a product from the product itself |
| $\overline{D}$ | Macroscopic strain rate |
| $D_0$ | First component of strain rate tensor |
| $D_k^N$ | Normal direction of the $k$-th lamina, also an axis for the lamina reference frame |
| $D_k^R$ | Rolling direction of the $k$-th lamina, also an axis for the lamina reference frame |
| $D_k^T$ | Transverse direction of the $k$-th lamina, also an axis for the lamina reference frame |
| $\overline{d}$ | Average grain size |
| $\Delta g$ | Volume of discretized bins in Fundamental Zone |
| $E$ | Young's modulus |
| $E_m(wxyz)$ | Fourier coefficients representing Young's modulus in the $wxyz$ direction for the $m$-th bin of the Fundamental Zone |
| $F$ | Estimated rate at which information is extracted from a product |
| $F_m$ | Fourier coefficients of crystal volume fraction in the $m$-th bin of the Fundamental Zone |
| $G$ | Shear modulus |
| $g$ | Euler angles from Sample to Crystal reference frames |
| $g_{wx}$ | Orientation matrix of Euler angles from Sample to Crystal reference frames |
| $\dot{\gamma}$ | Shear rate |
| $\dot{\gamma}_0$ | Reference shear rate |
| $K$ | Estimated or actual information contained by a product |
| $L$ | Distance between straight, parallel lines used to determine average grain size |
| $\lambda$ | The contraction ratio for the strain tensor |
| $M$ | Material class, (e.g., nickel, copper) |
| $M_0$ | Selected alloy from material class |
| $N$ | Number of laminae to be used in layer-by-layer creation of material |
| $n$ | Inverse rate sensitivity parameter |
| $n_c$ | Number of columns in the binned Fundamental Zone |
| $n_h$ | Number of layers in the binned Fundamental Zone |
| $n_r$ | Number of rows in the binned Fundamental Zone |
| $\nu$ | Poisson's ratio |
| $P$ | Estimated power exerted to extract information contained by a product |
| $\phi_{1,i}$ | Lamination orientation for the $i$-th layer |
| $S$ | A measure of a product's ability to contain information |
| $S_{11}$ | Material property constant obtained from literature for selected material class |
| $S_{12}$ | Material property constant obtained from literature for selected material class |
| $S_{44}$ | Material property constant obtained from literature for selected material class |
| $\overline{S}(wxyz)$ | Sample compliance (average crystal compliance) |
| $s$ | Slip systems. Comprised of slip plane normals, $\{111\}$, and slip directions $< 110 >$ |
| $\sigma'_{ij}$ | Deviatoric stress |
| $\sigma_y$ | Yield strength |
| $T$ | Estimated time to extract information $K$ |
| $t$ | Reference time frame for reverse engineering a product |
| $\tau$ | Reference time frame when all parameters are known |

| | |
|---|---|
| $\tau_0$ | Lattice friction stress |
| $\tau^*$ | Reference shear stress |
| $Y_m$ | Fourier coefficients representing yield strength physics |

**Subscripts, superscripts, and other indicators**

| | |
|---|---|
| $[\ ]^*$ | indicates total measure or effective property |
| $[\ ](t)$ | indicates [ ] is a function of time, in the $t$ domain |
| $[\ ](\tau)$ | indicates [ ] is a function of time, in the $\tau$ domain |
| $[\ ]_0$ | indicates [ ] is evaluated at time $t$ or $\tau$ equal to zero |
| $[\ ]_p$ | indicates [ ] is in the part reference frame |
| $[\ ]_c$ | indicates [ ] is in the crystal reference frame |
| $[\ ]_l$ | indicates [ ] is in the lamina reference frame |
| $[\ ]_t$ | indicates [ ] is the target value |

# 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 crticial to smooth operation fo 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 alternatives, or redundancy.

## 1.2 Objectives

The primary objective of this research is to develop a methodology and tool to evaluate the network redundancy 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 comparison. This report presents the results of this evaluation applied on 41 individual highway links.

## 1.3 Scope

The purpose of the resiliency model is to provide a working model that can be used to evaluate the potential economic costs were a highway link – or a set of highway links – to be damaged or destroyed temporarily in Utah. This model is based in 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 or designed for any purpose other than providing a comparative estimate of the effects of link loss by man-made or natural causes.

## 1.4 Outline of Report

This report is organized as follows:

- Chapter 1. This introductory chapter.
- Chapter 2. 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 a method for identifying vulnerable and potentially critical highway links by considering the location-based elevated risk issues. This chapter summarizes a previous study conducted by BIO-WEST.

- Chapter 5. A Model Application, describing and comparing the results of the model developed in Chapter 3 to the highway links identified in Chapter 4.
- Chapter 6. A Conclusions chapter summarizing the findings and providing additional recommendations to UDOT.

# 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:

- Resilience through Resistance: Resilient transportation networks have few and manageable vulnerabilities. This is typically addressed through robust facility-level engineering and risk management (e.g. [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 (e.g., [Zhang & Wang, 2016]).
- Resilience through Operability in Crisis: Resilient transport networks are able to operate effectively with damaged or unusable links. It is this definition that is most relevant in the context of this study ( [Berdica, 2002, Ip & Wang, 2011]).

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 therefore we primarily consider literature using the third definition.

Professionals 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. Here, rapidity is inversely related to the closure time and is used to measure how quickly a road can recover from a setback. Redundancy can be measured by the additional time or distance a user has to travel when a route is broken. 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. An attempt will be made to identify the first time that these terms surface in the reviewed literature.

We begin this review first by examining the study conducted by AEM on behalf of UDOT to identify vulnerable sections on the I-15 corridor. We then 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 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 (R&R) 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 include asset characterization, threat characterization, consequence analysis, vulnerability assessment, threat assessment, risk/resilience assessment, and risk/resilience management. From these steps AEM was able to provide recommendations to UDOT that would improve resiliency along the corridor based on the criticality of each segment at risk.

For the purpose of this study it is important to understand which threats AEM decided to analyze. For AEM to identify which threats to consider they needed, to use data that was available to them. AEM also ruled out certain threats based on their relevance. In the end 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. Then the available threat layers were intersected with assets (roadway, bridge, etc.), and if threat layers weren't available historical data was analyzed to determine their annual probability.

Once these threat layers were determined and the location of the threat- asset pairs along I-15 were found, AEM could then continue their analysis. This consisted of gathering characteristic data for 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 their paper using multiple different threat locations.

The AEM R&R 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 at risk are most critical, assessing a "criticality" score to the network based on the five data elements and categories given in Table 1. A key observation of these criticality scores is that they do not accommodate alternate routes that the traffic could use should the link become unavailable. Identifying the systemic resiliency of highway facilities – as implied by the third definition of resiliency – requires considering these alternate routes.

Insert table 1 here, AEM Criticality Score

### 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 behavior when critical links are suddenly disabled for an extended period of time. These events are the collapse of 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. 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 1.

Insert Figure 1 here

[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 matrices. Importantly, they analyze some pre-disaster data in their work. The authors provide evidence which indicates that drivers are reluctant to make mode choice changes, rarely doing so. This is likely due to reasons such as finances, time, or perceived difficulty of navigating a new mode of transport. At the same time, some drivers change destinations 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 data from surrounding freeways and traffic devices. The gathered data was analyzed to track changes in ADT over bridges and alternative routes in the area after the disaster as well as after mitigation was complete. Levinson and Zhu provide increased understanding about how a network's operability changes during a post-crisis environment.

[Xie & 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 calculate 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 travel model, the authors estimate that the bridge collapse cost the Twin Cities approximately $75,000 per day in increased travel times.

### 2.3.2 I-85/Piedmont Road Bridge Fire

In Atlanta, Georgia, a section of an I-85 bridge collapsed due to a massive fire under the bridge on March 30, 2017. The fire, which was started by a homeless man, 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; 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.

INSERT iMAGE 2 HERE

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 busses and trains were decreased to allow greater passenger volume. MARTA was able to add 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,MARTA, 2018]. It is likely that MARTA's efforts to mitigate passenger volumes greatly influenced the onset of negative effects of the bridge fire.

The section of I-85 that was closed impacted a large, upper income demographic in the greater Atlanta area who commuted across the bridge. This area was drastically impacted by the disaster. 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.

### 2.3.3 Attempts to Evaluate Systemic Resiliency

A number of researchers have conducted studies where they construct real or fabricated transportation networks, eliminate or degrade links in the network, and evaluate the changes the loss of these links introduced into some measure of network performance. [Berdica, 2002] atempts 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 NAME HERE, namely the methods that different researchers have used in examining network performance under duress. The measures can be consolidated in to 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?

The following sections discuss relevant studies in each group; Table 2.1 consolidates these studies by year and labels them with an applicable group.

### 2.3.4 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

Table 2.1: Attempts to Evaluate Systemic Resiliency

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

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.

[Guze, 2014] conducts a review of the known uses of graph theory before reviewing several other multi-criteria optimization methods. Guze's methodology as it relates to resiliency involves an analysis of the knapsack problem, however Guze tends to focus on flow theory in transportation systems as the best graph related analysis option. Graph theory is also 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 because of how it represents networks with links and nodes, and its ability to identify next shortest paths in the case of disaster. Guze's greatest contribution to transportation research is a simplified method for determining shortest path route options.

[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 graph that can be analyzed more directly for vulnerabilities. The authors acknowledge, however, 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.

Similarly, [Ip & 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.

[Vodák et al., 2019] develop an approach to identify critical links in a network by searching for the shortest independent loops in the network. 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.

[Osei-Asamoah & Lownes, 2014] adopt a network analysis methodology that is able to analyze resilience using the mode of a transportation network. In this article, the authors evaluate resilience by comparing the biological network of a common mold with a rail network. The author's methodology uses global efficiency and the size of the giant component, or connected components containing any number of a graph's vertices to determine network efficiency using the inverse of the shortest path while the giant component used to measure the ratio of link connections after disaster to those existing before disaster.

