A SOFTWARE TOOL FOR FREEWAY TRAVEL TIME RELIABILITY ANALYSIS: DEVELOPMENT AND TESTING

By

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A THESIS PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE

UNIVERSITY OF FLORIDA

2016

To my parents

ACKNOWLEDGMENTS

I am grateful to all the people that helped me along the way. I thank Dr. Washburn, my graduate instructor, for all the support and encouragement that helped me obtain my academic achievements. I thank my parents for always being there for me and raising me into a decent man. I thank Dr. Yin, Dr. Lily and Dr. Siva for their great courses, which helped me learn more about the transportation engineering field. I thank my peer students who have attended courses with me or worked with me, they made my graduate life here memorable.

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LIST OF ABBREVIATIONS

AP	Analysis Period
AADT	Annual Average Daily Traffic
CAF	Capacity Adjustment Factor
DAF	Demand Adjustment Factor
DP	Demand Pattern
FFS	Free-flow Speed
HCM	Highway Capacity Manual
PTI	Planning Time Index
RRP	Reliability Reporting Period
SP	Study Period
SAF	Free-flow Speed Adjustment Factor
SHRP2	Strategic Highway Research Program, Second Funding Implementation
TTI	Travel Time Index
TTR	Travel Time Reliability
VMT	Vehicle Miles Traveled
VHT	Vehicle Hours Traveled
VHD	Vehicle Hours of Delay

Abstract of Thesis Presented to the Graduate School
of the University of Florida in Partial Fulfillment of the
Requirements for the Degree of Master of Science

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May 2015

Chair: Scott S Washburn
Major: Civil Engineering

As traffic congestion continues to worsen, travel time reliability is receiving more attention as the appropriate performance measure for roadway facilities that regularly suffer from congestion. Motivated by its increasing importance in transportation planning and operation, various methods have been proposed to estimate and measure travel time reliability (TTR).

Two recently developed TTR analysis methods are effectively the current standard, generally referred to as the "SHRP2-L08" and "HCM" methods. This document describes the development and testing of, a software tool to execute the large scale and highly iterative calculations of the SHRP2-L08 and HCM travel time reliability analysis methodologies. The software tool was developed with the C# language and the .NET Framework. A user guide for the software was also developed, which also serves as guidance for researchers to conduct the travel time reliability analysis. Through the application of the software, the generated results are also verified for consistency with the documentation of the two TTR analysis methodologies.

CHAPTER 1
INTRODUCTION

Background

When it comes to traveling, the reliability to arrive at a certain destination safely and on time is a major concern for both the travelers and the transportation system managers. Congestion leads to more variable travel times for a facility, which results in travelers needing to plan extra travel time to account for the potential unreliability of arriving at their destination on time in any given trip.

The concept of travel time reliability is based on the analysis of a large number of trips taken over a given length of facility over an extended period of time (i.e., a travel time distribution). Other definitions of travel time reliability include the consistency or dependability in travel times from hours of the day, days of the week, and months or seasons of the year. Travel time reliability is also known as the variability between the expected travel time and the actual travel time. In general, travel time reliability is an indication of how often congested conditions occur, and how severe the differences between expected and actual travel times become.

Traffic congestion can be caused by various reasons, such as heavy demand relative to regular capacity, closing of road lanes due to incidents and severe weather events. Correspondingly, travel time reliability is then affected by high demand/capacity ratios, weather events and incident events.

In recent years, the significance of travel time reliability in transportation system planning and operation has been recognized. The application of travel time reliability in the transportation field involves: operational planning, congestion management, demand prediction, performance evaluation, and system optimization.

Considerable research has been conducted recently to analyze travel time reliability. Two recently developed TTR analysis methods are effectively the current standard: one based on the results of a Strategic Highway Research Program (SHRP) research project (hereafter referred to as “SHRP2-L08”) and the other a modified version of the SHRP2-L08 methodology that will be included in the forthcoming sixth edition of the Highway Capacity Manual (HCM), hereafter referred to as the “HCM” method.

The SHRP2-L08 and HCM TTR analysis methods are overall similar, but the latter applies some revisions to reduce the overall computational burden. An overview of both methods, as well as an identification of their specific differences is discussed more fully in Chapter 2.

Problem Statement

One thing common to both TTR analysis methods is that they are data intensive, and consequently computationally intensive. They both require a large number of scenarios (i.e., combinations of input conditions) to be processed with a complex facility analysis methodology (either a freeway or urban street). While the SHRP2-L08 project report and HCM document the respective analysis methodologies, it is not feasible to conduct the travel time analysis methods without software, given the large scale and highly iterative calculations.

