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TRAVEL-TIME RELIABILITY IN SIMULATION AND PLANNING MODELS: UTAH CASE STUDY (SHRP2 L04 IAP ROUND 7)

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UNIT CONVERSION FACTORS

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	When You Know	Multiply By	To Find	Symbol
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
AREA				
in ²	square inches	645.2	square millimeters	mm ²
ft ²	square feet	0.093	square meters	m ²
yd ²	square yard	0.836	square meters	m ²
ac	acres	0.405	hectares	ha
mi ²	square miles	2.59	square kilometers	km ²
VOLUME				
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft ³	cubic feet	0.028	cubic meters	m ³
yd ³	cubic yards	0.765	cubic meters	m ³
NOTE: volumes greater than 1000 L shall be shown in m ³				
MASS				
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
TEMPERATURE (exact degrees)				
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
ILLUMINATION				
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m ²	cd/m ²
FORCE and PRESSURE or STRESS				
lbf	poundforce	4.45	newtons	N
lbf/in ²	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	When You Know	Multiply By	To Find	Symbol
LENGTH				
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
AREA				
mm ²	square millimeters	0.0016	square inches	in ²
m ²	square meters	10.764	square feet	ft ²
m ²	square meters	1.195	square yards	yd ²
ha	hectares	2.47	acres	ac
km ²	square kilometers	0.386	square miles	mi ²
VOLUME				
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m ³	cubic meters	35.314	cubic feet	ft ³
m ³	cubic meters	1.307	cubic yards	yd ³
MASS				
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
TEMPERATURE (exact degrees)				
°C	Celsius	1.8C+32	Fahrenheit	°F
ILLUMINATION				
lx	lux	0.0929	foot-candles	fc
cd/m ²	candela/m ²	0.2919	foot-Lamberts	fl
FORCE and PRESSURE or STRESS				
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in ²

*SI is the symbol for the International System of Units. (Adapted from FHWA report template, Revised March 2003)

LIST OF ACRONYMS

AASHTO	American Association of State Highway and Transportation Officials
FHWA	Federal Highway Administration
MPO	Metropolitan Planning Organization
RWIS	Road Weather Information System
SHRP2	Strategic Highway Research Program 2
TRB	Transportation Research Board
UDOT	Utah Department of Transportation

EXECUTIVE SUMMARY

Travel-time reliability is a crucial indicator in transportation systems performance assessment. Previous studies mostly relied on historical detectors or trajectory data for reliability analysis; however, data availability and limited sample size create major obstacles for robust and comprehensive assessment. Moreover, such analysis that is only based on historical travel time does not allow transportation agencies to assess the effectiveness of new projects and strategies in improving reliability of transportation systems. This study fills this gap by presenting a framework to model and estimate travel-time reliability using microscopic simulation for planning and programming purposes. The framework consists of three major components: Scenario Manager, Scenario Processor, and traffic simulation model. The Scenario Manager captures exogenous sources of travel-time variability by generating multiple representative scenarios composed of various events (e.g. weather, incidents) based on historical records. The Scenario Processor then translates scenarios' attributes into inputs that can be fed into the microscopic simulation model and modifies simulation input parameters' values in real-time. The simulation model is further utilized to simulate the generated scenarios and to estimate the effects on travel-time reliability of the study corridor. The proposed framework is applied to the VISSIM model of a corridor along Interstate 15 in Utah County, Utah. Comparison of simulated travel time with observed travel time showed the effectiveness of the proposed framework in modeling travel-time reliability. This framework provides a platform for exploring how different unreliability sources act individually and in interaction with each other in affecting network-wide reliability.

1.0 INTRODUCTION

1.1 Problem Statement

The growing uncertainty in travel time has become a major concern for both travelers and transportation agencies, especially in metropolitan areas. The concept of travel-time reliability thus has been considered a critical indicator for highway performance. The Federal Highway Administration (FHWA) formally defines travel-time reliability as “the consistency or dependability in travel times as measured from day-to-day or across different times of day” (FHWA, 2018). While travel-time reliability is a contributing factor in travelers’ decisions, most operational and planning models rely on traditional performance measures such as delay and average travel time. This highlights the need for studies to investigate the impact of travel-time reliability on transportation network planning and traffic operation.

A myriad of studies have attempted to develop various reliability measures for practical use and to estimate perceived value of reliability for incorporating the concept into travel-planning models (Carrion and Levinson, 2012; Lomax et al., 2003; Cambridge Systematics, 2008; Fosgerau and Karlström, 2010; Abrantes and Wardman, 2011; Shires and Jong, 2009; Wardman, 2004; Zamparini and Reggiani, 2007; Small et al., 2007). Current practice includes using historical detector or trajectory data to calculate various reliability measures. Yet, data unavailability and limited sample size create major obstacles for transportation agencies to enable robust and comprehensive assessment. As an example, using historical data for non-recurrent congestion factors that rarely occur or with small sample size is not a viable approach to unveil their true impact on travel-time reliability. An alternative approach is to model reliability via simulation by generating travel-time distributions and capturing the impacts of various sources of travel-time unreliability.

To provide guidance to travel-time reliability analysis, TRB, AASHTO, and FHWA through the Strategic Highway Research Program 2 (SHRP2) launched a series of projects to help agencies and researchers better understand reliability, and incorporate the concept into the planning, programming and operation processes. Specifically, the SHRP2 L04 project “Incorporating Reliability Performance Measures in Operations and Planning Modeling Tools”

strived to provide application guidelines for incorporating reliability into simulation models and assist agencies to better produce performance measures in order to evaluate how certain projects could affect travel-time reliability (Kim et al., 2013). FHWA also sponsored the SHRP2 Implementation Assistance Program (IAP), through several rounds of highlighting SHRP2 products and offering funding, for transportation agencies to implement the SHRP2 tools in their projects and operations.

1.2 Objectives

Given the growing concerns regarding travel-time reliability, it is important for Metropolitan Planning Organizations (MPOs) and Departments of Transportation (DOTs) to incorporate it into their planning and operational models for programming assessment. This research paves this way by presenting a framework to model travel-time reliability via microscopic simulation. The conceptual framework developed by the SHRP2 program is used to create different representative scenarios capturing the impact of exogenous factors causing travel-time unreliability. A microscopic simulation model is then utilized to simulate the generated scenarios and to estimate their impact on reliability. A segment along the Interstate 15 (I-15) corridor in Utah County, Utah is used as a case study to showcase the applicability of the proposed framework. The result of this study creates a suitable tool for the assessment of projects and policies that are expected to improve travel-time reliability.

1.3 Outline of Report

The rest of the report is structured as follows. We review previous works on travel-time reliability analysis. Following upon that, we detail our proposed methodology which takes advantage of an SHRP2 product (Scenario Manager) and a new product developed by this study using neural network - Scenario Processor - to investigate the impact of weather and crash events on travel-time reliability. The result using a case study along the I-15 corridor is presented afterwards. We conclude with a discussion of the results and limitations of the proposed methodology.

2.0 LITERATURE REVIEW

2.1 Overview

This chapter presents the summary of previous studies on travel-time reliability measures and analysis methods.

2.2 Reliability Measures

Travel-time reliability quantifies the temporal uncertainty experienced by different travelers in their trips from one node to another within a traffic network. It could affect travel decisions regarding departure time, route choice, and mode choice that each traveler makes during his or her trip (Wang et al., 2014). Previous studies used various measures to quantify the variability in travel times across different time periods. The FHWA Office of Operations listed five standard measures of travel-time reliability as detailed below:

- 90th or 95th percentile travel time: the amount of experienced delay on heavily congested days;
- Travel-time index: the ratio of the mean experienced travel time to the free-flow travel time;
- Buffer index: Extra time allocated to ensure travel is on time most of the time, computed as the difference between 95th percentile travel time and mean travel time, divided by mean travel time;
- Planning time index: total time needed to plan for an on-time arrival 95% of the time, computed as 95th percentile travel time divided by free-flow travel time;
- Frequency that congestion exceeds a certain expected threshold: percentage of days or time that mean speed falls below a certain speed (Chen et al., 2016; Chen et al., 2019; Haghghi et al., 2019)

Travel-time variability results from a myriad of factors that affect both supply and demand sides of transportation systems. SHRP2 and FHWA recognize seven sources of travel-time variability including traffic incidents, work zones, weather, special events, traffic control devices, fluctuations in demand, and inadequate base capacity (FHWA, 2018). Several studies

have attempted to quantify travel-time reliability and its spatial and temporal variations using historical data directly obtained from probe vehicles, continuous point-based detectors or collected in periodic studies (Emam and Al-Deek, 2006; Chen et al., 2003; Recker et al., 2006; Lyman and Bertini, 2008; Chen et al., 2019). For example, Emam and Al-Deek (2006) used dual-loop detector data to estimate travel-time distribution on a section of Interstate 4 in Orlando, Florida. Four different statistical distributions including Weibull, exponential, lognormal, and normal were examined to identify the best one that can fit to the travel time. Chen et al. (2003) evaluated the incidents' effects on various travel-time statistics including median, mean, 10th percentile, and 90th percentile travel times using real-world data collected on a corridor along Interstate 5 in Los Angeles, California. They also compared mean and standard deviation of travel times under different levels of service and found that worse levels of service are associated with greater travel-time unreliability.

2.3 Travel-Time Reliability Analysis Methods

Using historical trajectory data is the easiest and the most ideal way to estimate travel-time distribution. However, most of the time this is not possible due to the unavailability of data or insufficiency of sample size. It is also difficult to explore how various unreliability sources act individually and/or in interaction with each other in determining network reliability. Moreover, historical data analysis does not allow transportation agencies to directly assess the effectiveness of new projects and strategies in improving reliability of transportation systems. An alternative approach is to generate unreliability scenarios based on historical data and resort to traffic simulation models to produce travel-time reliability measures under various conditions. Kim et al. (2013) used a mesoscopic traffic simulation tool, DYNASMART-P, to examine the impact of weather and incidents on travel-time variability. They developed a framework that features three components: Scenario Manager, traffic simulation models, and Trajectory Processor. Scenario Manager populates scenarios to capture exogenous sources of travel uncertainty. The generated scenarios were then modeled in a mesoscopic traffic simulation model to produce vehicle trajectories. The resulting vehicle trajectories were further processed in Trajectory Processor to produce various measures of travel-time reliability. The proposed framework was applied to a real-world network to investigate the impact of weather and incidents on travel-time reliability.

While Kim et al. provided valuable insights on how to integrate reliability into planning models, it is not clear how various weather and incident events were modeled in the DYNASMART-P environment (i.e. more like a black box). Moreover, there is a need for studies that can provide guidance for integrating reliability measures into microscopic traffic simulation models that mainly work based on car-following and lane-changing theories.

3.0 RESEARCH METHODS

3.1 Overview

Built upon the SHRP2 L04 project, this chapter describes a framework we developed to model and estimate travel-time reliability using microscopic simulation. The proposed framework consists of three major components: Scenario Manager, Scenario Processor, and a microscopic simulation model. **Fig. 1** illustrates the framework scheme. The primary objective of the Scenario Manager is to generate scenarios that can capture exogenous sources of travel-time variability. These scenarios represent any mutually consistent combinations of demand- and supply-sides random factors. The Scenario Processor then translates and incorporates scenarios' attributes to inputs that can be fed into the microscopic simulation model. During simulation, the traffic simulation model captures endogenous sources of travel-time variability such as heterogeneous driving behaviors. The resulting travel times are then processed to obtain travel-time distribution and other measures of travel-time reliability.