[Zhang et al., 2015] investigates the role of network topology, meaning the layout of the network. 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, Zhang determines that metrics such as throughput, connectivity and average reciprocal distance increase with greater linage, however they decrease as networks become larger. This is likely because larger networks have fewer node connections, and therefore are less redundant.

All of these graph theoretical approaches tend to break down to some degree on large, real-world networks where the number of nodes and links numbers in the tens of thousands, and the degree of connectivity between any arbitrary node pair is high.

### 2.3.5 Changes in Travel Time

Highway system network failures — in most imaginable cases — degrade the shortest or least cost path but typically do not eliminate it entirely. The degree to which travel time increases when a particular link is damaged could provide an estimate of the criticality of that link.

[Peeta et al., 2010] construct a model to efficiently allocate highway maintenance resources. 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. A Monte Carlo simulation revealed which allocation plan resulted in the least network degradation, and thus which links were most critical to the network's operations.

[Serulle et al., 2011] refines the previous work of other researchers to define resiliency under pre-event conditions. The authors accomplish this by clarifying 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 alternative heuristic 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. @omer2013 apply a similar methodology to a real-life intercity highway network. @jaller2015 extended this methodology with a static user equilibrium traffic loading step to provide an estimate of how the next-shortest path changes when congested.

[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 authors 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.

### 2.3.6 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,

$$A_i = \sum_j X_j I_{ij}; I_{ij} = \begin{cases} 1 \text{ if } d_{ij} \leq D \\ 0 \text{ if } d_{ij} > D \end{cases} \tag{2.1}$$

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,

$$A_i = \sum_j X_j f(d_{ij}) \tag{2.2}$$

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,

$$A_i = ln \sum_j \beta_d(d_{ij}) + X_j \beta \tag{2.3}$$

where the parameters $\beta$ are estimated from choice surveys or calibrated to observed data. The logsum term has numerous benefits outlined by [Handy & Niemeier, 1997] and [Geurs & 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 & van Wee, 2004] provide a review of accessibility measures such as those above up to 2004. Of the papers they reviewed, [Vickerman, 1974, Ben-Akiva and Lerman, 1979, Geurs and Ritsema van Eck, 2001] used isochrone type methods, [Stewart, 1947, Hansen, 1959, Ingram, 1971, and 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 desinged. The designed framework is capable of determining the ability of an indivudal to access an activity rather than travel between an OD pair (i.e. an activity-based model).

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 netsted MNL model. The main choice considered in the framework is activity choice followed by trip-base.

Taylor's proposed framework has been applied to an exisitng activity based choice model for the Adelaide region, however, the framework operates independently from the model in much the same way that the resiliency model is independent from the USTM model. The resiliency model uses similar inputs to the USTM model, but is a separate model.

Using the developed framework, Taylor calculates an "inclusive value" (IV) and a "consumer surplus" (CS) valuse, which are similar to the utility values calculated in the resiliency model. Both the IV and CS and the utliity values are vital in determining the benefit or disbenefit assicated with the change experienced by users in the individual model scenarios.

In Taylor's model, the IV and CS values are estiamted 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 investiates accessibility on a network for a large city, but could easily be applied to a larger network, such as in the resileincy model.

A key difference between the Adelaide and the resiliency model is that the resileincy model calculates utility values to estimate the overall logsum (benefit or disbenenfit caused by link failure) for each TAZ in the model in much the same way Taylor uses the IV and CS values. However, the resiliency model seeks to find the overall benefit or disbenefit calculated as the cost associated with link closure accross the state, rather than the local costs experienced at the TAZ level. The resiliency model could easily be adapted to accomplish localized costs if needed.

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

$$E(CS) = (1/\alpha)\log(\sum_{j=1}^{J}\exp(I_j)) + \beta \tag{2.4}$$

The logsum equation employed by Taylor is the exact same logsum used in the resiliency model. Perhaps the most important distinction between the two models is that the Adelaide model is an activity-based model while the resiliency model is a trip-based model.

Taylors research highlights the need for a comprehensive model capable of succinctly measuring the disbenefit 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 reseach specificaclly highlighted 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 newtork weaknesses

The resileincy model is a functional next step to Taylors research that adresses some of the gaps mentioned above. Specifically, the resliency model is desinged to work alongside a trip-based model (most statewide travel modesl in the United States are trip-based [Travel Forecasting Resource, 2021]), the resiliency model provides simpler vulnerability metrics, studies and seeks to identify techniques for identifying network weaknesses and important links, and seeks to understand statewide effect of link failure.

In addition to the work discussed in this report, several other papers expand on Taylor's appraoch in different yet important ways.

[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 a flow-based measure. [Nassir et al., 2016] applies a nested logit model to examine a transit network in Austrailia. The main contribution in [Nassir et al., 2016] is an improved methodology for calculating accessibiilty measures related to transit. 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 & Liu, 2012] takes another look at the after effects of the I-35W bridge collapse previously discussed. A key contribution of [He & Liu, 2012] is that people often intially base route choice on what they assume will be best based on past experience. So, over time, users will adjust to an altered network.

[Masiero & Maggi, 2012] uses 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, [Masiero & Maggi, 2012] uses a method provided in [Koppelman & Bhat, 2006] which uses model derived coefficients and values to determine the cost of an alternative. [Masiero & Maggi, 2012] implemented their model on a network consisting of a single travel corridor that has exprienced long (1 week to 2 months or more) closures in the past.

Taylor cites [Berdica & Mattsson, 2007], who attempt to examine the effects road degradation has on Stockholm's transportation network if one or more chokepoints were to become damaged or all-together innundated. The authors sought to determine how interuptions affect the system, and how overall system perfomrance was affected. Users in this method were only given the choice of an alternate route, and the authors acknowledge that this is not entirely reasonablein a real world situation. This method purely attempts to quantify delay experienced by users compared to the original equilibirum state, but does attempt to determine a moneatry value associated with closure or degradation.

[Winkler, 2016] proposes a travel demand model that is valid for all networks, especially those with more than one constraint, such as mode choice. Winkler's methodology utilizes an EVA model, or a model that uses production, distribution, and mode choice as inputs. The methodology shows that an EVA model can be used to help determine outputs for multi-constraint Multinomial Logit Models (MNL) to help determine consumer surplus. Logsums like Winkler's also allow for consumer surplus, measured as utility, to be estimated across the transportation network being modeled.

[Ganin et al., 2017] attempts 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 the network 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, the authors were able to estimate the average annual delay per commuter. They used this to determine network efficiency. Ganin noted that traffic delay times increases significantly as road segments are broken.

### 2.4 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 the costs, of these potential changes in modeled crisis events. We are able to learn from these methodologies to create a methodology on a state-wide level. oogly moogly

# 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.

We first 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, its implementation within the CUBE travel demand modeling software.

## 3.2 Utah Statewide Travel Model

The Utah Statewide Travel Demand Model (USTM) is developed and maintained by the Travel Demand Modeling group at UDOT. 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 and covers the rural areas lying outside of the MPO model regions. In these regions, UDOT is responsible for transportation planning. Consequently, USTM covers the highway facilities accross 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).

Each of the local travel demand models and USTM employ a gravity-based trip distribution model. The gravity model assumes that trips between origin- destination (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 locations attractiveness) and the friction factor between the OD pair. A mathematical representation of the gravity model is given by:

$$T_{ij} = P_i * (A_j F_{ij}) / \sum (A_j F_{ij}) \tag{3.1}$$

Where:

- $T_{ij}$ represents that trips made between an origin $i$ and a destination $j$
- $P_i$ represents the productions at origin $i$
- $A_j$ represents the attractions ad destination $j$
- And $F_{ij}$ is the friction factor between and $OD$ 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 $\alpha$ and $\beta$ 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. if there are 100 productions, there must 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 destinations size (as represented by $A_j$ in 3.1). The friction factor in 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 destination choice model will not be able incorporate this.

Alternatively, logit-based destination choice models improve model accuracy when compared with gravity and four-step models, and are advantageous because of an increased ability to introduce additional variables and reflect other statistical assumptions [Travel Forecasting Resource, 2021]. The ability to incorporate improved methods for determining trip distribution, mode choice, and destination choice all allow logit-based models to more accurately estimate trips between OD pairs on a road network. Consequently, logit-based travel demand models can estimate the choice-based effects of major changes to a road network given adverse natural or man-made events. More accuracy in a model's estimation process returns a more precise estimate of benefit or disbenefit experienced by users than could otherwise be made using another type of model.

Destination choice models, on the other hand, explicitly consider multimodal accessibility. The ability to consider multimodal accessibility allows 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) and other socioeconomic data, which are made available through the Utah Household Travel Survey (UHTS) conducted in 2017. The socioeconomic data primarily comprises the size term of the destination choice. The DC size term is a measure of the appeal or attractiveness of a destination when compared to another destination. The DC size term is discussed in further detail in 4.

A critical feature of logit-based choice models – described in 2 – is that they are more versatile than traditional modeling methods, with the ability to incorporate different types of data — *and* account for user choice — to be used for analysis which is highly important for a model that is constrained. 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 increasinlgy common in four- step and other modern travel models. However, no logit-based destination choice models have been implemented within and 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 report. Therefore, a new standalone model must be developed.

## 3.3 Model Design

This section outlines the design and implementation of a model to evaluate critical link resiliency in Utah.