Furthermore, given the complexity of applying these TTR analysis methods, there are considerable demands on the software in terms of user friendliness and functional capabilities. Prior to the development of the software created for this project, the only existing software implementations of these analysis methodologies were in the form of an Excel spreadsheet, which had significant limitations in both of these areas (i.e., user friendliness and functional capabilities).

Research Objective and Supporting Tasks

The objective of this project is to develop a software tool for executing the SHRP2-L08 and HCM TTR analysis methodologies (but specific to just freeway facilities), as well as another methodology that will be introduced in Chapter 3. Furthermore, this software tool must be of "commercial grade"—that is, be able to meet the user friendliness and functional requirement standards of transportation practitioners such that the application of these TTR analysis methodologies will be as intuitive and efficient as possible.

The following tasks were conducted to support the accomplishment of this objective:

- Review of freeway travel time analysis methodologies.
- Develop the software tool for the travel time analysis methodologies. As part of this task, obtain input on software design features from stakeholders.
- Verify that the analysis methodologies have been correctly implemented into the software. As part of this task, document methodology calculation processes that were not identified in the original report.
- Develop a user guide for how to operate the software tool for each of the methodologies.

Document Organization

In the remainder of the document, Chapter 2 contains an overview of freeway TTR analysis methodologies. Chapter 3 provides an overview of the software development and process flow, as well as the process flow of different scenario generation methodologies. Chapter 4 conducts the verification of the software tool, and provides the computational documents for both SHRP2-L08 and HCM methods in Mathcad. Chapter 5 provides a summary of this project.

CHAPTER 2
OVERVIEW OF FREEWAY TRAVEL TIME RELIABILITY ANALYSIS METHODOLOGIES

Overview

This chapter provides an overview of the freeway TTR analysis methodologies. First, a background of TTR analysis methodologies is provided. Second, the procedures of the SHRP2-L08 methodology, which are documented in the 5th edition of the HCM (TRB, 2010), are presented. Third, the procedures of the revised SHRP2-L08 method, which will be included in the forthcoming sixth edition of the HCM (TRB, 2016), and referred to as the HCM method, are presented.

Background

Travel time reliability relies on the scenario, a specific combination of inputs to the freeway facility analysis methodology, generation methods to enumerate a sufficiently complete set of scenarios that represent the variability of demand levels, weather events, and incident events over a certain long-term time period (e.g., a year). A desirable scenario generation method is one that produces a set of scenarios that will yield results that match the field conditions with reasonable accuracy, but also keeps the number of scenarios to a minimum because of the highly iterative and complex nature of the calculation process.

The SHRP2-L08 method uses a deterministic approach to generate scenarios. In order to model every possible combination of demand levels, weather events and incidents, the deterministic approach generates a fairly large number of scenarios. In this case, a series of assumptions are used to simplify the combinations, such as:

- The start time period for weather or incident events can only be the beginning or middle time period of the study period.
- The location of incident events can only be the first, middle or last segment of the studied facility.

- The occurrence of multiple incidents is substituted by a single incident with a long duration.

Even though the application of the simplifying assumptions above may reduce the otherwise numerous number of scenarios, this deterministic approach could still lead to some limitations:

- The relatively large amount of scenarios to be generated, which may increase the runtime.
- The complexity of the scenario generation about the start times, durations and locations assignment, also possible bias may be resulted from the assumptions.
- The lack of consistence with the field observations for the tail of the travel time distribution.

The HCM method was proposed by the NCHRP 3-115 (HCM major update) research project team, which was meant to serve as an enhancement to the SHRP2-L08 method for freeway travel time reliability scenario generation. The team's objectives were mainly to obtain more realistic scenarios that match the field observations, while reducing the number of scenarios generated.

The highlight of this scenario generation method is that it combines the deterministic approach with a more stochastic approach (Monte Carlo methods). The method uses a deterministic way to generate a fixed number of scenarios, then applies the random assignment to each scenario generated, by picking random numbers based on the specific distribution.

Basic Definitions

Following are some basic definitions for the terms used in the travel time reliability methodologies:

- Analysis period (AP) or time period, is the time interval for one single application of the travel time reliability methodology, the basic facility conditions must stay unchanged, usually 15 min in duration.