Note that the two major functions of the Scenario Processor the research team developed include modeling crash events and modeling weather events in the VISSIM environment. The crash events are populated based on historical records collected along the I-15 study corridor in Utah County for the entire year of 2017 and described by start time, end time, latitude, and longitude. Generated crashes were mapped onto the VISSIM network model by determining the link and coordinates of each crash. Weather impact is modeled through modified traffic flow characteristics, where the loop detector and Road Weather Information System (RWIS) data are jointly collected along I-15 in Salt Lake County to capture the heterogeneity in traffic flow patterns.

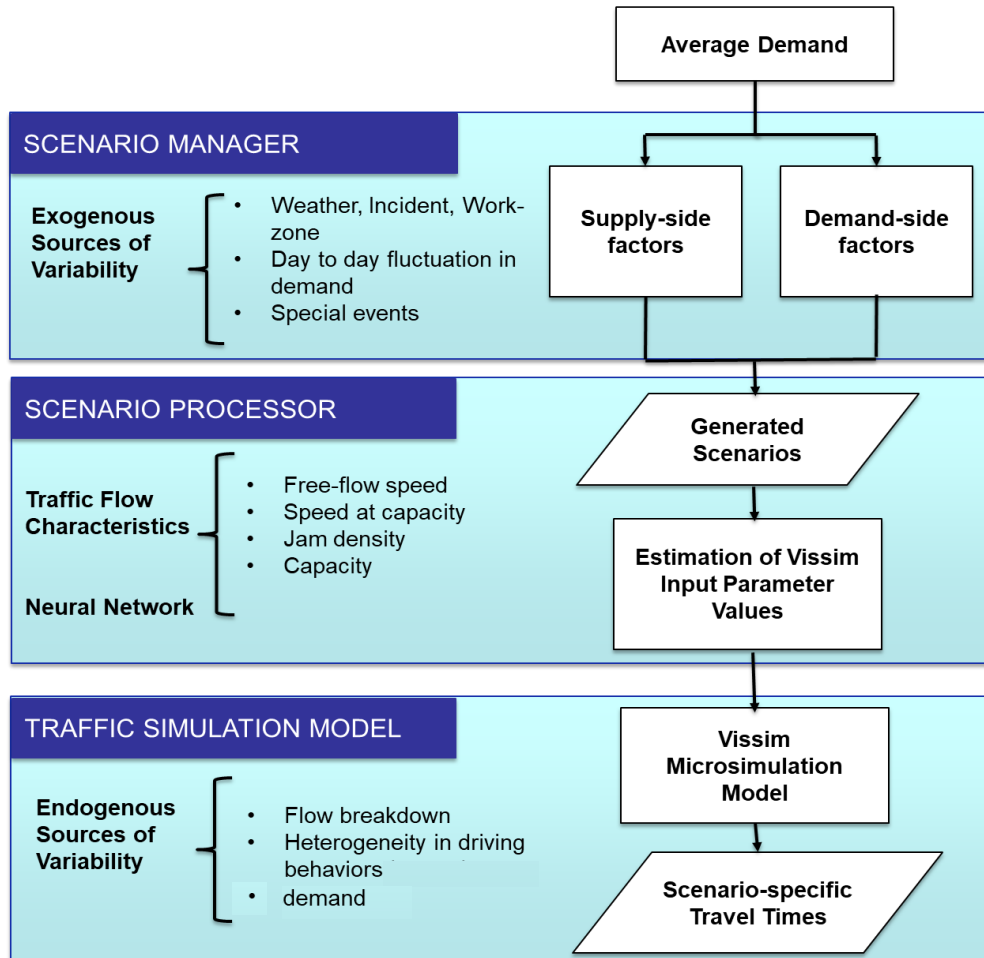


Figure 1. Framework scheme.

3.2 Scenario Manager

Scenario Manager provides an environment for scenario-based reliability analysis by generating scenarios to capture exogenous sources of travel-time variability. One of the main issues in generating scenarios is capturing dependencies in certain scenario components. For example, weather condition can significantly affect the frequency and severity of crashes and such dependency needs to be addressed in the scenario generation process. Scenario Manager takes these dependencies into account by following a generation order to allow components that affect others to be generated first. For instance, it first generates weather scenarios and then incidents are sampled from incident distribution on top of the weather condition of the given scenario.

The main objective of scenario-based reliability analysis is to assess variability in the resulting travel-time distribution by controlling input parameters. Scenario Manager utilizes a built-in Monte Carlo sampling function to generate hypothetical scenarios for analysis and design purposes. Each scenario is composed of a sequence of event instances. The event instance is the smallest unit in the scenario structure and contains information about start and end times, location, and intensity. Let S denote each input scenario for the microsimulation model and X an event instance that represents a supply- or demand-side random factor such as weather, incident, special event, work zone, or day-to-day demand variation. Scenario S is characterized by a sequence of event instances:

$$S = \{X_1, X_2, \dots, X_J\} \quad j = 1, 2, \dots, J \quad (1)$$

where each event instance X_j is a vector of various attributes describing temporal, spatial, and intensity properties of an event instance for a given factor. Distribution of travel times for each scenario can be obtained as follows:

$$T_i = g(NN(S_i)) \quad i = 1, 2, \dots, N \quad (2)$$

where T_i is a set of travel times for a given path link generated using traffic simulation under the conditions of i th scenario S_i , $g(x)$ represents the given traffic simulation model, and $NN(x)$ represents the function developed under Scenario Processor which translates scenario components to the inputs required for VISSIM.

3.3 Scenario Processor

Since most simulation models such as VISSIM do not provide the ability to directly model certain scenario components such as weather and incident events, we developed a Scenario Processor to translate scenario attributes to the VISSIM inputs. The Scenario Processor includes a COM script (see the Appendix) written in MATLAB which is designed to automatically incorporate each scenario's events into the simulation environment by modifying VISSIM input parameters. The two major functions of the Scenario Processor include modeling crash events and modeling weather events in the VISSIM environment, and are detailed in the following sections.

3.3.1 Modeling Crash Events

To generate crash events, 2017 crash data were obtained from the Utah Department of Transportation (UDOT) and fed into the Scenario Manager. The crash data include crash start time, end time, latitude, longitude, and crash description for the entire year of 2017. Using such dataset, Scenario Manager populated crash events according to their temporal and spatial distributions. The populated scenarios thus include crash events for the I-15 study corridor in Utah County described by start time, end time, latitude, and longitude. Generated crashes were mapped onto the VISSIM network model by determining the link and coordinates of each crash. To model each crash in the VISSIM environment, a traffic signal is placed at the location of the crash and set to red light from a crash start time to its end time to “block” the traffic on a specific lane. After crash end time, the traffic signal would be set back to green again to allow traffic to proceed which represents the condition that the crash is cleared from the roadway.

3.3.2 Modeling Weather Events

Scenario Processor models various weather conditions by modifying a series of VISSIM input parameters. It first determines the impact of different weather conditions on traffic flow parameters (i.e., free-flow speed, speed at capacity, and jam density) using traffic data collected from loop detectors on the study corridor. Then it calibrates VISSIM input parameters based on a certain weather event to generate a simulated traffic stream that has consistent characteristics with the observed traffic stream under each specified weather condition.

3.3.2.1 Estimate traffic-flow characteristics

To investigate the impact of various weather conditions on traffic-flow characteristics, 2017 traffic and weather data were collected on I-15 during the PM peak period of 4:00-6:00 PM. The collected traffic data include 5-min speed, flow, and occupancy obtained from inductive loop detectors along I-15 in Salt Lake County. Weather data are retrieved from two different sources: RWIS operated by UDOT and Automated Surface Observing System (ASOS) operated by National Weather Service (NWS). RWIS hosts environmental sensors installed on the roadside or in the roadway that collect real-time local atmospheric and pavement conditions (Kwon and Fu, 2013). ASOS is a primary climatological observing network in the United States

designed to support weather forecast and aviation operations. Most ASOS stations are located near airports and do not provide road surface condition data. The closest ASOS station in the study area is located in Salt Lake City International Airport which is several miles away from the study corridor. Due to the proximity of RWIS stations to the study corridor and also their availability of road-surface condition data, RWIS data were used for the analysis. RWIS data includes 10-min air temperature, road temperature, wind speed, visibility, precipitation intensity, and pavement condition data. Weather condition is reported by precipitation intensity (i.e., Light Precipitation, Moderate Precipitation, and Heavy Precipitation), but the accuracy of the reported intensity level is questionable. Moreover, visibility readings are missing for most of the RWIS stations. Consequently, the research team chose to only use pavement condition data for this study.

To link traffic data with weather data, we extracted data from loop detectors that are located within a 2-mile radius of RWIS stations. For each loop detector, 5-min traffic data were collected and were labeled to 10-min weather data obtained from the closest RWIS station. **Fig. 2** shows loop detectors and RWIS stations selected for data collection. Three weather categories including clear with dry pavement, rain with wet pavement, and snow with snowy or slushy pavements were considered for this study.

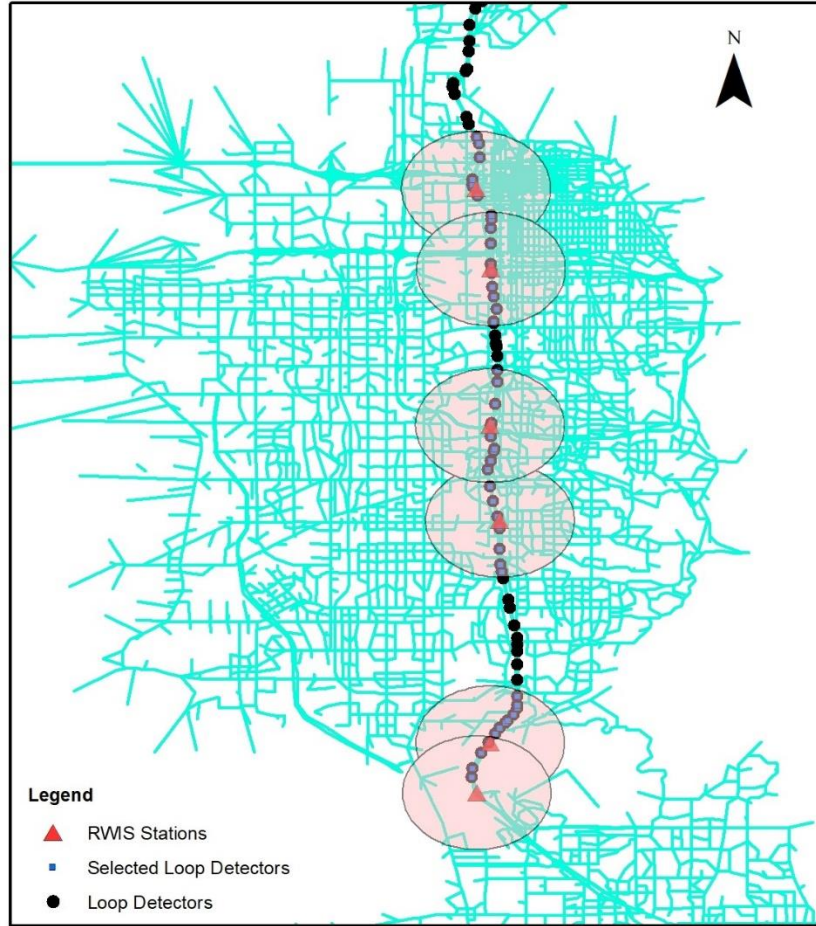


Figure 2. Selected RWIS stations and loop detectors selected for data collection along I-15 corridor in Salt Lake County.