### 3.3.1 Model Framework

An initial model framework was created to show how a resiliency model would appear in order to create a logit-based model. The model framework consists of the following steps:

- Skim Network
  - In this step, the model determines the shortest path by travel time on the USTM network between each origin and destination. The model also determines the corresponding distance.
- Mode Choice Logsum
  - The mode choice logsum is a function of the travel impedances estimated in the highway and peak transit skims and serves as an accessibility term in the destination choice model.
  - The mode choice logsum uses utility functions to determine the probability and logsum associated with travel between each original and destination.
  - The mode choice model uses constants and coefficients to calibrate and adjust the utility equations and determine 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.
  - The attraction size term is determined using socioeconomic data for each destination zone.
- Destination Choice

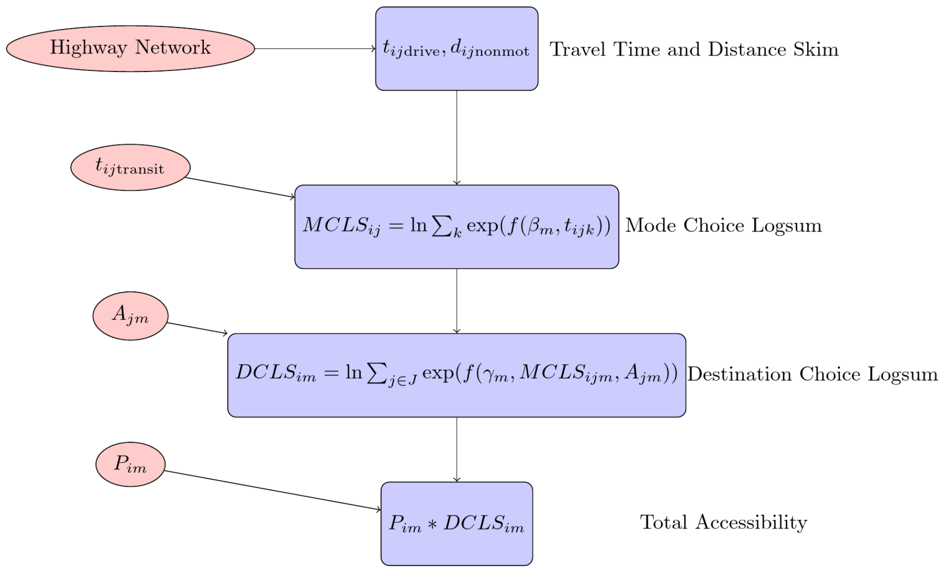


Figure 3.1: Model framework.

  - Allocates trip productions to destination zones based on information from the destination choice logsum.

- Mode Choice

  - Allocates trip productions attracted to each zone to specific modes based on the mode choice logsum.

- Trip Assignment

  - A static user equilibrium assignment loads all estimated trips onto the network based on origin, destination, and mode choice. Congestion, if present, will be shown on the network using this step. Highway volume-capacity functions from the USTM model will be applied.

- Check $\delta$ Assignment and Feedback

  - If the assignment changes substantially between rounds, it is an indication that traffic congestion is substantially affecting the mode and destination choice models. The model is then run iteratively to ensure equilibrium is achieved on the network.

In June 2020, the proposed model framework was altered based on feedback from the UDOT Technical Advisory Committee (TAC), such that it no longer included trip assignment or a feedback loop. The new framework can be seen in 3.1. In the new framework, trip assignment is still included because the total number of trips occurring must be calculated, though those trips are not specifically assigned to the network. Instead, calibration matrices are used to track trips by purpose and mode between OD pairs. With a feedback loop, these trips would have been assigned back onto the network before looping back through the framework.

The decision to not include a feedback loop in the framework shown in 3.1 introduces limitations on the ability of the model to accurately estimate the effects of link closure on travel time. This limitation stems from the decision to not include a feedback loop. This limits the ability of the model to estimate accurate changes in travel time because the increases in travel time due to congestion cannot be accurately measured after one iteration. The limitation has further negative impacts becaues the model cannot accurately estimate costs associated with link closure either. If a feedback loop had been included, the model would have been run several times for each scenario until the specifications of a convergence factor had been met, which would have allowed for more accurate estimation of increased travel times and more accurate route choices between OD pairs.

The model framework as currently used is presented in Figure 3.1, and is designed to capture the utility-based accessibility for a particular origin zone $i$ and trip purpose $m$. The model begins with a travel time skim procedure, to determine the congested travel time from zone $i$ to zone $j$ by auto as well as the shortest network distance for non motorized modes. The transit travel time skim is fixed, assuming that transit infrastructure would not be affected by changes to the highway network. Throughout this section, lower-cased index variables $k$ belong to a set of all indices described by the corresponding capital letter $K$

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

$$\mathscr{P}_{ijm}(k) = \frac{\exp(f(\beta_m, t_{ijk}))}{\sum_K \exp(f(\beta_m, t_{ijk}))} \tag{3.3}$$

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

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

$$\mathscr{P}_{im}(j) = \frac{\exp(f(\gamma_m, MCLS_{ijm}, A_j))}{\sum_J \exp(f(\gamma_m, MCLS_{ijm}, A_j))} \tag{3.4}$$

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

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

$$\Delta_{im} = DCLS_{im}^{\text{Base}} - DCLS_{im}^{\text{Scenario}} \tag{3.5}$$

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

$$\text{Cost} = \sum_I \sum_M -1/\beta_{\text{cost},m} * P_{im}\Delta_{im} \tag{3.6}$$

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

$$\text{Cost}' = \sum_I \sum_J \sum_M \frac{\beta_{\text{time},m}}{\beta_{\text{cost},m}} T_{ijm} t_{ijm} \tag{3.7}$$

### 3.3.2 Roanoke Model

An existing CUBE model from the Roanoke Valley Transportation Planning Organization (RVTPO) was used as a template to create a working logsum-based model that could be applied to the USTM network in the resiliency model. RVTPO includes an extensive transit network, a large feedback loop, and additional trip purposes not considered in USTM. The scenario network is also much smaller, consisting of 267 zones compared with USTMs 8775 zones, and has 61 external zones compared with USTMs 27 external zones. Additionally, the RVTPO model takes approximately 20 minutes to run the base scenario, which is extremely advantageous regarding time management during model creation.

The RVTPO model provided a helpful framework to understand key aspects of a functioning logit based destination choice model. The Mode and destination choice scripts were of particular interest for reference because there are often multiple ways to achieve the same result when coding. Some methods of coding are computationally faster than others, and the existing CUBE scripts were used to check that faster functions were used within the model code. Additionally, specific attention was given to the application of the mode and destination choice utility equations in the RVTPO model to ensure their design was understood, and properly adapted into the resiliency model.

Inputs included in RVTPO were also considered before implementation in the resiliency model. The original utility equations were extensively adjusted to match existing data options from USTM before being migrated to the resiliency model. This process ensured that the equations could be properly applied to the purposes needed while creating the resiliency model.

### 3.3.3 Model Implementation in Utah

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

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

The main inputs of the model are all extracted from USTM. The three main inputs to the framework are:

- *Highway Network*: including free flow and congested travel speeds, link length, link capacity estimates, etc.
- *Zonal Productions* $P_{im}$: available for all zones by purpose, including those in the MPO region areas.
- *Zonal Socioeconomic Data*: the destination choice model described in Equation (3.4) calculates attractions $A_{jm}$ from the USTM zonal socioeconomic data based on the utility coefficients in 3.1.
- *Calibration Targets*: USTM base scenario estimates of mode split and trip length were used to calibrate the utility coefficients as described below.

### 3.3.4 Transportation Networks

The resileincy 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.

### Highway Network

The USTM highway network was applied to the resiliency model. 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 ID (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 distance between the OD pair with the shortest AM travel time.

The highway skim module creates an output matrix (or highway skim) of travel times and distances between origin destination (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 Skims

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 (3.3); the zonal travel time between the smaller WFRC / MAG model zones was averaged to the larger USTM zones using a crosswalk, 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.

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 cannot influence transit availability on the network.

### 3.3.5 Non-Motorized Trips

The NMOT trips are also held fixed. We determined that the longest distance a pedestrian would commute via a NMOT mode is 2.5 miles or less. Accordingly, the upper limit for NMOT trips in the NMOT utility equation was set at 2.5 miles. The decision to hold these trips constant was made for several reasons, mainly because pedestrians often cut through construction zones, or can find shorter detours on side streets that may not be viable for large amounts of traffic.

### 3.3.6 Trip Attractions and Socioeconomic Data

The resiliency model uses socioeconomic data to estimate the productions at each zone. The socioeconomic data 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. This information is useful when determining the DC size term.

Trip attractions are calculated using the size term, which denotes the significance of a *TAZ* in attracting trips. The size term is built using various DC parameters and the socioeconomic data to determine the size or attractiveness of a zone. The size term equation was adapted from the Oregon Statewide Integration Model (SWIM), which is one of the most comprehensive destination choice models.

### 3.3.7 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 MC constants as inputs.

Table 3.1: Choice Model Coefficients

| Variable | HBW | HBO | NHB |
|---|---|---|---|
| **Destination Choice** | | | |
| Households | 0.0000 | 1.0187 | 0.2077 |
| Office Employment | 0.4568 | 0.4032 | 0.2816 |
| Other Employment | 1.6827 | 0.4032 | 0.2816 |
| Retail Employment | 0.6087 | 3.8138 | 5.1186 |
| Distance | -0.0801 | -0.1728 | -0.1157 |
| Distanceˆ2 | 0.0026 | 0.0034 | 0.0035 |
| Distanceˆ3 | 0.0000 | 0.0000 | 0.0000 |
| **Mode Choice** | | | |
| Shared | -1.1703 | 0.0164 | -0.0336 |
| Transit | -0.3903 | -1.9811 | -2.2714 |
| Non-Motorized | -1.2258 | -0.3834 | -0.8655 |
| Travel Time [minutes] | -0.0450 | -0.0350 | -0.0400 |
| Travel Cost [dollars] | -0.0016 | -0.0016 | -0.0016 |
| Walk Distance (less than 1 mile) [miles] | -0.0900 | -0.0700 | -0.0800 |
| Walk Distance (1 mile or more) [miles] | -0.1350 | -0.1050 | -0.1200 |

The MC constants and coefficients used in the resiliency model were extracted from USTM where applicable or adapted from SWIM. The $IVTT$, $COST$, $WALK1$, and $WALK2$ coefficients for the $HBW$, $HBO$,and $NHB$ purposes were extracted directly from the USTM mode choice model. The values for each of the coefficients are in Table 3:

The utility coefficients for the destination and mode choice models are presented in Table 3.1. The mode choice coefficients were adapted from USTM and supplemented with coefficients from the Roanoke (Virginia) Valley Transportation Planning Organization (RVTPO) travel model. This model was selected as a source for these coefficients due to its simplicity and analogous data elements to the proposed model. The alternative-specific constants were calibrated to regional mode choice targets developed from the 2015 Utah Household Travel Survey (UHTS) using methods described by [Koppelman & Bhat, 2006].