- Study period (SP) is certain time interval in a day, which consists of one or more analysis periods, usually 1h to 6h in duration.
- Reliability reporting period (RRP) is the time over which the travel time reliability is measured, usually 1 year in duration.
- Demand pattern (DP) represents a group of days within the RRP that have similar demand level.
- Demand adjustment factors (DAF) represent the variability of demand through days in week or months in year, which are used to adjust the original demand in the base file.
- Capacity adjustment factors (CAF) represent the variability of capacity caused by weather or incident events, which are used to adjust the original capacity in the base file.
- Free-flow speed adjustment factors (SAF) represent the variability of FFS, which are used to adjust the original FFS in the base file.
- Scenario is one single realization of the study period, which contains the relative demand level, weather and incident event information, e.g. demand pattern 1, medium rain starts from AP 5 with a duration of 30 minutes, shoulder closure on segment 3 starts from AP 2 with a duration of 45 minutes.
- Demand multiplier is the ratio of demand for the specified day and month to the AADT used.
- Annual average daily traffic (AADT) is the total volume of vehicle traffic for a year divided by the number of days in that year.

SHRP2-L08 Methodology

The SHRP2-L08 methodology uses a deterministic approach to generate scenarios that can represent conditions such as demand level, weather and incident events. First, a set of base scenarios with their initial probabilities are generated. The base probability represents the portion of time under the specified condition during RRP. Second, the probabilities of the base scenarios are adjusted to the study period probabilities, which represent the portion of time under the specified conditions in the study period. Then, an expected travel time can be estimated for each scenario based on the relative DAF, CAF and SAF. Finally, the calculated travel times from all scenarios with their probabilities can be compiled into a travel time distribution, which will be used to evaluate the travel time reliability of the studied facility.

An overview of the SHRP2-L08 analysis methodology, which is described in more detail in the SHRP2-L08 working paper (1) follows.

Stage 1 Base scenario generation

When generating the base scenarios, the objective is to generate a set of scenarios that combines the demand levels, weather events, and incidents conditions.

Step 1. Create the base file

Base file contains the basic facility information, such as facility geometry (segment type, number of lanes, etc.), terrain, jam density, capacity, truck percentage, demand entry flow rates, FFS, AP, SP, RRP, etc.

Step 2. Configure demand patterns

To represent the variabilities of demand in days of week or months of year, demand patterns are proposed, each demand pattern represent a certain demand condition. The number of demand pattern is the number of day groups multiplied by the number of month groups.

For example, demand patterns usually consist three weekday groups (Monday and Friday, Tuesday to Thursday and weekends) and four month groups (seasons), which will give us twelve demand patterns.

Each scenario contains one demand pattern, demand level of the demand pattern is determined by the demand multipliers. The demand multipliers represent the variability of demand in days of week or months of year. The demand multiplier for a demand pattern is the weighted demand multipliers based on the day groups and month groups of the demand pattern. The base file demand multiplier is the ratio of base file demand to AADT.

DAF of the demand pattern (scenario) equals to the demand multiplier of that scenario divided by the base file demand multiplier.

$$DAF_s(tp, seg) = DM(s)/DM(base) \tag{2-1}$$

$DAF_s(tp, seg)$ is the demand adjustment factor associated with scenario *s* analysis period *tp* and segment *seg*

$DM(s)$ is the demand multiplier associated with scenario *s*

$DM(base)$ is the demand multiplier associated with the base file for analysis period *tp*

The probability of a demand pattern is the duration (min) of the demand pattern in the RRP divided by the total RRP duration.

$P_{DP}(N)$ is defined as the probability of demand pattern *N*, and is computed from the following:

$$P_{DP}(N) = \frac{Sum\ of\ SP\ minutes\ within\ demand\ pattern\ N}{Sum\ of\ SP\ minutes\ in\ RRP} \tag{2-2}$$

Step 3. Configure weather data

Usually there are eleven weather categories: medium rain, heavy rain, light snow, light-medium snow, medium-heavy snow, heavy snow, severe cold, low visibility, very low visibility, minimal visibility, non-severe weather (Normal).

The weather data should be collected and classified into the weather categories above. The probabilities of these weather types are stated by month. Weather data for each weather type include probability, duration, and adjustment factors.

For data-rich environments, analysts may estimate the probabilities of weather types from the following:

$$P_W(i, j) = \frac{Sum\ of\ all\ SP\ durations\ (\mathrm{min})\ in\ month\ j\ that\ weather\ type\ i\ is\ present}{Sum\ of\ all\ SP\ druations\ (\mathrm{min})\ in\ month\ j} \tag{2-3}$$

If analysts do not have access to the detailed local weather data to estimate the weather probabilities, they can use the 10-year average weather probabilities of the nearby metropolitan areas in HCM.