Traffic data under each weather category were extracted and key traffic flow characteristics (i.e., free-flow speed, speed at capacity, jam density, and capacity) were then estimated by fitting the Van Aerde's traffic flow model to the observed data under that weather category. Equations 3 through 6 show the functional form of the Van Aerde model.

$$k = \frac{1}{c_1 + \frac{c_2}{u_f - u} + c_3 u} \quad (3)$$

$$c_1 = \frac{u_f}{k_j u_c^2} (2u_c - u_f) \quad (4)$$

$$c_2 = \frac{u_f}{k_j u_c^2} (u_f - u_c)^2 \quad (5)$$

$$c_3 = \frac{1}{q_c} - \frac{u_f}{k_j u_c^2} \quad (6)$$

where k , u , u_f , u_c , q_c , and k_j denote traffic flow density, traffic flow space-mean speed, free-flow speed, speed at capacity, and capacity, respectively. Interested readers can refer to Van Aerde and Rakha (1995), Rakha and Crowther (2002), and Rakha (2005) for more detail on the model.

A heuristic algorithm (SPD_CAL) developed by Rakha et al. (2008) was then implemented to fit Van Aerde's model in a three-dimensional (speed-flow-density) space. **Fig. 3** illustrates fitted traffic flow models under different weather categories.

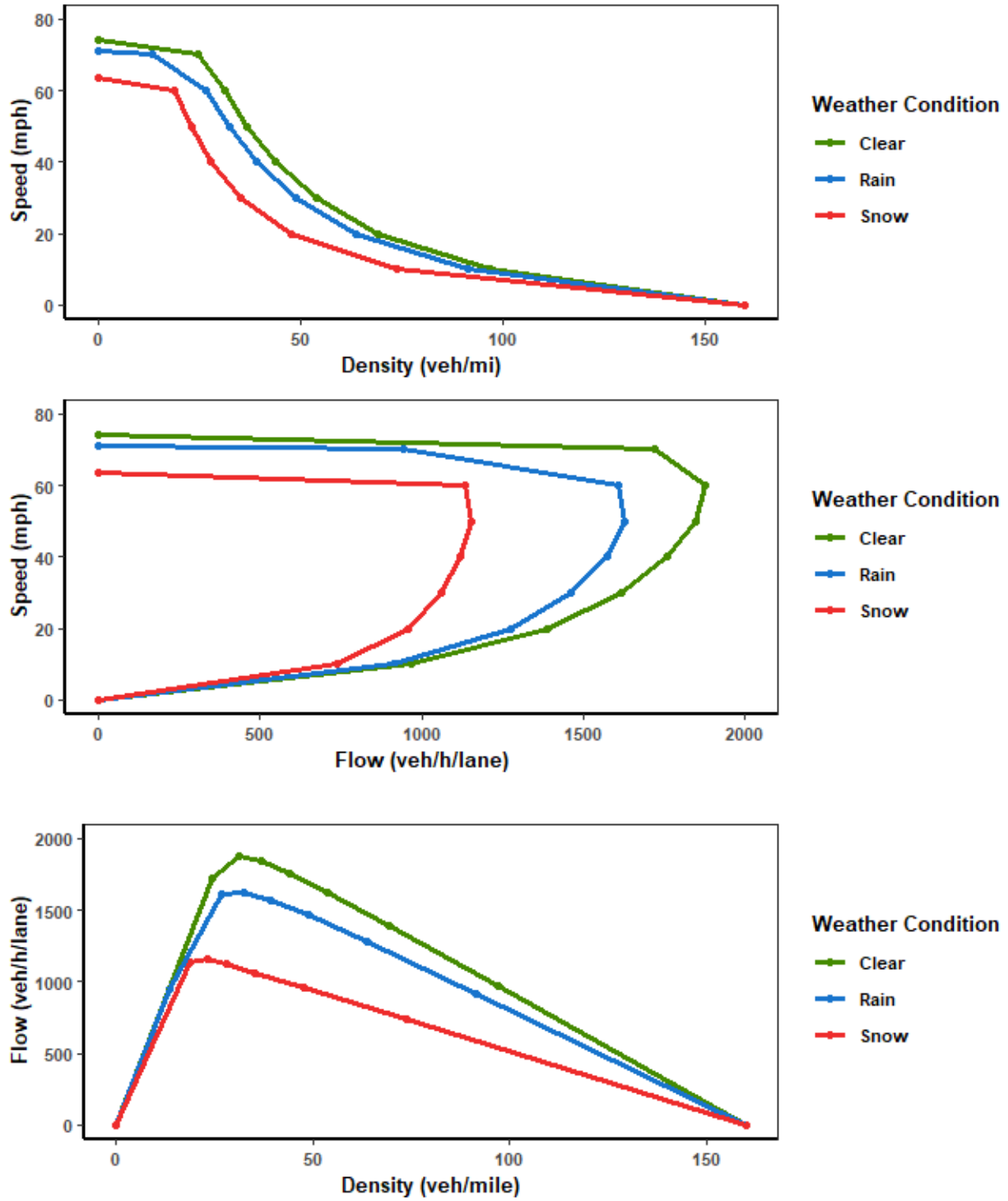


Figure 3. Van Aerde model fitted to observed traffic data under defined weather categories.

3.3.2.2 Determine VISSIM input parameter values

To translate the estimated traffic flow characteristics into VISSIM input parameters, a neural network model developed by Golshan Khavas et al. (2017) is used. This neural network predicts appropriate driving behavior parameters that can generate traffic stream with desirable characteristics (e.g., specific capacity, free-flow speed, and jam density). The model requires free-flow speed, speed at capacity, capacity, and jam density as inputs and provides values for nine VISSIM behavior parameters (i.e. Accepted Deceleration Own, Accepted Deceleration Trail, Safety Distance Reduction Factor, Standstill Distance (CC0), Headway Time (CC1), Negative Following Threshold (CC4), Positive Following Threshold (CC5), Oscillation Acceleration (CC7), and Acceleration at 80 km/h (CC9)). These nine behavior parameters were identified from previous studies to have the greatest impact on the output of the traffic simulation model, and properly selected values can produce traffic flow characteristics that are consistent with field observations (Ge and Menendez, 2012; Gomes et al., 2004; Park and Qi, 2006; Lownes and Machemehl, 2006). The neural network model was trained on 225,000 simulations conducted on a hypothetical network with different combinations of these nine parameters.

Key traffic flow characteristics (i.e., free-flow speed, speed at capacity, jam density, and capacity) under rain and snow weather conditions were used as input to the trained neural network, and appropriate driving behavior parameters and desired speed distributions were predicted. Among predicted parameters, CC0 and CC1 in the car-following model are most commonly calibrated in previous studies since they are more influential to the roadway capacity and other traffic flow characteristics (Gomes et al., 2004; Lownes and Machemehl, 2006; Ge and Menendez, 2012). Other parameters have marginal impact on traffic flow characteristics. Consequently, only CC0, CC1, and desired speed distributions were modified to generate desirable flow under rain or snow conditions. To simulate scenarios with rain or snow weather events, modifications were made to the base-model driving-behavior parameters specifically on CC0, CC1, and desired speed distributions. Table 1 shows some of the input parameters used for simulating various weather events.

Table 1. VISSIM input parameters used for simulating each weather category.

Weather Category	Precipitation Type	Pavement Condition	CC0	CC1	CC4	CC5	CC7	CC9
Clear (base)	None	Dry	14.42	1.2	-0.7	0.7	0.82	4.92
Rain	Rain	Wet	16	1.7	-0.7	0.7	0.82	4.92
Snow	Snow	Snowy/Slushy	17	2.5	-0.7	0.7	0.82	4.92

3.4 Microscopic Simulation Model

The proposed framework is applied to a VISSIM model of a segment along the I-15 corridor in Utah County, Utah. **Fig. 4** shows the selected corridor boundaries. The model includes mainline I-15, the interchanges of 1600 North/I-15 (Exit 273), Pleasant Grove Blvd./I-15 (Exit 275), 500 East/I-15 (Exit 276), and American Fork Main St. (Exit 278). The model is created in VISSIM version 10.00-05 and is calibrated for the base scenario (i.e., clear weather which includes neither weather events nor crash events), a weekday PM peak period (4:00-6:00 PM) using 2017 traffic data. The calibration procedure includes modifying driving behavior parameters to obtain the best match between observed and simulated saturation flow rates, major movements hourly flow, average corridor travel time, and queue length. Table 2 illustrates the difference between the simulated and the observed traffic volumes. A modified Chi-Squared statistic test, GEH statistic was used to compare two sets of traffic volumes. Equation 7 shows the formulation of GEH statistics.

$$GEH = \sqrt{\frac{2(M - C)^2}{(M + C)}} \quad (7)$$

where M is the simulated hourly traffic volume and C is the observed hourly traffic count. $GEH < 5$ is considered a good fit for this model (Dowling et al., 2004).

Table 2. I-15 PM Peak simulated and observed traffic volumes

Direction	Segment		PM Peak			
	From	To	Model Volume	Field Volume	Difference (%)	GEH Factor
Northbound	1600 North Off-ramp	1600 North On-ramp	7834	7828	0.1	0.07
	1600 North On-ramp	Pleasant Grove Blvd. Off-ramp	8952	8999	0.5	0.50
	Pleasant Grove Blvd. Off-ramp	Pleasant Grove Blvd. On-ramp	8019	7995	0.3	0.27
	Pleasant Grove Blvd. On-ramp	500 East Off-ramp	9313	9333	0.2	0.21
	500 East Off-ramp	500 East On-ramp	8381	8368	0.2	0.14
	500 East On-ramp	Pioneer Crossing Off-ramp	9404	9459	0.6	0.57
	Pioneer Crossing Off-ramp	Pioneer Crossing On-ramp	6919	6887	0.5	0.39
	Pioneer Crossing On-ramp	Lehi Main St. Off-ramp	7479	7480	0.0	0.01
Southbound	Pioneer Crossing Off-ramp	Pioneer Crossing On-ramp	6606	6577	0.4	0.36
	Pioneer Crossing On-ramp	500 East Off-ramp	8143	8119	0.3	0.27
	500 East Off-ramp	500 East On-ramp	7683	7594	1.2	1.02
	500 East On-ramp	Pleasant Grove Blvd. Off-ramp	8714	8647	0.8	0.72
	Pleasant Grove Blvd. Off-ramp	Pleasant Grove Blvd. On-ramp	7759	7624	1.8	1.54
	Pleasant Grove Blvd. On-ramp	1600 North Off-ramp	9148	9047	1.1	1.06
	1600 North Off-ramp	1600 North On-ramp	8239	8062	2.2	1.96

Table 3 shows the average travel times for three different study segments along the study corridor. Simulated average travel times were compared to observed average travel times obtained from UDOT’s HERE data – aggregated from probe sample that is good for speed and travel-time estimates (<https://udot3p.iteris-pems.com/>). For this model, the following criteria on travel times were used for the calibration procedure. As shown in Table 3, the criteria for travel times are met.