Mode constants for the mode choice model are extracted from USTM, however thees values are adjusted during the model calibration process. Mode constants typically represent the effects of all factors on the mode choice, but are not limited to those values included in the utility equations [Koppelman & Bhat, 2006].

$$U_{AUTO} = C_{IVTT} * TravelTime + C_{COST} * AUTOCOST * DISTANCE \tag{3.8}$$

$$U_{TRANSIT} = K_{TRN} + C_{IVTT} * TRANSITTIME \tag{3.9}$$

$$U_{NMOT} = K_{NMOT} + 20 * (C_{WALK1} * DIST_{<1MILE} + C_{WALK2} * DIST_{>1MILE} \tag{3.10}$$

From the equations above, several commonalities between the three MC utility equations are apparent. First, the transit and $NMOT$ utility equations both have a constant, denoted by a $K$, 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 distance, 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 probability associated with each mode of travel for an OD pair. The equation used to accomplish this can be seen in the equation below:

$$Probability_i = \exp U_i / \sum \exp U \tag{3.11}$$

Due to the way that the transit utility was calculated, the probability that a user would choose transit in an area with no available transit was often 100%. The cause of this was that the transit time matrix only shows a time value if there is transit available between an OD pair. The zero values that corresponded to areas with no transit availability caused the transit utility to be very small, or less negative in most cases compared to all the other modes considered. As a result, users had a greater probability of choosing transit as a mode even if it was not an available option between an OD pair. To troubleshoot this, we filtered the sum of the exponentiated utilities and reassigned values equal to zero to be equal to 1, so that the total sum of the exponentiated utilities would be 1. After implementing this change, the calculated probabilities added up correctly between modes, and areas with no transit service available returned a transit probability of zero.

### 3.3.8 Destination Choice Model

The DC module includes the highway skim, MCLS output from the previous module, the socioeconomic data extracted from USTM, and DC parameters as inputs. The destination choice utility equation consists of three parts: a size term, a travel impedance term, and a calibration polynomial. Coefficients for the size term and travel impedance terms were adapted from the Oregon Statewide Integrated Model (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 parameters can be seen in 3.1

The DC equation, seen in Equation 8, 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.

$$\begin{aligned} U = C_{LSUM} * MCLS + \log(SIZETERM) + C_{DIST} * DIST \\ + C_{DISTSQ} * DISTSQ + C_{DISTCUB} * DISTCUB + C_{LOGDIST} * \log DIST \end{aligned} \tag{3.12}$$

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 friction factor in the gravity model discussed in 2 . Feeding the MCLS value into the DC module is what allows users to choose a destination rather than having fixed destination choices. 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:

$$\begin{aligned} SIZETERM = C_{HH} * TOTHH + C_{OFFICE} * OFFICE + C_{RETEMP} * RETEMP \\ + C_{OTHEMP} * (ALLEMP - OFFICE - RETEMP \end{aligned} \tag{3.13}$$

Other employment was not included in the socioeconomic data, which was problematic. A way to determine a value for other employment was found by subtracting the other employment purposes considered from the *ALLEMP* value. Doing this left only the employment data that had not already been accounted for in each *TAZ* behind to be multiplied by the proper coefficient.

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

$$DCLS = \exp(ROWSUM(U_{DC}) \tag{3.14}$$

The purpose of taking the log of the entire row is to measure the logsum between a zone and all the other zones at the same time. By doing this, we can determine the overall change in logsum 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 estimating trips 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 ($TRIPS_IJ$) and by mode ($TRIPS_IJK$). To find the trips by purpose ($TRIPS_IJ$), the probability of a trip occurring between an OD pair needed to be determined. Likewise, to find the trips by purpose and mode ($TRIPS_IJK$), we multiplied the $TRIPS_IJ$ by the MC probabilities calculated during the MC module. A mathematical representation of this can be seen in the equations below:

$$TRIPS_{ij} = HHPROD_i * DCPROBABILITY_{ij} \tag{3.15}$$

$$TRIPS_{ijk} = TRIPS_{ij} * MCPROBABILITY_{ij} \tag{3.16}$$

### 3.4.2 Calibrating Choice Constants

After the resiliency model MC and DC scripts are created, it is necessary to calibrate the model by iteratively adjusting the MC constants and DC parameters to ensure accurate output estimation.

#### 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 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 3.3 presents the original statewide mode split targets from the UHTS, and Table 3.4 shows the final calibrated mode splits in the resiliency model. Figures 3.2, 3.3 3.4 show 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

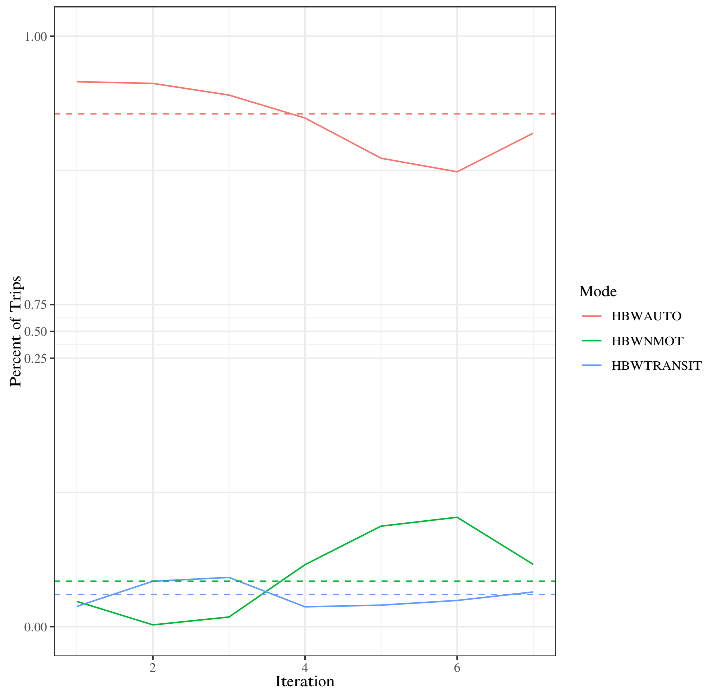


Figure 3.2: HBW Mode Choice Split.

calibration polynomial that adjusts the implied utility to match a target number of trips extracted from USTM. In this model, we include a cubic polynomial as the destination choice calibration term seen in the equation below:

$$U_{ij} = \beta size(size) + \beta MCLS(MCLS) + \kappa 1(dist) + \kappa 2(dist)^2 + \kappa 3(dist)^3 \tag{3.17}$$

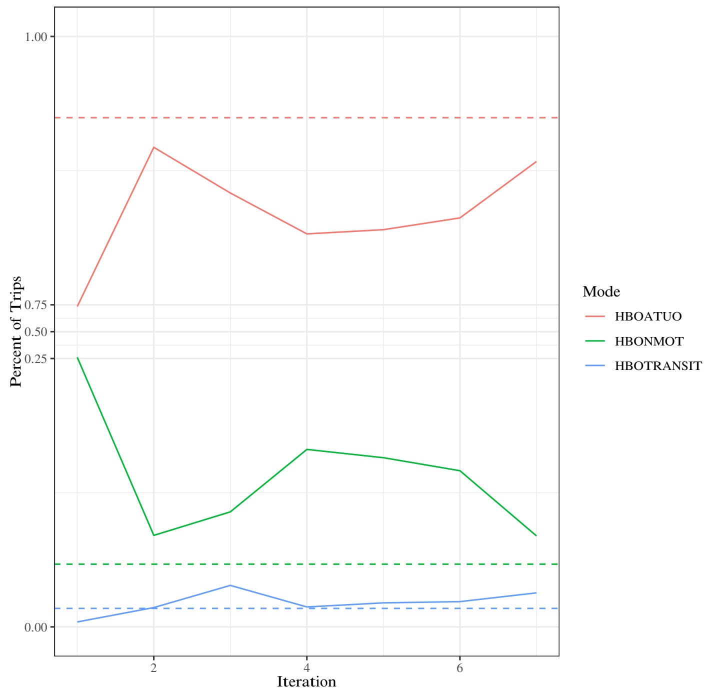


Figure 3.3: HBO Mode Choice Split.

With $\kappa_1, \kappa_2, \kappa_3$ calibrated to re-create best fit estimates of the difference between the model and target total. The target values for calibration are derived from USTM. The cubic polynomial in 3.17, which is part of the utility equation, was applied and calibrated to match the target TLFD values from USTM. The calibration of the three polynomial parameters can be seen in Figure 6, Figure 7, and Figure 8. Table 3.2 presents the polynomial coefficient values. Figures 3.5 and 3.6 show the best fit trendlines for the DC parameters at each iteration.