The SHRP2-L08 assumes that a weather event occurs either at the start of the study period or in the middle of the study period with equal probability. In this case, considering 11 weather types and 2 possible start times, there will be 22 weather scenarios.

Adjustment factors are assigned to the analysis periods from the weather start time to the end time based on the start time period and weather duration, and weather affects all segments of the facility. Since weather types are mutually exclusive, if two or more weather types are generated at the same time period, the weather event is assigned to the weather type with the greatest capacity reduction effect.

Step 4. Configure incident data

The incident data must be collected and classified into one of the following incident categories: no incident, shoulder closure, one-lane closure, two-lane closure, three-lane closure, and four or more lane closure.

For data-rich environments, the time based probability of incident type *i* in month *j* is estimated by the following:

$$P_{Inc}(i,j) = \frac{Sum\ of\ all\ SP\ durations\ (\mathrm{min})\ in\ month\ j\ that\ incident\ type\ i\ is\ present}{Sum\ of\ all\ SP\ durations\ (\mathrm{min})\ in\ month\ j} \quad (2\text{-}4)$$

If analysts do not have access for local incident data to directly estimate the incident probabilities, they can use local incident rates or crash rates to obtain the incident probabilities. The incident probability for incident type *i* of month *j* can be calculated from:

$$P(i,j) = 1 - EXP(\left(-N_j \times G(i) \times \frac{D_i}{SP}\right)) \quad (2\text{-}5)$$

D_i is the mean duration of incident type *i*

$G(i)$ is the incident distribution probability of incident type *i*

N_j is the expected incident frequency of month *j*

The distribution of incident severities $G(i)$ can be specified by the analyst, default distribution is as following:

$$G(i) = \begin{cases} 0.75 & i = 1 \\ 0.20 & i = 2 \\ 0.05 & i = 3 \\ 0.00 & i = 4 \\ 0.00 & i = 5 \end{cases}$$

i is the incident severity type, 1 = shoulder closure, 2 = one-lane closure, 3 = two-lane closure, 4 = three-lane closure, 5 = four or more lane closure.

The expected frequency N_j per study period in month *j* can be calculated using:

$$N_j = IR_j * DM_j \times VMT_{base} \tag{2-6}$$

VMT_{base} is the vehicle miles traveled (VMT) in the base file

IR_j is the incident rate per 100 million VMT for month *j*

DM_j is the weighted average demand multiplier of the all days in month *j* relative to base demand multiplier

If incident rates are not available directly, analyst can convert the crash rates into incident rates using the following equation:

$$IR_j = CR_j \times ICR \tag{2-7}$$

CR_j is the crash rate per 100 million VMT for month *j*

ICR is the local incident to crash ratio

If crash rates are not available directly, analyst can use the HERS model to calculate crash rates based on the following equation:

$$CR = (154 - 1.203 \times ACR + 0.258 \times ACR^2 - 0.00000524 \times ACR^5) \times e^{(0.0052 \times (12 - L_w))} \quad (2\text{-}8)$$

L_w is the lane width, usually 12 ft

ACR is the average crash rate, can be calculated from the following equation:

$$ACR = \frac{AADT}{C \times N_L} \quad (2\text{-}9)$$

C is the two-way hourly capacity

N_L is the average number of lanes for all segments of the facility, can be calculated using the following equation:

$$N_L = \frac{\sum_{i=0}^{i=n} n_i \times l_i}{\sum_{i=0}^{i=n} l_i} \quad (2\text{-}10)$$

n is the number of segments of the facility

n_i is the number of lanes for segment *i*

l_i is the length of segment *i*

The method assumes that incident can only happen at three locations of the facility (first, middle or last basic segment of the facility) and two start times (beginning or middle of the study period), so the maximum number of incident scenarios should be: 2 (start times) × 3 (incident durations) × 3 (incident locations) × 5 (incident severities) + 1 (no incident) = 91 incident scenarios. Adjustment factors of the incident will be assigned to the relative time periods and locations.