- Average corridor travel times need to fall within $\pm 15\%$ of the observed travel times for more than 85% of the cases
- Average corridor travel times need to fall within ± 30 seconds of the observed travel times for more than 85% of the cases

Table 3. I-15 simulated travel times compared to observed travel times

Direction	Segment	Distance	Hour	Simulated Travel Time	Observed Travel Time	Difference (%)	<30 sec Difference Corridor	
Northbound	1600 North to Pleasant Grove Blvd	14203	4:00-5:00 PM	139.74	137	2.0	Y	
	Pleasant Grove Blvd to 500 East	5333		53.5	51.5	3.9		
	500 East to Pioneer Crossing	10982		110.9	106.1	4.5		
	Northbound	1600 North to Pleasant Grove Blvd	14203	5:00-6:00 PM	141.7	145.3	2.5	Y
		Pleasant Grove Blvd to 500 East	5333		58.19	58.9	1.2	
		500 East to Pioneer Crossing	10982		136.44	131.3	3.9	
Southbound	Pioneer Crossing to 500 East	10983	4:00-5:00 PM	108.32	106	2.2	Y	
	500 East to Pleasant Grove Blvd	4752		46.38	46.5	0.3		
	Pleasant Grove Blvd to 1600 North	13570		137.58	133.5	3.1		
	Southbound	Pioneer Crossing to 500 East	10983	5:00-6:00 PM	108.73	106.8	1.8	Y
		500 East to Pleasant Grove Blvd	4572		46.6	48.5	3.9	
		Pleasant Grove Blvd to 1600 North	13570		138.4	144.6	4.3	

For the purpose of this study, we focus on assessing travel-time reliability along a segment on I-15 northbound from 1600 North to Pioneer Crossing/American Fork Main Street during a weekday-evening peak period in winter. The trip distance and free-flow travel time along this section of I-15 are 5.8 miles and 4.6 minutes, respectively. Inclement weather and crash events were considered as the major sources of travel-time uncertainty.

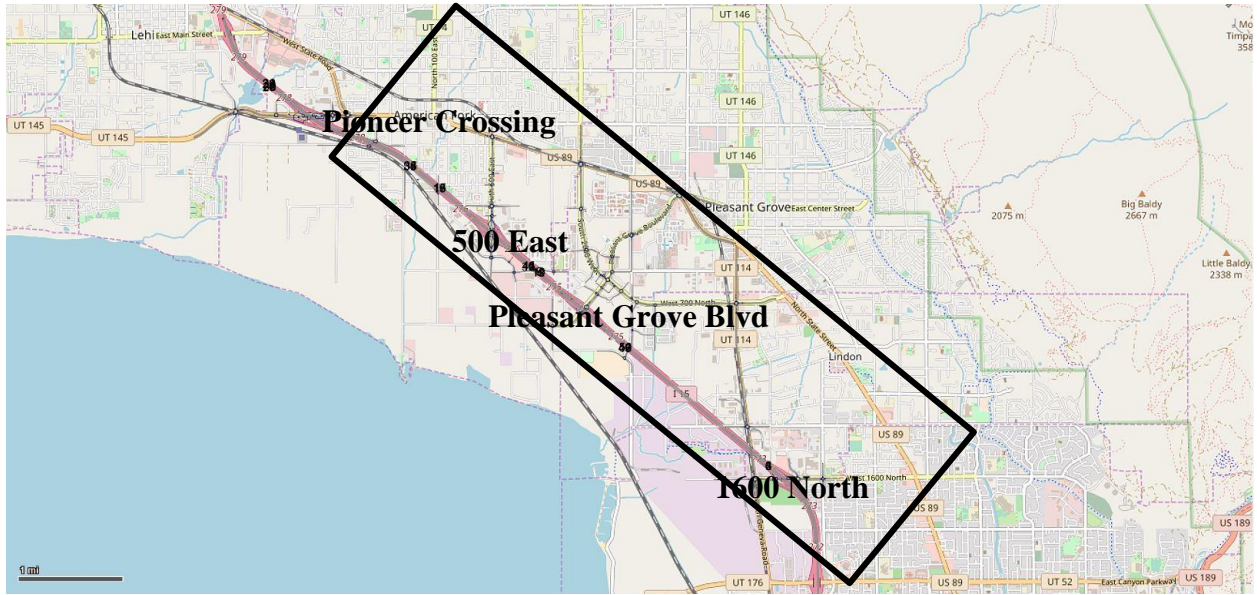


Figure 4. Study area.

4.0 RESULTS

4.1 Overview

The proposed methods are applied to the VISSIM simulation model described in Section 3.4. The following presents the travel-time reliability results generated from the simulation model.

4.2 Reliability Simulation Results and Analysis

Using the Scenario Manager, forty scenarios including rain with possible crash events (Rain Scenarios) and forty scenarios including snow with possible crash events (Snow Scenarios) were generated for the study corridor and compared with the base scenario (i.e., clear weather which includes neither weather events nor crash events). Generated scenarios differentiate from each other by precipitation type, duration, and crash occurrence. **Fig. 5** shows the distribution of precipitation duration across generated scenarios. Scenario Processor was then utilized to automatically translate the generated scenarios into appropriate driving behavior parameters that can be fed into VISSIM. Each scenario was simulated using five different random seeds, and vehicle travel times under rain and snow scenarios were obtained for the study corridor (I-15 Northbound between 1600 North and Pioneer Crossing interchanges). **Fig. 6** illustrates distributions of travel times under the conditions of generated scenarios for the mainline I-15 Northbound between 1600 North and Pioneer Crossing interchanges. As shown in **Fig. 6**, dispersion in travel-time distributions increase as the weather condition degrades from clear to snow. Highest dispersion is observed under snow condition.

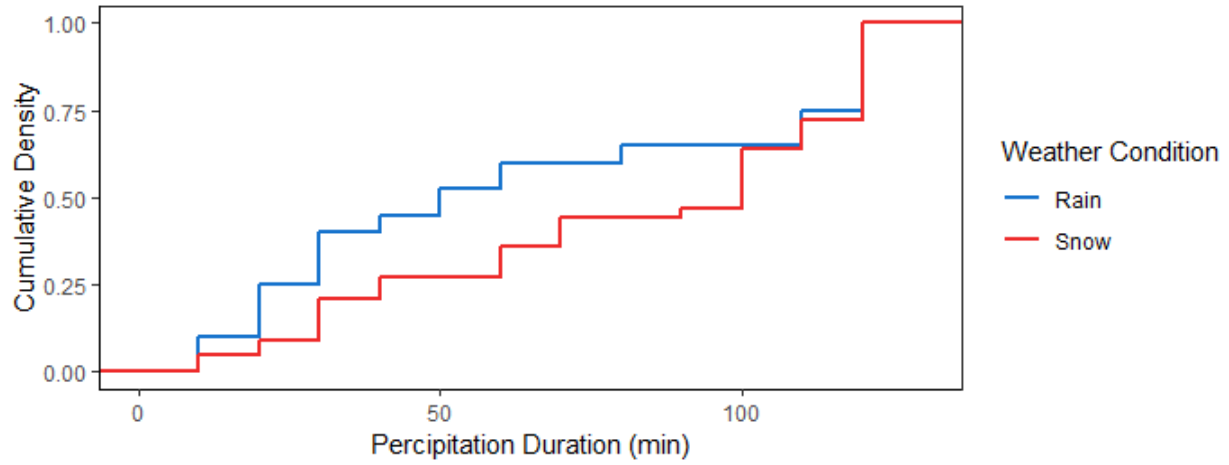
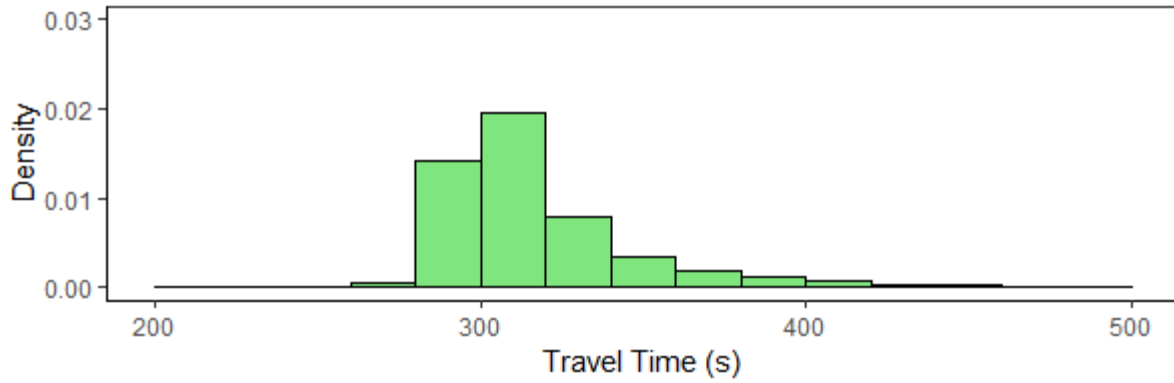
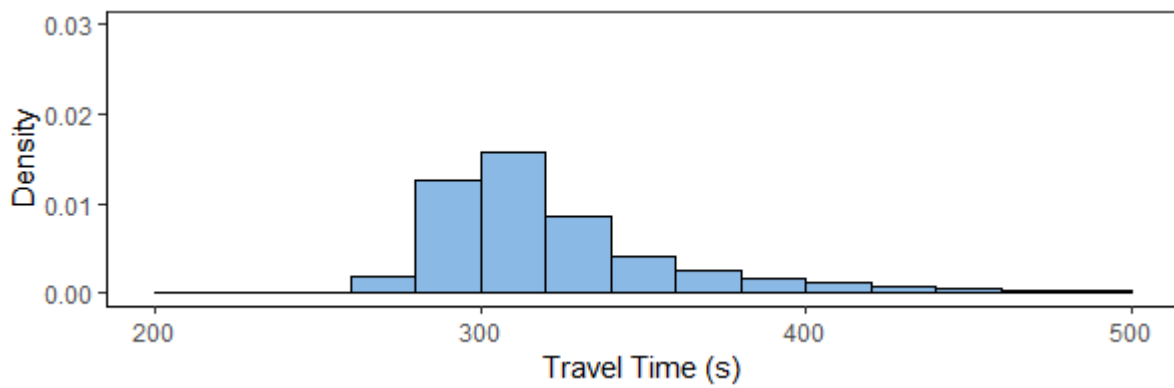


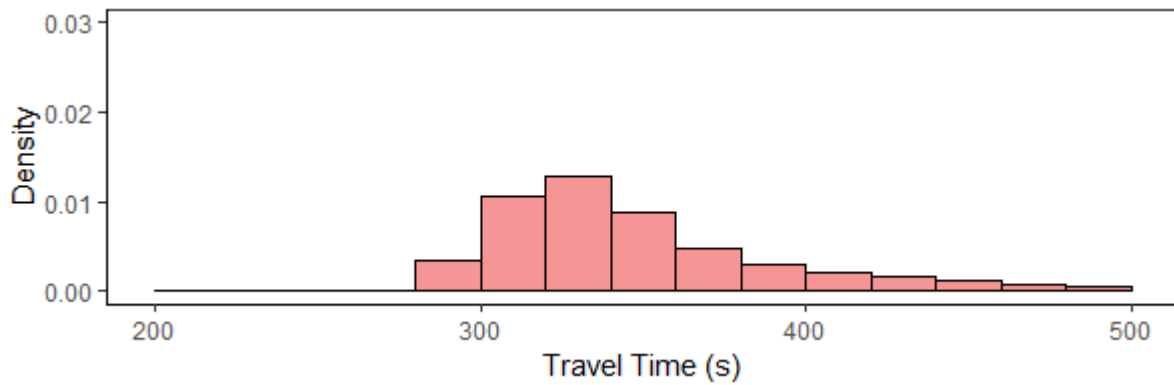
Figure 5. Distribution of precipitation duration across generated scenarios.