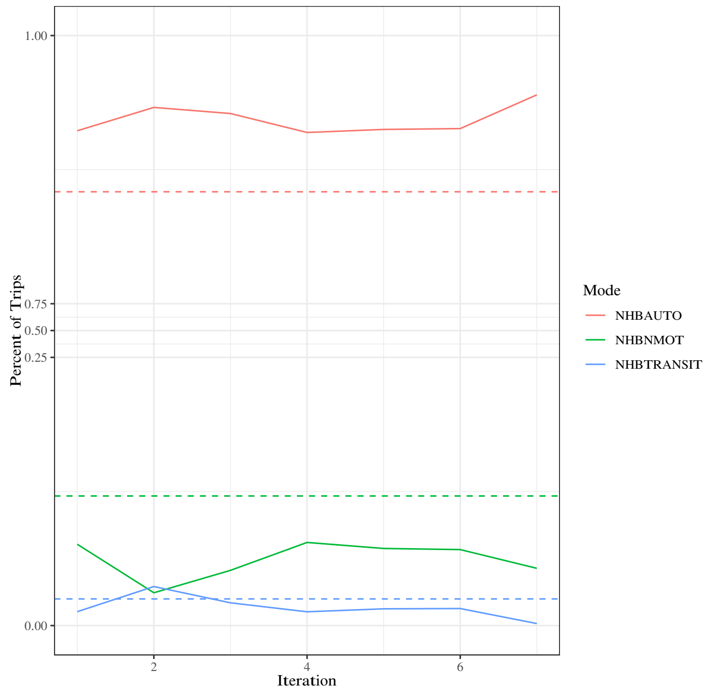


Figure 3.4: NHB Mode Choice Split.

Table 3.2: Final DC Parameters

| | HBW | HBO | NHB |
|---|---|---|---|
| CDIST | -0.1956000 | -0.16060 | -0.210200 |
| CDISTSQ | 0.0021000 | 0.00290 | 0.011200 |
| CDISTCUB | -0.0000061 | -0.00001 | -0.000012 |

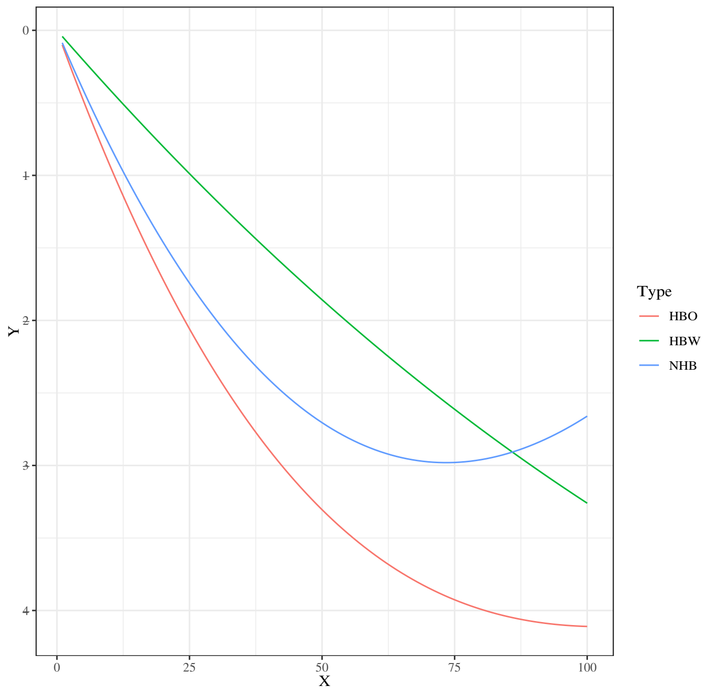


Figure 3.5: Initial Destination Choice Parameter Trendlines.

### 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 trip length frequency distribution (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

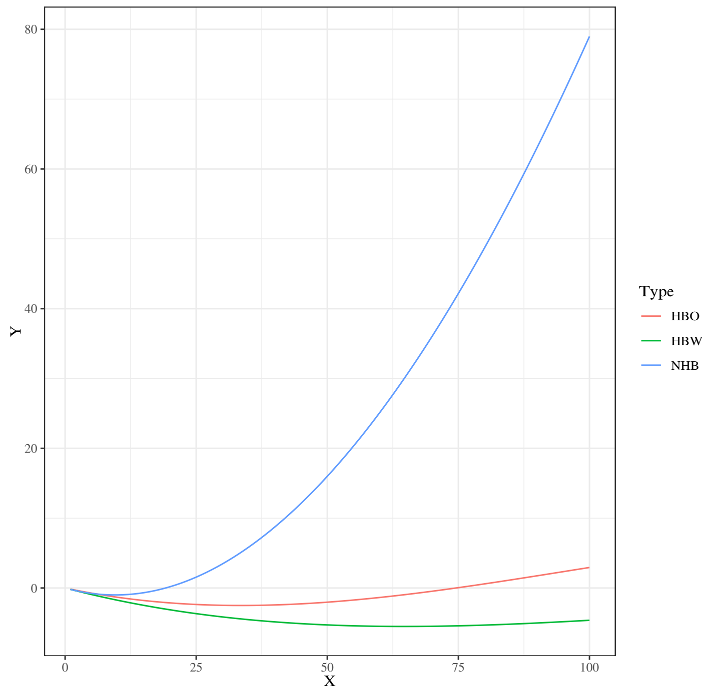


Figure 3.6: Final Destination Choice Parameter Trendlines.

that we could ensure trips in the resiliency model were being conserved. Trip totals were compared using the TLFD outputs to ensure trips of similar lengths were being estimated, and to the total trips by purpose and mode to ensure trip conservation.

Final trip length distributions for each purpose are similar to the extracted USTM target values for both the TLFD comparison and the overall total value comparison. There is some variation between the two graphs below, however the TLFD targets have been matched to an acceptable

Table 3.3: Target Splits

| Mode | HBW | HBO | NHB |
|---|---|---|---|
| Auto | 92.8% | 85.4% | 92.4% |
| NMOT | 4.2% | 12.1% | 5.8% |
| Transit | 3.0% | 2.5% | 1.7% |

Table 3.4: Model Splits after Calibration

| Mode | HBW | HBO | NHB |
|---|---|---|---|
| Auto | 91.0% | 88.4% | 94.5% |
| NMOT | 5.8% | 8.5% | 5.3% |
| Transit | 3.2% | 3.2% | 0.2% |

margin of error between the target and the resiliency model for this purpose. The TLFD results for both the original USTM and the calibrated resiliency model can be seen in Tables 3.3 and 3.4.

Additionally, Figure 3.7 and 3.8 show the final percent capture rates for the USTM and resilience models.The fit for both is similar, though there is some variation present.

### 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.

#### 3.5.1 Travel Time Difference

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. We chose to simply

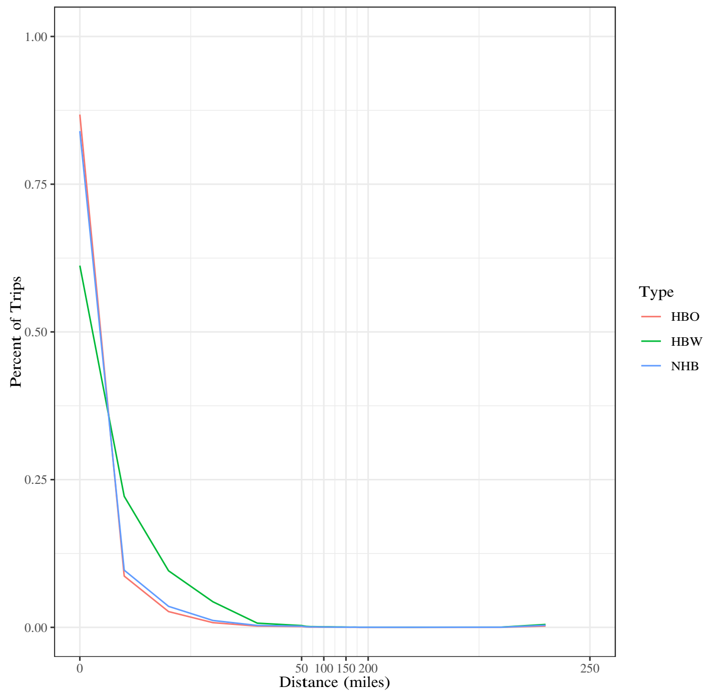


Figure 3.7: USTM Trip Length Frequency Distribution.

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 could become

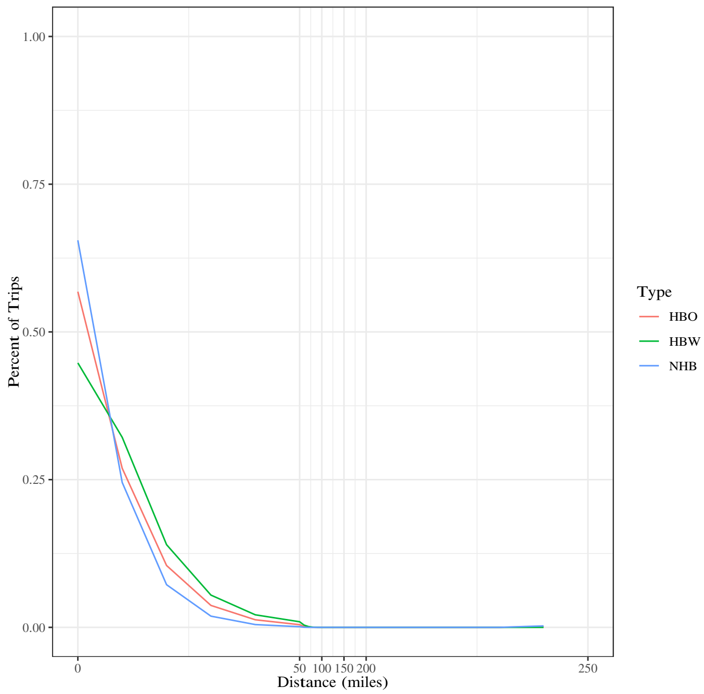


Figure 3.8: Resiliency Trip Length Frequency Distribution.

shorter, as the shortest distance between an OD pair was not always the fastest by time. 3.18 shows a representation of how differences in travel time were calculated:

$$\Delta TIME = ScenarioTime - BaseTime \tag{3.18}$$

Table 3.5: Values of Time for Time Difference Calculations

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

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.