(a)



(b)



(c)

Figure 6. Scenario-specific travel-time distributions: (a) clear, (b) rain, and (c) snow.

Table 4 summarizes various reliability performance measures calculated based on travel-time distributions. Mean, median, and standard deviation of travel time increase as the weather condition changes from clear to snow. Higher dispersion of travel-time distributions explain the

greater standard deviation for rain and snow conditions. These findings are consistent with previous studies showing more cautious driving behavior during inclement weather conditions.

Comparing travel-time quantiles across different weather conditions revealed that they approximately follow the same trends from clear to snow weather conditions, although more noticeable differences exist between higher percentiles. Significant changes can also be observed in the planning time index, which is the 95th percentile travel time divided by the free-flow travel time. Comparison of three travel-time reliability indices approved by FHWA – buffer index, travel-time index, and planning-time index – showed that they approximately follow the same trend along the corridor. The buffer index might be a relatively conservative measure to use for reliability analysis.

Table 4. Simulation results and travel-time reliability measures

Weather Condition	Clear (base)	Rain	Snow
Distance (mi)	5.78	5.78	5.78
Number of simulated scenarios	1	40	40
Number of observed vehicles	53905	2172012	2157860
Mean travel time (s)	315	321	358
Median travel time (s)	307	310	338
95th percentile (s)	376	402	476
Standard deviation (s)	29	41	79
Buffer index (s)	0.19	0.25	0.33
Planning-time index	1.25	1.32	1.45
Travel-time index	1.05	1.06	1.09

Fig. 7 illustrates mean and standard deviation (error bars depict plus and minus one standard deviation) of travel time along the study corridor under different weather conditions. Travel time and its standard deviation across the corridor vary significantly throughout the PM peak period. Under clear weather condition, both mean and standard deviation of travel time spiked highest around 17:40 probably because of higher demand at the end of peak period. Rain

and snow conditions increased the mean travel time at 5-min intervals up to 8% and 25%, respectively.

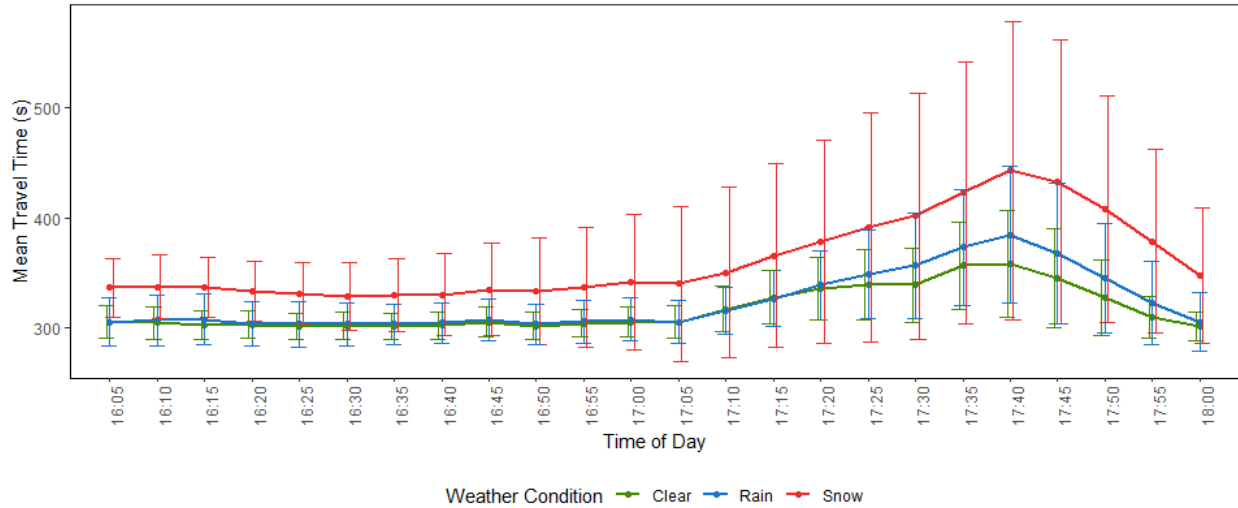
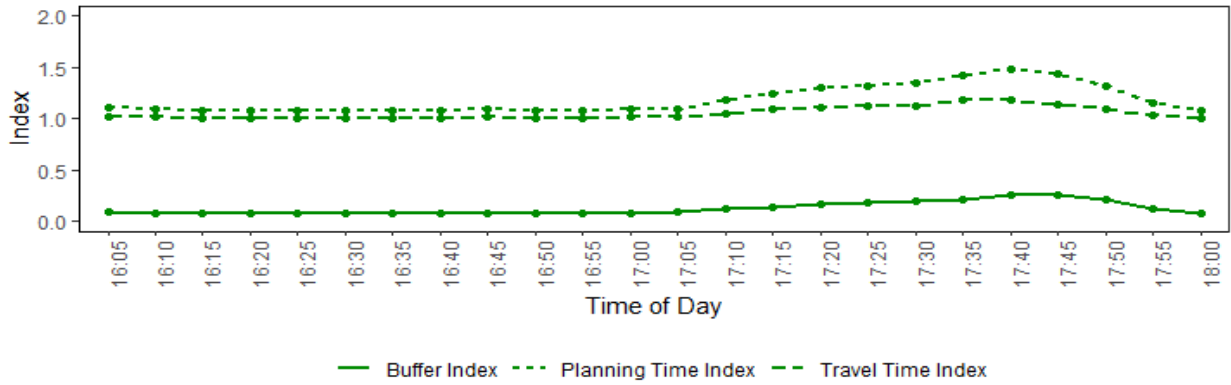


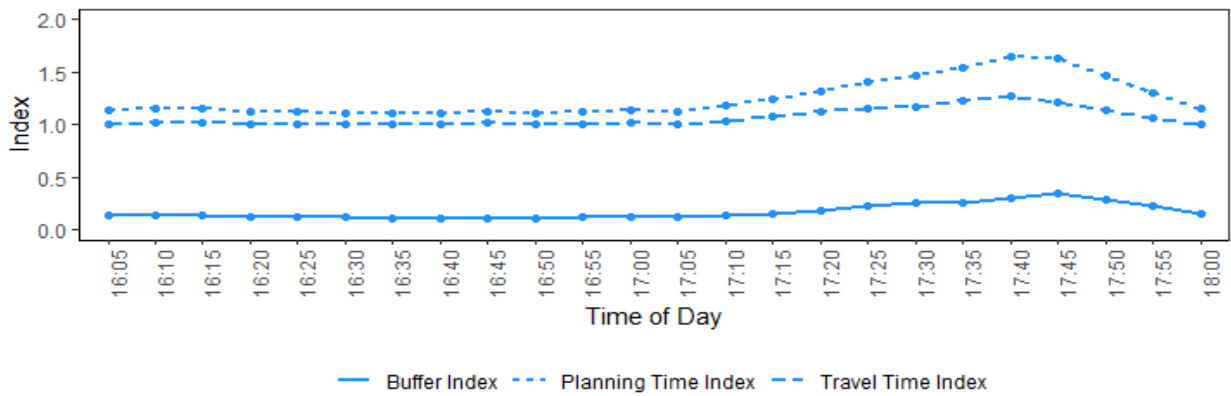
Figure 7. Mean travel time along the study corridor.

Approximately the same trends of mean travel time and its standard deviation throughout the peak period can be observed under different weather conditions. However, the difference between travel times under three weather conditions will be amplified at the end of the peak period where recurrent congestion occurs on the corridor. The underlying reason is that in the beginning of the peak period where the corridor is experiencing free-flow condition, desired speed distributions mainly cause travel-time differences but when congestion occurs, modified driving behavior parameters (standstill distance and headway time) come into play and induce considerable changes in travel time. **Fig. 8** shows the buffer index, travel-time index, and planning-time index estimated for the study corridor over the PM peak period. Buffer index helps travelers to estimate how much extra time needs to be allocated to account for uncertainty in travel conditions. Under snowy scenarios, the maximum buffer index is approximately 0.5, so for average travel time of 7.2 minutes, buffer time equals 3.6 minutes. Consequently, under the worst congestion condition, travelers should allow 10.8 minutes (as opposed to 7.2 minutes under clear weather) for a normal trip under snowy weather along this corridor to ensure on-time arrival with 95% certainty. The planning-time index reports the time needed for an on-time arrival 95% of the time. The maximum planning-time index is approximately 1.9 under snowy

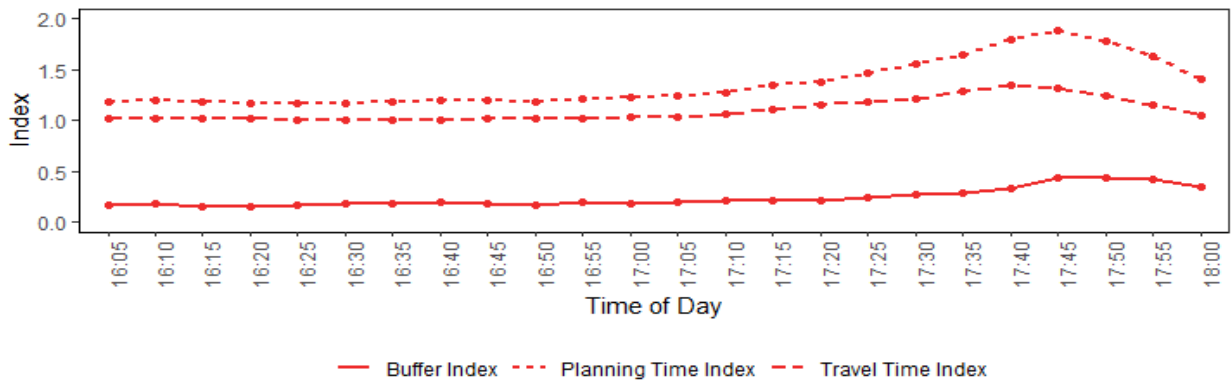
condition and free-flow travel time equals 5.5 minutes, meaning that under the worst congestion condition, an individual needs to plan 10.4 minutes to ensure on-time arrival with 95% certainty. Approximately similar trends are observed for the three indices. However, the planning-time index seems to exaggerate the trend more than the other two. The buffer index is found to be the most conservative index to measure travel-time reliability.