### 3.5.2 Value of Time

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 [Utah Department of Transportation, 2020].

The VOT (shown in Table 3.5) used was then multiplied by the number of trips for each purpose in the resiliency model as well as the purposes not included in the resiliency model. This was done to allow for more thorough analysis of overall model results.

### 3.5.3 Vulnerable Link Identification

To develop evaluation scenarios on which to apply the model, we used information contained in the UDOT Risk Priority Analysis online map [CITATION]. This map considers the probability of various events that could impact road performance including rock falls, avalanches, landslides, and other similar occurrences. The map indicated 41 non-redundant highway facilities on which to apply the model.

### 3.6 Summary

We now have a logit-based model that is sensitive to user mode and destination choice. The model also accounts for modes that are not as flexible in the case of link closure as well. Using the model, we can input scenarios with broken links to evaluate the effects that link loss may have on user mode and destination choice, as well as estimate the overall disbenefit experienced by road users per day.

# CHAPTER 4. MODEL APPLICATION

## 4.1 Overview

In this chapter, we summarize the methodology used to identify vulnerable links on Utah's highway network. We also apply the model to scenarios where critical highway links are removed from the model network. This includes first a detailed analysis of a single scenario, where I-80 between Salt Lake and Tooele Counties is severed. We compare the model output to an alternative method that measures only the change in travel time and does not allow for mode or destination choice. The model was then applied to 41 individual link closure scenarios throughout the state.

## 4.2 Vulnerable Link Identification

Two methodologies were developed to identify vulnerable network links in Utah. The first method resembles the process used by AEM to determine threat categories, and threat proximity thresholds to highway links. This methodology was ultimately not used in the resiliency model due to its complicated nature which involved identifying multiple risk factors. The second method uses an online Risk Priority Analysis map created by UDOT combined with familiar knowledge of Utah's road system. Using this second method, links were identified due to their location in relation to populations or geography. Many were suspected choke points or were points of interest to the BYU team or UDOT officials.

## 4.3 Single Scenario Analysis

This section outlines an in-depth analysis that was conducted to ensure the resiliency model was accurately capturing trips with OD pairs in the targeted area around a closed link (in an urban area, most trips would be generated or terminate in areas directly adjacent to the broken link). This analysis was done on a link between Tooele and Salt Lake City, Utah.

Scenario 50, located along I-80 between Tooele and Salt Lake Counties, was examined to ensure the resiliency model was capturing trips in the vicinity of a broken link. Analyzing the model outputs at a localized level was necessary to ensure that the model was appropriately estimating trips and capturing them in the areas that were expected. In scenario 50, if many effected trips had not been originated or terminated in Tooele and Salt Lake counties, that would have signaled that a problem was present in the model. This localized analysis shows that a broken link mainly effects the area surrounding that link, and the key takeaway here is that the model functions as intended.

Another method we used to estimate trip costs is the travel time method, which serves to capture trips that have fixed OD pairs such as freight and recreational trips. This localized analysis also looks at this method.

Table 4.1 compares the overall costs between the logsum and travel time methods, the specific cost for trips originating in Tooele and ending in Salt Lake and includes a trip comparison as well. From Table 4.1, we can see that the logsum method captures about \$53,897 in experienced expense due to the closure of the link. Specifically, between Tooele and SLC, the logsum based resiliency model captures \$20,746 of expense, which is approximately 51.89% of the total expense as seen in Table 4.2. This shows that the resiliency model is effectively capturing trips in the correct areas based on the percent comparison capture rate in Table 4.2. 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 \$437,401 and \$406,899 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 resileincy model and in the travel time method for determining cost. HBW, HBO, and NHB trip purposes can be compared because all three trip purposes are represented by each method of cost estimation.

The travel time method measures the difference in travel time between the base scenario and any other scenario caused by link closure, and then multiplies that difference by the VOT for each trip purpose and the number of trips estimated for each trip purpose. For external trips, freight trips, and REC trips, these were all extracted directly from USTM. Attempting to include

Table 4.1: Tooele Table

| ...1 | Total Overall Costs | ...3 | Tooele - SLC Cost | ...5 | Base Trips | ...7 |
|---|---|---|---|---|---|---|
| Purpose | Logsum | Travel Time | Logsum | Travel Time | Tooele - SLC | Who |
| HBW | $15397.06 | $244275.72 | $12143.11 | $233373.56 | 7980 | 1684 |
| HBO | $12882.89 | $108412.94 | $3577.62 | $98163.53 | 6665.86 | 4593 |
| NHB | $25635.92 | $84712.36 | $5025.24 | $75361.98 | 1025 | 2611 |
| REC | $398.72 | $398.72 | $40.73 | $40.73 | 3 | 2385 |
| XXP | $3690.26 | $55870.17 | $55870.17 | | 0 | 2235 |
| Freight | $911254.89 | $10883835.01 | $111772.5 | $111772.5 | 515811 | 8751 |
| Total Logsum | $53897.87 | $437401.02 | $20745.97 | $406899.06 | 15672 | 8888 |
| Total | $969241.74 | $437401.02 | $132559.20 | $406899.06 | 531486 | 9788 |

Table 4.2: Tooele Table Again

| Logsum / Base | ...2 | Logsum / Tooele - SLC Logsum | Travel Time / Tooele - SLC Travel Time |
|---|---|---|---|
| All Trips | Tooele - SLC | | |
| 0.0630 | 0.0342 | 0.5189 | 0.9554 |
| 0.1188 | 0.0679 | 0.5174 | 0.9055 |
| 0.3026 | 0.0136 | 0.0400 | 0.8896 |

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 areincluded in the resiliency model.

The HBW, HBO, and NHB purposes are also estimated using the logsum model. Calculating the costs associated with the change in logsum provides a more precise and accurate estimate of the costs experienced by these users due to link loss. Ultimately, the logit-based model is more sensitive to changes in the network for those purposes which are included in the resiliency model, but a way to account for all purposes must be developed as well. Thus, by combining elements from the travel time method and the resileincy model, an estimate can be made that represents all traffic on the USTM network.

### 4.4 Comparative Scenario Results

We now apply the model to compare 40 additional scenarios where individual highway facilities are removed from the model highway network. These scenario locations are shown in Figure 4.1, and were identified in a report by [AEM, 2017] and the research team. AEM approached the idea of systemic resiliency by attempting to classify various types of threats toward specific infrastructure types. This method, while valid, was difficult to implement statewide. Some facilities have obvious natural threats such as earthquake, flood, or landslide, or are natural choke points on the USTM network. Because of the difficulty associated with identifying links in a similar method to AEM, the BYU team identified links using UDOTs risk analysis tool.

The following sections will present the results of the 41 scenarios analyzed. First, Table 4.3 shows each of the scenarios we examined, labeled “road10” for scenario 10, and “road11” for scenario 11. 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.

#### 4.4.1 Link Rankings by Both Methods

The logsum method results are as follows in Table **??**. The results are ranked from the road with the largest (most positive cost to the road with the smallest cost.

We can see that road 27, which corresponds to I-84 between Ogden and Morgan, experiences the largest cost per day according to the resiliency model. Following road 27, roads 50, 37, 30, and 17 make up the five most important roads according to the cost estimation provided by the resiliency model. Each of these roads with the exception of SR-18 in St. George, is an Interstate or State Highway facility in Northern Utah, which is heavily populated. Some roads, such as road 10, road 11, or road 33, which are located in remote parts of the state, experiences no measurable change to HBW, HBO, or NHB traffic. This is likely due to the location of the highway link that was cut. A ranking is provided for all of the roads in Table 4.4.

Table 4.5 contains the ranking results from the travel time method. Here, we see that the first five roads differ from the results of the logsum model. Instead, road 48 becomes the most important road due to costs experienced. Road 48 is a part of I-70 near Green River, Utah. The other four roads that make up the top five most important roads in the travel time method analysis

Table 4.3: Link Table

| LINK_ID | ROUTE | LOCATION |
|---|---|---|
| road10 | SR-95 | near Hite |
| road11 | US-6 | near King Top |
| road12 | I-15 | in Bountiful |
| road13 | I-70 | at Dragon Point (W of Green River) |
| road14 | I-15 | in Orem between Univ. Ave & Center St |
| road15 | SR-199 | near Rush Valley |
| road16 | SR-153 | between Beaver & Junction |
| road17 | SR-18 | just North of St. George |
| road18 | I-15 | near Rocky Ridge (between Payson & Nephi) |
| road19 | I-15 | near I-70 & Filmore |
| road20 | I-15 | near New Harmony |
| road21 | US-40 | East of Strawberry Reservoir |
| road22 | US-6 | in Carbon County North of Helper |
| road23 | Legacy Parkway | near West Bountiful |
| road24 | UT-35 | outside of Francis |
| road25 | Timp Highway | at the base of AF Canyon |
| road26 | SR-14 | in Cedar Canyon |
| road27 | I-84 | between Ogden and Morgan |
| road28 | SR-65 | on the border of Salt Lake County & Morgan County |
| road29 | SR-101 | East of Hyrum |
| road30 | US-91 | between Brigham City & Mantua |
| road31 | SR-62 | East of Kingston |
| road32 | US-89 | between Logan and Bear Lake |
| road33 | SR-24 | in Capitol Reef National Park |
| road34 | Bangerter | near Bluffdale |
| road35 | SR-191 | between Helper & Duchesne |
| road36 | SR-24 | near Steamboat Point |
| road37 | I-80 | in Parley's Canyon |
| road38 | I-15 | at the Point of the Mountain |
| road39 | I-80 | in SLC near Sugar House and 1300 E |
| road40 | I-15 | in SLC between 2100 S & 1300 S |
| road41 | I-215 | near Taylorsville |
| road42 | Bangerter | near West Valley City |
| road43 | I-215 | near Cottonwood Heights |
| road44 | MVC (UT-85) | West of West Jordan |
| road45 | US-89 | near the Border of Arizona by Lake Powell |
| road46 | SR-189 | up Provo Canyon near Vivian Park |
| road47 | US-6 | up Spanish Fork Canyon near Diamond Fork Rd |
| road48 | I-70 | near Green River (NW of Moab) |
| road49 | I-70 | near Richfield & Filmore |
| road50 | I-80 | between SLC and Tooele |