(a)



(b)



(c)

Figure 8. Travel-time reliability indices for the study corridor: (a) clear, (b) rain, and (c) snow.

To validate simulation results, probe vehicle data were used to estimate observed travel-time distributions. HERE travel-time data for 2017 along the study corridor were collected and linked to the closest RWIS station. Data include 2666, 148, and 13 travel-time observations at 10-min granularity under clear, rain, and snow weather conditions, respectively (iPeMS, 2018). Travel-time distributions under clear, rain, and snow weather conditions were estimated and compared with the simulated distributions. **Fig. 9** illustrates the distributions of travel times under different weather conditions estimated based on simulated and observed data. Note that the simulated data are extracted from every vehicle's trajectory for the base scenario (representing clear weather condition), 40 raining scenarios, and 40 snowy scenarios, respectively. Observed data are obtained from HERE for clear, rain and snowy conditions, separately. Comparison of simulated distributions with observed ones revealed that the trends of simulated distributions under clear and rain conditions are consistent with the observed ones. Inconsistency between simulated and observed distributions was noticed for snowy weather condition. This inconsistency might be explained with the small sample size of observed travel-time data (only 13 travel-time observations in 2017) under snowy condition. This example of travel-time distribution under snowy condition shows that for non-recurrent congestion events that rarely occur or with limited sample size, modeling travel-time reliability via simulation is a viable approach to unveil its impacts.

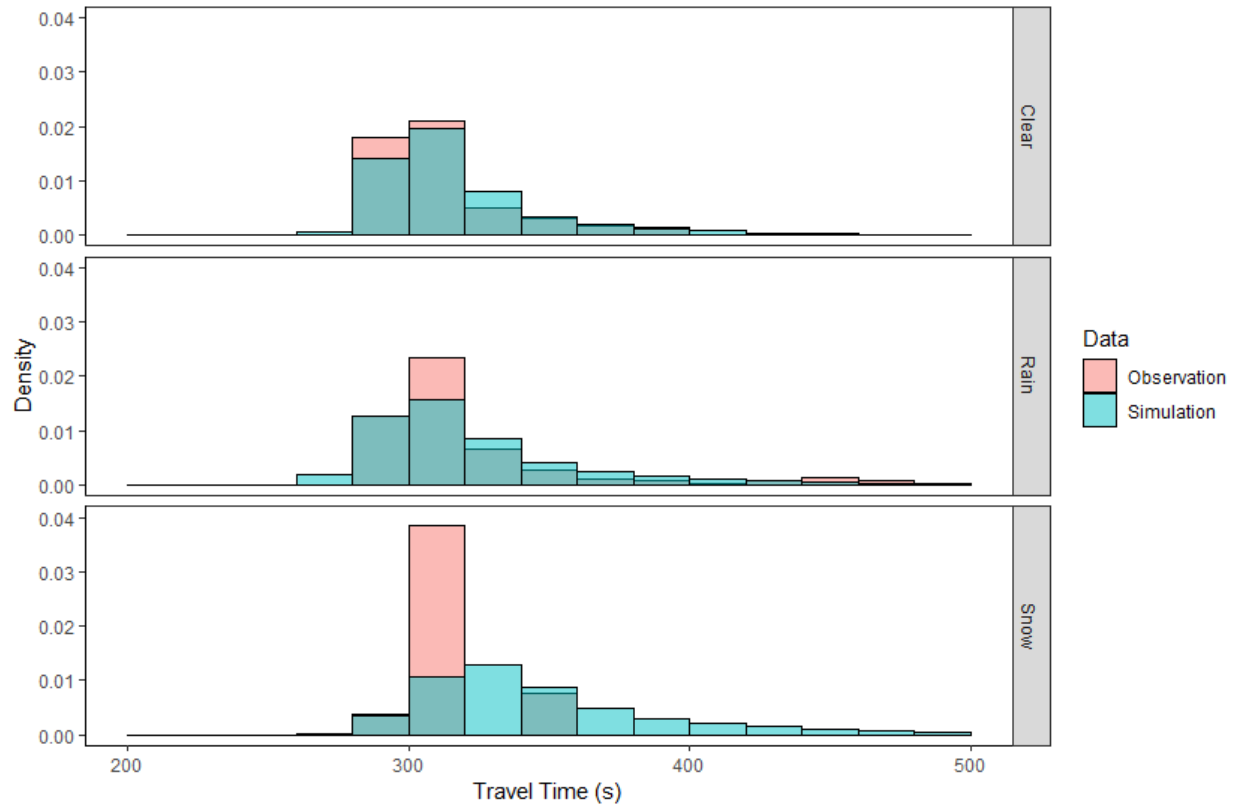


Figure 9. Comparison of simulated travel-time distributions with observed distributions.

To further compare the simulated results with observed data, simulated mean travel time throughout the PM peak period is compared with the observed mean travel time under rain condition (see **Fig. 10**). Results reveal that considering non-recurrent factors in simulation can increase the accuracy of mean travel-time estimation over the peak period. Considering the impact of other non-recurrent factors such as special events, work zones, and travel-demand variation might improve the accuracy of travel-time estimations.

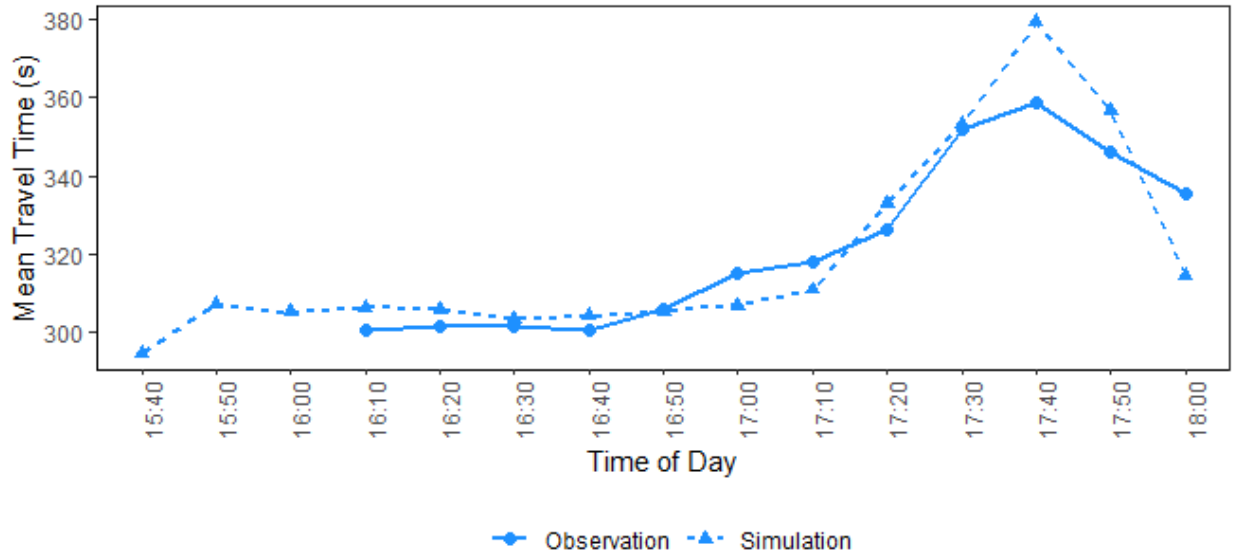


Figure 10. Comparison of simulated mean travel time with observed mean travel time under rain condition.

Fig. 11 illustrates the buffer index comparison of three sub-segments along the study corridor during the PM peak period. The figure shows how buffer index varies under each weather condition for each segment. For all, buffer index and its standard deviation increase when weather condition degrades from clear to snow condition. Moreover, while there is no significant difference between segments’ buffer indices under clear weather, inclement weather and incident events magnify the difference. The segment between Pleasant Grove Blvd and 500 E has the highest buffer index under rain and snow conditions. This might be explained by the proximity of two interchanges causing weaving movements along this short segment and also more cautious driving behaviors under inclement weather conditions. This finding shows the importance of integrating reliability measures into traffic operation models. The proposed framework can help DOTs and other transportation agencies to pinpoint segments with poor performance and in the next step, assess effectiveness of various strategies such as modifying ramp meter timing for improving the performance of the study segment.

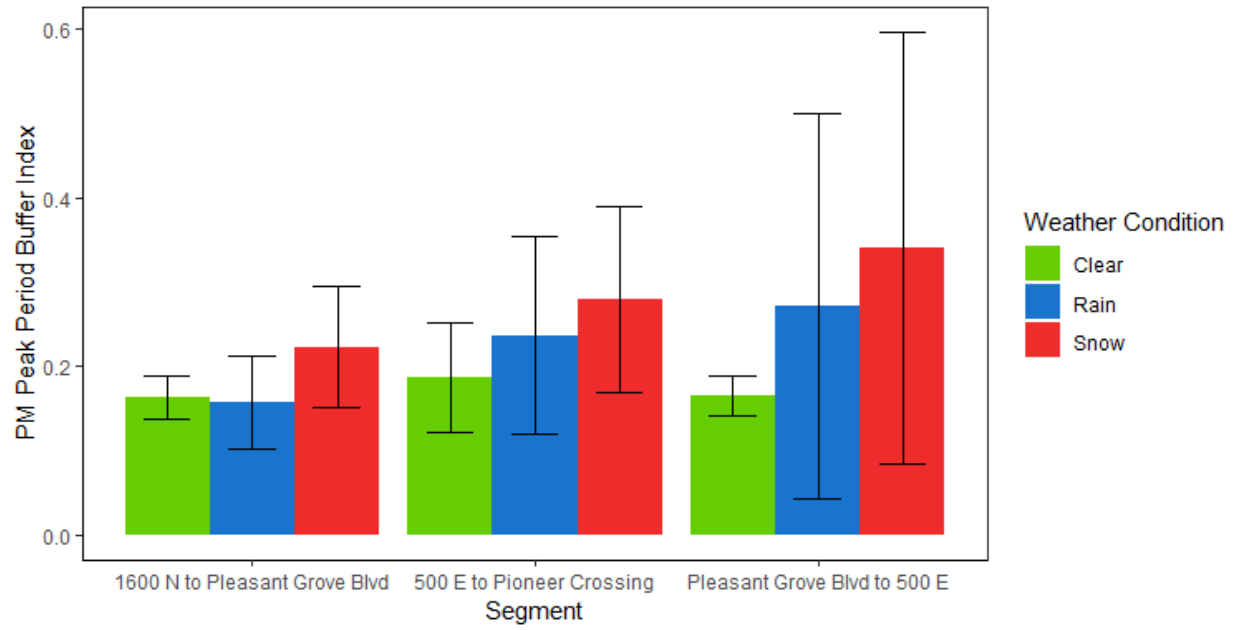


Figure 11. Buffer index comparison of three segments along the study corridor during p.m. peak period.

5.0 CONCLUSIONS

5.1 Summary

Travel-time reliability has been identified as an important factor impacting travel behaviors and subsequently traffic operation. Review of previous studies revealed that these studies mostly relied on historical detectors or trajectory data for reliability analysis; however, data availability and limited sample size create major obstacles for robust and comprehensive assessment. Moreover, reliability analysis only based on historical travel time does not allow transportation agencies to assess the effectiveness of new projects and strategies in improving reliability of transportation systems. An alternative approach is to model reliability via simulation by generating travel-time distributions and capturing the impacts of various sources of travel-time unreliability. Many DOTs and other transportation agencies have not yet begun or are only at the initial phase to integrate reliability as a performance measure into planning and operation models. This research paved the way by presenting a framework to model travel-time reliability via microscopic simulation.