Table 4.4: Link Analysis Results

| Scenario | Delta | Cost Value | Route | Location |
|---|---|---|---|---|
| ROAD27 | -23830.208 | 14893880.000 | I-84 | between Ogden and Morgan |
| ROAD50 | -19686.788 | 12304242.500 | I-80 | between SLC and Tooele |
| ROAD37 | -8932.691 | 5582931.875 | I-80 | in Parleys Canyon |
| ROAD30 | -7511.948 | 4694967.500 | US-91 | between Brigham City & Mantua |
| ROAD17 | -5243.828 | 3277392.500 | SR-18 | just North of St. George |
| ROAD46 | -4911.457 | 3069660.625 | SR-189 | up Provo Canyon near Vivian Park |
| ROAD38 | -4422.194 | 2763871.250 | I-15 | at the Point of the Mount |
| ROAD18 | -3186.967 | 1991854.375 | I-15 | in Rocky Ridge (between Payson & Nephi) |
| ROAD42 | -2657.614 | 1661008.750 | Bangerter | near West Valley City |
| ROAD41 | -1700.167 | 1062604.375 | I-215 | near Taylorsville |
| ROAD25 | -1139.020 | 711887.500 | Timp Highway | at the base of AF Canyon |
| ROAD24 | -387.467 | 242166.875 | UT-35 | outside of Francis |
| ROAD23 | -297.882 | 186176.250 | Legacy Parkway | near West Bountiful |
| ROAD20 | -253.712 | 158570.000 | I-15 | near New Harmony (between Cedar City & St. Ge |
| ROAD47 | -142.671 | 89169.375 | US-6 | up Spanish Fork Canyon near Diamond Fork Rd |
| ROAD26 | -125.740 | 78587.500 | SR-14 | in Cedar Canyon |
| ROAD15 | -67.634 | 42271.250 | SR-199 | near Rush Valley |
| ROAD32 | -60.883 | 38051.875 | US-89 | between Logan and Bear Lake |
| ROAD14 | -45.386 | 28366.250 | I-15 | in Orem between Univ. Ave & Center St |
| ROAD29 | -41.595 | 25996.875 | SR-101 | East of Hyrum |
| ROAD31 | -40.108 | 25067.500 | SR-62 | East of Kingston |
| ROAD22 | -30.394 | 18996.250 | US-6 | in Carbon County North of Helper |
| ROAD49 | -17.768 | 11105.000 | I-70 | near Richfield & Filmore |
| ROAD45 | -17.029 | 10643.125 | US-89 | near the Border of Arizona by Lake Powell |
| ROAD21 | -11.267 | 7041.875 | US-40 | East of Strawberry Reservoir |
| ROAD36 | -10.170 | 6356.250 | SR-24 | near Steamboat Point |
| ROAD16 | -9.724 | 6077.500 | SR-153 | between Beaver & Junction |
| ROAD48 | -9.717 | 6073.125 | I-70 | near Green River (NW of Moab) |
| ROAD19 | -7.623 | 4764.375 | I-15 | near I-70 & Filmore |
| ROAD35 | -3.762 | 2351.250 | SR-191 | between Helper & Dechesne |
| ROAD13 | -0.135 | 84.375 | I-70 | at Dragon Point (W of Green River) |
| ROAD28 | -0.103 | 64.375 | SR-65 | on the border of Salt Lake County & Morgan Cou |
| ROAD10 | 0.000 | 0.000 | SR-95 | near Hite |
| ROAD11 | 0.000 | 0.000 | US-6 | near King Top |
| ROAD33 | 0.000 | 0.000 | SR-24 | in Capitol Reef National Park |
| ROAD12 | 894.999 | -559374.375 | I-15 | in Bountiful |
| ROAD44 | 2149.291 | -1343306.875 | MVC (UT-85) | West of West Jordan |
| ROAD43 | 4043.132 | -2526957.500 | I-215 | near Cottonwood Heights |
| ROAD40 | 5576.276 | -3485172.500 | I-15 | in SLC between 2100 S & 1300 S |
| ROAD39 | 7434.744 | -4646715.000 | I-80 | in SLC near Sugar House and 1300 E |
| ROAD34 | 9362.283 | -5851426.875 | Bangerter | near Bluffdale |

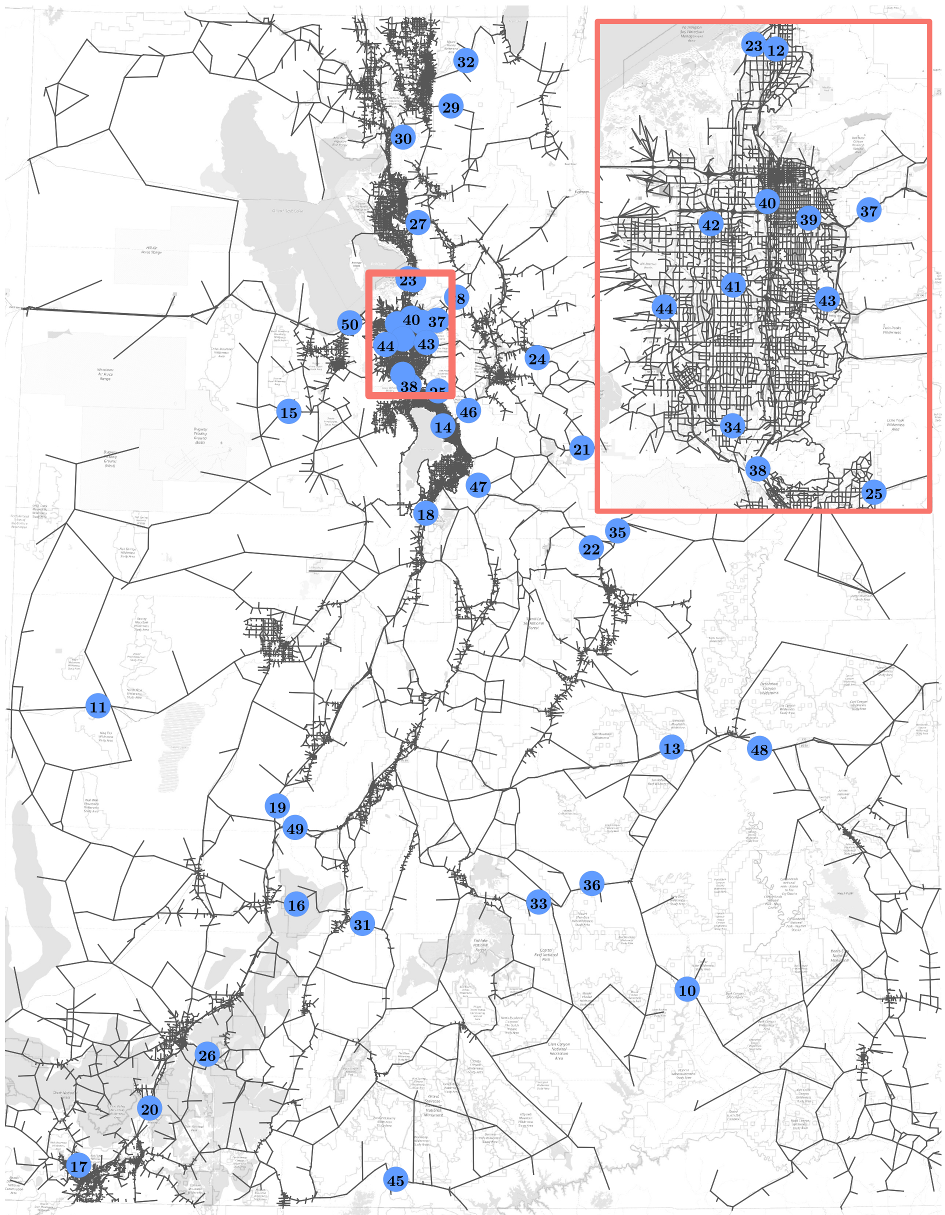


Figure 4.1: Links Identified for Analysis.

are road 13, road 20, road 50, and road 49. Some of these roads appear in both the logsum and travel time methods. Here again, several of the roads that are most important are located in Northern Utah. It is important to note that the main driving factor as to why a road was important or not in the travel time analysis was how much freight and external traffic it experienced along that route. Including the freight, even with the logsum results, changes the rankings drastically because of the significantly higher value of time associated with freight trips.

Table 4.5: Travel Time Analsyis Results

| ROAD | IIF | XXF | IXF | HBW | HBO | NHB | RE |
|---|---:|---:|---:|---:|---:|---:|---:|
| 48 | 9.907799e+05 | 8.454694e+07 | 0.0217 | 195.8176 | 256.6567 | 28.9348 | 15447.549 |
| 13 | 8.399095e+04 | 2.513068e+07 | 0.0000 | 0.0000 | 3.2527 | 0.0000 | 210.518 |
| 20 | 5.685583e+05 | 1.871674e+07 | 175.0997 | 2873.2413 | 2640.2752 | 1208.8308 | 11372.095 |
| 50 | 6.087866e+05 | 1.027499e+07 | 53.5297 | 244275.7151 | 108412.9438 | 84712.3575 | 398.729 |
| 49 | 3.079064e+05 | 7.810609e+06 | 0.0000 | 78.0622 | 59.2752 | 17.6232 | 155.555 |
| 18 | 3.935367e+06 | 1.847822e+06 | 1148.1140 | 20436.1302 | 21163.5461 | 15362.6359 | 13839.556 |
| 27 | 1.854494e+05 | 4.359448e+06 | 664.2652 | 35891.3868 | 20811.4770 | 52515.3604 | 207.631 |
| 19 | 2.307693e+06 | 1.069414e+06 | 104.3208 | 67.2237 | 70.0649 | 13.2078 | 6829.191 |
| 37 | 1.080281e+06 | 9.788824e+05 | 1127.7596 | 46220.2113 | 36178.1897 | 37631.6332 | 675.126 |
| 47 | 1.411715e+06 | 6.163554e+05 | 8.1666 | 1631.6607 | 373.0056 | 468.6302 | 2600.304 |
| 38 | 1.341423e+06 | 3.911825e+05 | 153.2942 | 75916.0675 | 88791.1404 | 84969.5325 | 2485.999 |
| 14 | 7.120600e+05 | 2.383607e+05 | 4.8294 | 31899.2443 | 35721.9390 | 38114.5497 | 1723.705 |
| 30 | 9.099365e+05 | 8.036293e+02 | 514.7669 | 15379.0610 | 12882.8926 | 25635.9186 | 624.348 |
| 39 | 1.681473e+05 | 6.624298e+05 | 297.8676 | 15712.6821 | 15091.4466 | 19512.5202 | 135.499 |
| 22 | 4.217119e+05 | 2.608851e+05 | 7.9739 | 4.4674 | 27.9534 | 17.1794 | 1163.651 |
| 45 | 8.637883e+02 | 5.509410e+05 | 145.7363 | 183.9739 | 232.6245 | 78.5503 | 13.442 |
| 21 | 5.378431e+05 | 0.000000e+00 | 0.3000 | 26.3054 | 89.7595 | 38.6124 | 422.864 |
| 40 | 2.662065e+05 | 1.040071e+05 | 1.0558 | 19182.8100 | 19129.6986 | 20511.6397 | 266.817 |
| 12 | 2.993304e+05 | 7.818270e+04 | 0.1602 | 12585.8118 | 9574.6810 | 12507.6326 | 251.214 |
| 35 | 1.812866e+05 | 0.000000e+00 | 0.0000 | 16.8416 | 69.7900 | 1.0298 | 355.157 |
| 46 | 8.059370e+04 | 1.041404e+03 | 99.7032 | 15111.9443 | 21009.6172 | 12684.3356 | 924.324 |
| 41 | 1.515385e+04 | 0.000000e+00 | 0.4593 | 11092.2455 | 17748.7203 | 22620.5138 | 44.218 |
| 34 | 1.951111e+04 | 0.000000e+00 | 0.2150 | 8202.9795 | 11805.6401 | 14453.2904 | 57.319 |
| 32 | 4.771497e+04 | 8.089437e+02 | 0.9723 | 736.0051 | 596.8124 | 124.5756 | 5.320 |
| 43 | 4.898116e+03 | 0.000000e+00 | 32.3321 | 6214.8820 | 10069.7932 | 13886.2694 | 84.351 |
| 16 | 3.053316e+04 | 0.000000e+00 | 0.1102 | 35.2392 | 0.8310 | 30.9960 | 118.409 |
| 42 | 4.319564e+03 | 0.000000e+00 | 1.0689 | 6623.8202 | 3955.9950 | 4711.9401 | 0.995 |
| 17 | 2.085366e+03 | 0.000000e+00 | 0.1453 | 2384.3859 | 3350.5890 | 6416.1449 | 1.453 |
| 44 | 3.495956e+03 | 0.000000e+00 | 0.0112 | 3577.6774 | 1909.6427 | 5214.1316 | 2.377 |
| 11 | 7.576949e+03 | 0.000000e+00 | 0.0000 | 0.0206 | 2.7587 | 0.0505 | 0.507 |
| 24 | 1.884429e+03 | 0.000000e+00 | 0.0000 | 847.0520 | 276.3691 | 1828.9714 | 0.603 |
| 33 | 4.088993e+03 | 0.000000e+00 | 0.0479 | 2.6681 | 4.8372 | 0.0000 | 23.974 |
| 25 | 5.627087e+01 | 0.000000e+00 | 0.0000 | 516.3094 | 272.7545 | 1852.3708 | 0.288 |
| 36 | 1.920113e+03 | 0.000000e+00 | 0.0000 | 12.8155 | 33.8723 | 12.5058 | 17.932 |
| 26 | 7.331829e+02 | 0.000000e+00 | 0.0779 | 261.0639 | 214.9443 | 189.3878 | 18.414 |
| 31 | 2.595082e+02 | 0.000000e+00 | 0.0000 | 324.7364 | 482.7504 | 157.8675 | 0.573 |
| 10 | 3.459434e+02 | 0.000000e+00 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 780.466 |
| 15 | 2.097366e+02 | 0.000000e+00 | 0.0032 | 221.0662 | 258.3935 | 67.3873 | 4.424 |
| 23 | 1.682285e+02 | 0.000000e+00 | 0.0026 | 84.6450 | 52.9403 | 123.9602 | 0.010 |
| 29 | 1.928357e+00 | 0.000000e+00 | 0.0058 | 122.3929 | 0.3114 | 62.3210 | 0.000 |
| 28 | 5.780939e+00 | 0.000000e+00 | 0.0000 | 0.0239 | 0.0477 | 0.0636 | 12.870 |
| Base | 0.000000e+00 | 0.000000e+00 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.000 |

Some other interesting findings are that in the top 10 of each analysis methods, three scenarios appear in both rankings. Road 50, which corresponds to I-80 between Tooele and SLC, road 27 which corresponds to I- 84 in Weber Canyon, road 37 which corresponds to I-80 in Parley's Canyon, and road 27 which is I-84 between Ogden and Morgan, are included in the top 10 scenarios for both methods of analysis. This is likely due to the number of passenger trips along these routes and the number of freight trips that occur along these routes as well. Several of these routes are the only way through mountain ranges in the routes geographic location.

### 4.4.2 Positive Benefit Scenarios

Five of the scenarios indicated a benefit resulting from highway link closure. These scenarios were examined more closely to determine what possible causes could exist beghind these atypical and unexpected results. The affected links are all located in 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.

It was determined that a likely cause which explains these atypical r esults is that the shortest path by time is not the shortest path by distance. 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 as might be more preferable. Additionally, it was found that the alternative route between Grouse Creek, UT and SLC, the alternative route was nearly twice as long in the case where I-80 was closed between Toeele and Salt Lake. This discovery led us to understand that not all route chocies become logical when made using only the model data. In reality, it is much more likely that a user would find a shorter route which consists of roads that are not all in the state highway system.

Another discovery we made, is that When a highway link is broken, the new shortest path by time is longer than in the base scenario with this link available. But 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.

This occurence 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 (50 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 more sensitive to network changes than the travel time comparison. 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 4.4 and Table 4.5 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 important road, while the travel time method, or total priority, indicates that I-70 near Green River is the most important 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 and 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 yet more accurate for estimations made using the resiliency model. The resiliency models 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 the true costs associated with long term highway closure.

The recommendations resulting from the adaptation of a logit-based model on the USTM network are that logit-based modeling returns more sensitive estimations of the value of a link in the network. This is a highly important outcome 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.

## 5.3 Obtaining the Model and it's Documentation

The model is hosted in an online GitHub repository which is maintained by the BYU Transportation Lab. The repository can be found here:

https //github.com/byutranspolab/ustm_resiliency

## 5.4 Limitations and Next Steps

Overall implementation of a logit-based travel demand model that more accurately captures demand on the USTM network is a highly important tool for continued development. Updating USTM to include a logit-based travel demand model instead of a gravity-based model would increase the accuracy of travel demand estimates moving forward. This, in turn, would allow for better travel estimates between TAZ across the state, and would likely cause more accurate estimations of traffic volumes on the road network to be estimated, and therefore future development and maintenance activities could be adjusted to accomodate future travel needs in Utah. Updating USTM to have a logit-based model would increase overall highway network capacity to accurately estimate travel demand on Utah's road network.

The non-motorized (NMOT) distance threshold was originally set at 50 miles because we believed that this would cap the most extreme trips but still allow the possibility of longer NMOT trips. NMOT trips are heavily penalized per each additional mile, but NMOT trips have improved access to short- and medium-range destinations, which clearly creates a problem when trips become longer and can be assigned NMOT as a mode. Setting the threshold at 50 miles was a mistake; the 90th percentile walk and cycling trips in the Utah Household Travel Survey (UHTS) are less than 2 and 5 miles respectively. In order to better represent NMOT trips, an upper threshold of 2.5 miles was assigned. Additionally, the NMOT skim was held constant throughout each iteration. This was done because pedestrians and cyclists typically have better access to side streets, or are more likely to find shorter routes not represented on the USTM network when presented with a closed link.

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 allows for better estimates of the true change in travel time due to both route change and increased 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 TAC decided to not include a feedback loop to save time on model development for Phase 1. A feedback loop and sensitivity analysis will be included as part of Phase 2.

It is not unreasonable to assume that in the event of an earthquake or similar widespread disaster event, that multiple links could become damaged. The ability to analyze the results of simultaneous multiple link loss will be included as a part of Phase 2 as well. 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.

## 5.5 Summary

The development of a logit-based travel demand model can improve the ability of UDOT to accurately estimate the costs per day of link loss that Utahn's would experience. The resiliency model provides sensitive estimates that more accurately represent the costs associated with link closure than a travel time increase methodology by itself would be able to capture. Using the logsum, estimations sensitive to user choice were found, which can help professionals to better evaluate risk to Utah's infrastructure. User choice is highly important in modern modeling practices because user choice allows a model to estimate information more precisely and accurately. The information provided by the resiliency model should be used to prioritize link importance to the functionality of Utah's highway network. The resiliency model more accurately estimates costs experienced by Utahn's due to link loss than traditional methods for determining costs.

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