Using a corridor along Interstate 15 in Utah County, Utah, as a case study, we showcased the effectiveness of the proposed framework for freeway reliability analysis. The Scenario Manager was utilized to capture exogenous sources of travel-time variability by generating scenarios based on historical data. The Scenario Processor was then used to translate scenarios' attributes to inputs that can be fed into the microscopic traffic simulation model. Generated scenarios were then simulated in VISSIM, and individual vehicle travel times were collected as output of the microsimulation model. The distributions of travel times were constructed and compared with observed distributions to investigate the performance of the proposed framework in capturing the impacts of non-recurrent congestion factors on travel-time reliability. Results revealed the viability of the proposed framework for unveiling the impact of non-recurrent congestion events that rarely occur on travel-time reliability. Lastly, we compared the performance of three segments along the study corridor from the reliability perspective to show how transportation agencies can potentially use the proposed framework to determine freeway segments with the highest need for reliability improvements. The proposed framework developed a suitable tool for evaluation of projects and strategies that can improve reliability measures.

This framework also provides a platform for exploring the individual and combined effects of different unreliability sources on network-wide reliability.

5.2 Future Work

While we only focused on the impact of weather and crash events in this application, there are other factors that would affect travel-time variability, such as work zone, special events, and travel-demand variations. The proposed framework has the flexibility to model any other event that can be characterized by start time, end time, and intensity. Consequently, modeling the impact of special events, work zone, demand fluctuation, and flow breakdown are some of the potential extensions of this study.

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APPENDIX

This appendix includes a COM script written in MATLAB which is designed to automatically incorporate each scenario's events (in Scenario Processor) into the simulation environment by modifying VISSIM input parameters. The two major functions of the Scenario Processor include modeling crashes and modeling various weather conditions in the VISSIM model. The detailed modeling approach is described in Section 3.0 of the report.

```
clc
clear
%% Import data from text file.
% Script for importing data from the following text file:
%
%   C:\Users\Nima\Desktop\Sharp2\current
test\SHRP2_L04_ScenarioManagerUsersGuideAndSoftware\SHRP2_L04_ScenarioManager
UsersGuideAndSoftware\slc net\2017_scenarios_rain.csv
%
% To extend the code to different selected data or a different text file,
% generate a function instead of a script.

% Auto-generated by MATLAB on 2018/07/14 11:20:59

%% Initialize variables.
filename = 'C:\Users\Nima\Desktop\Sharp2\current
test\SHRP2_L04_ScenarioManagerUsersGuideAndSoftware\SHRP2_L04_ScenarioManager
UsersGuideAndSoftware\new_scenarios\rain_scen.csv' ;

%'C:\Users\Nima\Desktop\Sharp2\current
test\SHRP2_L04_ScenarioManagerUsersGuideAndSoftware\SHRP2_L04_ScenarioManager
UsersGuideAndSoftware\slc net\2017_scenarios_rain.csv'
delimiter = ',';
startRow = 2;

%% Read columns of data as strings:
% For more information, see the TEXTSCAN documentation.
formatSpec = '%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%[\n\r]';
```

```

%% Open the text file.
fileID = fopen(filename, 'r');

%% Read columns of data according to format string.
% This call is based on the structure of the file used to generate this
% code. If an error occurs for a different file, try regenerating the code
% from the Import Tool.
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter,
'HeaderLines' ,startRow-1, 'ReturnOnError', false);

%% Close the text file.
fclose(fileID);

%% Convert the contents of columns containing numeric strings to numbers.
% Replace non-numeric strings with NaN.
raw = repmat({''}, length(dataArray{1}), length(dataArray)-1);
for col=1:length(dataArray)-1
    raw(1:length(dataArray{col}), col) = dataArray{col};
end
numericData = NaN(size(dataArray{1},1), size(dataArray,2));

for col=[1,2,3,10,11,12,14,15,17,19]
    % Converts strings in the input cell array to numbers. Replaced non-numeric
    % strings with NaN.
    rawData = dataArray{col};
    for row=1:size(rawData, 1);
        % Create a regular expression to detect and remove non-numeric prefixes
and
        % suffixes.
        regexstr = '(?<prefix>.*?)(?<numbers>([-
]*(\d+[\,]*)+[\.]{0,1}\d*[eEdD]{0,1}[-+]*\d*[i]{0,1})|([-
]*(\d+[\,]*)*[\.]{1,1}\d+[eEdD]{0,1}[-+]*\d*[i]{0,1})) (?<suffix>.*)';
        try
            result = regexp(rawData{row}, regexstr, 'names');
            numbers = result.numbers;

```

```

% Detected commas in non-thousand locations.
invalidThousandsSeparator = false;
if any(numbers==' ');
    thousandsRegExp = '^\\d+?(\\,\\d{3})*\\.\\{0,1}\\d*$';
    if isempty(regexpi(thousandsRegExp, ',', 'once'));
        numbers = NaN;
        invalidThousandsSeparator = true;
    end
end

% Convert numeric strings to numbers.
if ~invalidThousandsSeparator;
    numbers = textscan(strrep(numbers, ',', ''), '%f');
    numericData(row, col) = numbers{1};
    raw{row, col} = numbers{1};
end
catch me
end
end
end

%% Split data into numeric and cell columns.
rawNumericColumns = raw(:, [1,2,3,10,11,12,14,15,17,19]);
rawCellColumns = raw(:, [4,5,6,7,8,9,13,16,18,20,21,22]);

%% Create output variable
scenariosrain = raw;
%% Clear temporary variables
clearvars filename delimiter startRow formatSpec fileID dataArray ans raw col
numericData rawData row regexstr result numbers invalidThousandsSeparator
thousandsRegExp me rawNumericColumns rawCellColumns;

num_scen=20;
%Start Vissim

```

```

Vissim = actxserver('Vissim.Vissim-64.10');
% Load network
Vissim.LoadNet('C:\Users\Nima\Desktop\Sharp2\pilot vissim model\VISSIM
Traffic Model_16MAR18 (2)\VISSIM Traffic Model_16MAR18\2017 Existing
PM\15605_PG Blvd Interchange.inpx')
% Choose random seed
Random_Seed = [42 57 72 90 110];
Driving_Behav=xlsread('C:\Users\Nima\Desktop\Sharp2\pilot vissim model\VISSIM
Traffic Model_16MAR18 (2)\VISSIM Traffic Model_16MAR18\2017 Existing
PM\Driving_Behav.xlsx', 'A2:D10')
DesSpeedDist8_Normal=Vissim.Net.DesSpeedDecision.GetMultiAttValues('DesSpeedD
istr(8)');
DesSpeedDist9_Normal=Vissim.Net.DesSpeedDecision.GetMultiAttValues('DesSpeedD
istr(9)');
DesSpeedDist10_Normal=Vissim.Net.DesSpeedDecision.GetMultiAttValues('DesSpeed
Distr(10)');
%Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(8)',DesSpeedDis
t8_Normal)
LinkBehavType=Vissim.Net.Links.GetMultiAttValues('LinkBehavType');
Normal_LinkBehavType=LinkBehavType;
Wet_LinkBehavType=Normal_LinkBehavType;
Snowy_LinkBehavType=Normal_LinkBehavType;
%%% Define various driving behaviors parameters for wet(10) and snowy (11)
condition
for i=1:size(LinkBehavType,1)
    if LinkBehavType{i,2}=='3'
        Wet_LinkBehavType{i,2}=10;
        Snowy_LinkBehavType{i,2}=11;
    end
end

All_Links=Vissim.Net.Links.GetAll;
cn=0;
%%% Read Driving Behaviors and Desired Speed Decisions
for i=1:size(LinkBehavType,1)
    if LinkBehavType{i,2}=='3' | LinkBehavType{i,2}=='9';
        cn=cn+1;
    end
end

```

```

        Freeway_Link(cn,1)=get(All_Links{i}, 'AttValue', 'No');
    end
end
DesSpeedDec=Vissim.Net.DesSpeedDecision.GetMultiAttValues('Lane');
DesSpeedDist9_Wet=Vissim.Net.DesSpeedDecision.GetMultiAttValues('DesSpeedDist
r(9)');
DesSpeedDist10_Wet=Vissim.Net.DesSpeedDecision.GetMultiAttValues('DesSpeedDis
tr(10)');
DesSpeedDist9_Snowy=Vissim.Net.DesSpeedDecision.GetMultiAttValues('DesSpeedDi
str(9)');
DesSpeedDist10_Snowy=Vissim.Net.DesSpeedDecision.GetMultiAttValues('DesSpeedD
istr(10)');
Signal_Use=[NaN NaN NaN NaN];
Signal_Names=[10001 10002 10003 10004];
for i=1:size(DesSpeedDec,1)
    Link_Lane=strsplit(char(DesSpeedDec{i,2}),'-');
    Link=Link_Lane{1,1};
    if ismember(str2num(Link),Freeway_Link)>0
        DesSpeedDist9_Wet{i,2}='88';
        DesSpeedDist10_Wet{i,2}='90';
        DesSpeedDist9_Snowy{i,2}='89';
        DesSpeedDist10_Snowy{i,2}='90';
    end
end

end

scenarios_table=cell2table(scenariosrain);
%%
%%% Start Simulating Scenarios
for i=1:num_scen
    Curr_Event_Ind=0;
    simRuns = Vissim.Net.SimulationRuns.GetAll;
    for simRunNo = 1 : length(simRuns)
        Vissim.Net.SimulationRuns.RemoveSimulationRun( simRuns{simRunNo} );
    end
end

```



```

% Find the break point matrix and also number of crashes occurring in the
scenario
curr_scen=scenarios_table(scenarios_table.scenariosrain2==i,:);
num_crash=sum(strcmp(curr_scen.scenariosrain4,'Incident'));
if num_crash>4
    error('Error occurred,number of crashes more than 4 for the scenario')
end
ind_crash=strcmp(curr_scen.scenariosrain4,'Incident')==1;

BreakPoint_mat=sort(transpose([curr_scen.scenariosrain10(curr_scen.scenariosr
ain10>0);max(curr_scen.scenariosrain11)]));
BreakPoint_mat=BreakPoint_mat*60+1800;
CrashEnd=transpose(table2array(curr_scen(ind_crash,11)));
CrashEnd=CrashEnd*60+1800;
Crashes_Location_mat=table2array(curr_scen(ind_crash,20:22));

%Assign each signal to a specific crash and move the signal head to the
%crash location, note that the location of signal head can not be
%modified in the middle of the simulation
for k=1:num_crash
    link=str2double(Crashes_Location_mat(k,1));
    lane=str2double(Crashes_Location_mat(k,2));
    xcoordinate = str2double(Crashes_Location_mat(k,3));

set(Vissim.Net.SignalHeads.ItemByKey(Signal_Names(k),'AttValue','Lane',strca
t(num2str(link),'-',num2str(lane)));

set(Vissim.Net.SignalHeads.ItemByKey(Signal_Names(k),'AttValue','Pos',xcoord
inate);
    Signal_Use(k)=k;
end

% Find simulation breakpoints, simulation stops at each breakpoint;
%BreakPoint_Type determines if the breakpoint is for a crash end (which
is not a new scenario) or a new scenario (crash or weather)

```

```

    % Breakpoints include all events start time, crash events end times, and
the maximum of all events end time

BreakPoint_Type=[zeros(1,size(BreakPoint_mat,2)),ones(1,size(CrashEnd,2))];
    BreakPoint_mat=[BreakPoint_mat,CrashEnd];
    BreakPoint=[BreakPoint_mat; BreakPoint_Type];
    [temp, order] = sort(BreakPoint(1,:));
    BreakPoint = BreakPoint(:,order); % Sorted breakpoints and their type
matrix
for s=1:5
    simRuns = Vissim.Net.SimulationRuns.GetAll;
    for simRunNo = 1 : length(simRuns)
        Vissim.Net.SimulationRuns.RemoveSimulationRun( simRuns{simRunNo} );
    end
    Curr_Event_Ind=0;
    set(Vissim.Simulation, 'AttValue', 'RandSeed', Random_Seed(s));

Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(8)',DesSpeedDist
8_Normal);

Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(9)',DesSpeedDist
9_Normal);

Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(10)',DesSpeedDis
t10_Normal);

Vissim.Net.Links.SetMultiAttValues('LinkBehavType',Normal_LinkBehavType) ;
    crash_cnt=0;
    for j=1:size(BreakPoint,2)
        if j==1
            m=j+1;
        else
            m=j;
        end
        j
        m

```

```

Curr_Event_Ind
    if BreakPoint(2,m-1)~=1

        Curr_Event_Ind=Curr_Event_Ind+1
        if curr_scen.scenariosrain10(Curr_Event_Ind)<9000
            if
strcmp((curr_scen.scenariosrain4(Curr_Event_Ind)), 'Weather')==1
                'weather'
                if curr_scen.scenariosrain14(Curr_Event_Ind)==1

%Vissim.Net.Links.SetMultiAttValues('LinkBehavType',Normal_LinkBehavType)
                %
Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(8)',DesSpeedDist
8_Normal)

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'AccDecelOwn', Driving
_Behav(1,1));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'AccDecelTrail', Drivi
ng_Behav(2,1));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'SafDistFactLnChg', Dr
iving_Behav(3,1));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc0', Driving_Beha
v(4,1));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc1Distr', Driving
_Behav(5,1));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc4', Driving_Beha
v(6,1));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc5', Driving_Beha
v(7,1));

```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc7', Driving_Behav(8,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc9', Driving_Behav(9,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'AccDecelOwn', Driving_Behav(1,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'AccDecelTrail', Driving_Behav(2,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'SafDistFactLnChg', Driving_Behav(3,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc0', Driving_Behav(4,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc1Distr', Driving_Behav(5,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc4', Driving_Behav(6,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc5', Driving_Behav(7,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc7', Driving_Behav(8,1));
```

```
set (Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc9', Driving_Behav(9,1));
```

```

Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(9)',DesSpeedDist
9_Normal);

Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(10)',DesSpeedDis
t10_Normal);

                                elseif
curr_scen.scenariosrain14(Curr_Event_Ind)==2|curr_scen.scenariosrain14(Curr_E
vent_Ind)==3|curr_scen.scenariosrain14(Curr_Event_Ind)==4

%Vissim.Net.Links.SetMultiAttValues('LinkBehavType', Wet_LinkBehavType)
                                %
Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(8)',DesSpeedDist
8_Wet)

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'AccDecelOwn', Driving
_Behav(1,2));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'AccDecelTrail', Drivi
ng_Behav(2,2));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'SafDistFactLnChg', Dr
iving_Behav(3,2));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc0', Driving_Beha
v(4,2));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc1Distr', Driving
_Behav(5,2));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc4', Driving_Beha
v(6,2));

set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc5', Driving_Beha
v(7,2));

```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc7', Driving_Behav(8,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc9', Driving_Behav(9,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'AccDecelOwn', Driving_Behav(1,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'AccDecelTrail', Driving_Behav(2,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'SafDistFactLnChg', Driving_Behav(3,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc0', Driving_Behav(4,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc1Distr', Driving_Behav(5,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc4', Driving_Behav(6,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc5', Driving_Behav(7,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc7', Driving_Behav(8,2));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc9', Driving_Behav(9,2));
```

```
Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(9)',DesSpeedDist  
9_Wet);
```

```
Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(10)',DesSpeedDis  
t10_Wet);
```

```
else
```

```
%Vissim.Net.Links.SetMultiAttValues('LinkBehavType', Snowy_LinkBehavType)
```

```
%
```

```
Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(8)',DesSpeedDist  
8_Snowy)
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'AccDecelOwn', Driving  
_Behav(1,3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'AccDecelTrail', Drivi  
ng_Behav(2,3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'SafDistFactLnChg', Dr  
iving_Behav(3,3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc0', Driving_Beha  
v(4,3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc1Distr', Driving  
_Behav(5,3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc4', Driving_Beha  
v(6,3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc5', Driving_Beha  
v(7,3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc7', Driving_Behav(8, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(3), 'AttValue', 'W99cc9', Driving_Behav(9, 3)) ;
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'AccDecelOwn', Driving_Behav(1, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'AccDecelTrail', Driving_Behav(2, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'SafDistFactLnChg', Driving_Behav(3, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc0', Driving_Behav(4, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc1Distr', Driving_Behav(5, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc4', Driving_Behav(6, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc5', Driving_Behav(7, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc7', Driving_Behav(8, 3));
```

```
set(Vissim.Net.DrivingBehaviors.ItemByKey(7), 'AttValue', 'W99cc9', Driving_Behav(9, 3)) ;
```



```
Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(9)',DesSpeedDist  
9_Snowy);
```

```
Vissim.Net.DesSpeedDecision.SetMultiAttValues('DesSpeedDistr(10)',DesSpeedDis  
t10_Snowy);
```

```
end
```

```
end
```

```
if
```

```
strcmp((curr_scen.scenariosrain4(Curr_Event_Ind)), 'Incident')
```

```
    crash_cnt=crash_cnt+1
```

```
    Curr_Signal=Signal_Names(crash_cnt);
```

```
    %Incident_start=
```

```
curr_scen.scenariosrain10(Curr_Event_Ind)*60
```

```
%Incident_end=curr_scen.scenariosrain11(Curr_Event_Ind)*60
```

```
%link=str2double(curr_scen.scenariosrain20(Curr_Event_Ind))
```

```
%lane=str2double(curr_scen.scenariosrain21(Curr_Event_Ind))
```

```
    %xcoordinate =
```

```
str2double(curr_scen.scenariosrain22(Curr_Event_Ind))
```

```
%set(Vissim.Net.SignalHeads.ItemByKey(Curr_Signal), 'AttValue', 'Lane', strcat(n  
um2str(link), '-', num2str(lane)))
```

```
%set(Vissim.Net.SignalHeads.ItemByKey(Curr_Signal), 'AttValue', 'Pos', xcoordina  
te)
```

```
    SignalController =
```

```
Vissim.Net.SignalControllers.ItemByKey(Curr_Signal)    ;
```

```
    SignalGroup = SignalController.SGs.ItemByKey(1);
```

```
    set(SignalGroup, 'AttValue', 'SigState', 'RED')
```

```
;
```

```

        end
        set(Vissim.Simulation, 'AttValue', 'SimBreakAt',
BreakPoint(1,j));
        Vissim.Simulation.RunContinuous;

        end
    else
        'crash end'
        % find which crash needs to be removed from the network
        Curr_Crash_End=find(BreakPoint(1,j-1)==CrashEnd) ;
        % find the index of signal associated with this crash
        %Curr_Signal_End_Ind=find(Signal_Use==Curr_Crash_End)
        %Curr_Signal_End=Signal_Names(Curr_Signal_End_Ind)
        Curr_Signal_End=Signal_Names(Curr_Crash_End);
        SignalController =
Vissim.Net.SignalControllers.ItemByKey(Curr_Signal_End) ;
        SignalGroup = SignalController.SGs.ItemByKey(1);
        set(SignalGroup, 'AttValue', 'SigState', 'OFF') ;
        set(Vissim.Simulation, 'AttValue', 'SimBreakAt',
BreakPoint(1,j));
        Vissim.Simulation.RunContinuous;
    end
end

    newname=strcat('C:\Users\Nima\Desktop\Sharp2\pilot vissim model\VISSIM
Traffic Model_16MAR18 (2)\VISSIM Traffic Model_16MAR18\2017 Existing
PM\direct
output2\',sprintf('scenario_%d.rsr',i),sprintf('_seed%d.csv',Random_Seed(s)))
    movefile('C:\Users\Nima\Desktop\Sharp2\pilot vissim model\VISSIM Traffic
Model_16MAR18 (2)\VISSIM Traffic Model_16MAR18\2017 Existing PM\direct
output\15605_PG Blvd Interchange_001.rsr',newname)
    for k=1:8

Data_Collection_No=Vissim.Net.DataCollectionMeasurements.GetMultiAttValues('N
o')

        DC_measurement =
Vissim.Net.DataCollectionMeasurements.ItemByKey(Data_Collection_No{k,2})
        for l=1:30

```

```

        Volume(1,k)=get(DC_measurement, 'AttValue',
strcat('Vehs(1,',sprintf('%d',1),',All)'))
        Occupancy(1,k)=get(DC_measurement, 'AttValue',
strcat('OccupRate(1,',sprintf('%d',1),',All)'))
        Speed(1,k)=get(DC_measurement, 'AttValue',
strcat('SpeedAvgArith(1,',sprintf('%d',1),',All)'))
        SpeedHarm(1,k)=get(DC_measurement, 'AttValue',
strcat('SpeedAvgHarm(1,',sprintf('%d',1),',All)'))
    end
end
    xlswrite(strcat('C:\Users\Nima\Desktop\Sharp2\pilot vissim model\VISSIM
Traffic Model_16MAR18 (2)\VISSIM Traffic Model_16MAR18\2017 Existing PM\data
collection2\',sprintf('scenario_Vol%d',i),sprintf('_seed%d.csv',Random_Seed(s
))),Volume)
    xlswrite(strcat('C:\Users\Nima\Desktop\Sharp2\pilot vissim model\VISSIM
Traffic Model_16MAR18 (2)\VISSIM Traffic Model_16MAR18\2017 Existing PM\data
collection2\',sprintf('scenario_Occup%d',i),sprintf('_seed%d.csv',Random_Seed
(s))),Occupancy)
    xlswrite(strcat('C:\Users\Nima\Desktop\Sharp2\pilot vissim model\VISSIM
Traffic Model_16MAR18 (2)\VISSIM Traffic Model_16MAR18\2017 Existing PM\data
collection2\',sprintf('scenario_Speed%d',i),sprintf('_seed%d.csv',Random_Seed
(s))),Speed)
    xlswrite(strcat('C:\Users\Nima\Desktop\Sharp2\pilot vissim model\VISSIM
Traffic Model_16MAR18 (2)\VISSIM Traffic Model_16MAR18\2017 Existing PM\data
collection2\',sprintf('scenario_SpeedHarm%d',i),sprintf('_seed%d.csv',Random_
Seed(s))),SpeedHarm)
end
end

```