Step 5. Overall base scenarios

If we consider all the possible scenarios, a maximum number of scenarios of: 12 (demand patterns) × 22 (weather scenarios) × 91 (incident scenarios) = 24,000 scenarios will be generated. These scenarios are called base scenarios. The basic assumption of base scenario is that contributing factors such as demand patterns, weather events and incident events are independent. Thus, the probability of a base scenario is the product of the probability of all contributing factors using the following equation:

$$\mathrm{P}(\text{base scenario n}) = P(Demand\ level\ i) \times P(\text{Weather j}) \times \mathrm{P}(\text{Incident k}) \qquad (2\text{-}11)$$

However, the probabilities of weather or incident are given on a monthly basis, the probabilities of demand level are by demand pattern. In this case, the scenario's weather or incident probability must first be aggregated across the demand pattern and then used in Equation (2-1) to calculate the base scenario probability.

The aggregation of weather and incident probabilities across demand patterns are based on the following equations. In the equations below, *i* refers to a demand pattern, *j* refers to a weather type, *k* refers to an incident type, *m* refers to a month.

$$P_w^{DP}(i,j) = \frac{\sum_{m\in DP} P_W(j,m)\times N_{DP}(i,m)}{\sum_{m\in DP} N_{DP}(i,m)} \qquad (2\text{-}12)$$

$P_w(j,m)$ is the weather probability of weather type *j* and month *m*

$N_{DP}(i,m)$ is the number of days of demand pattern *i* and month m in RRP

$$P_{Inc}^{DP}(i,k) = \frac{\sum_{m\in DP} P_{Inc}(k,m)\times N_{DP}(i,m)}{\sum_{m\in DP} N_{DP}(i,m)} \qquad (2\text{-}13)$$

$P_{Inc}(k,m)$ is the incident probability of incident type k and month m

Equation (2-11) can be rewritten in the form of Equation (2-14):

$$\mathrm{P}_{Base}(\mathrm{DP = i, W = j, Inc = k}) = P_{DP}(i) \times P_w^{DP}(i,j) \times P_{Inc}^{DP}(i,k) \qquad (2\text{-}14)$$

In this case, there could be some base scenarios with very low probabilities, a threshold is set to remove these scenarios. Base scenario with a probability lower than the threshold is removed and its probability is assigned to the rest of the scenarios proportionally.

User can specify the value of the threshold, which is defaulted as 0.1%. The threshold can reduce the total number of scenarios generated. However, a large value of threshold is not recommended, since that would result in a significant loss of scenarios, which will affect the accuracy of travel time distribution.

Stage 2 Study period scenario generation

The base scenarios describe the time the facility will be under the specified condition during the RRP. However, they need to represent the time the facility will be under certain condition during the study period. So the weather or incident event durations are considered to adjust the base scenario probabilities into the study period scenario probability. The computational procedures to convert probabilities of base scenarios into the study period probabilities are as following (on a demand pattern basis):

For the selected demand pattern, the base scenario probabilities are classified into four categories:

- Category 1, demand only
- Category 2, demand and weather
- Category 3, demand and incident
- Category 4, demand, weather and incident

Note that the sum of probabilities of all scenarios in this demand pattern remains the same after the following adjustment procedures:

1) Compare the weather and incident events durations

Since the SHRP2-L08 method uses 15 minutes as the analysis period, weather and incident durations are rounded into the nearest 15 minutes for the following calculations.

Calculate the minimum durations of each weather and incident combinations using Equation (2-15), which is the time that both weather and incident events occur in category 4 scenarios.

$$\omega_{ij} = Min(Round(D_i^W), Round\left(D_j^{Inc}\right)) \qquad (2\text{-}15)$$

D_i^W is the duration of weather type *i*

D_j^{Inc} is the duration of incident type *j*

Calculate the difference between weather and incident duration of each combination using the following equation:

$$\Delta_{ij} = \left|Round(D_i^W) - Round\left(D_j^{Inc}\right)\right| \tag{2-16}$$

2) Adjust the category 4 scenario probabilities

For weather event *i* and incident event *j*, the study period probability π_{ij} can be calculated from the following:

$$\pi_{ij} = P_{ij} \times \left(\frac{SP}{\omega_{ij}}\right) \tag{2-17}$$

P_{ij} is the base scenario probability of weather event *i* and incident event *j*

The sum of all adjusted category 4 probabilities should be less than the sum of the base scenario probabilities of the demand pattern using Equation (2-14).

$$\sum_{\substack{i=1\ to\ n_W \\ j=1\ to\ n_{Inc}}} \pi_{ij} < \sum_{\substack{i=1\ to\ n_W \\ j=1\ to\ n_{Inc}}} P_{ij} \tag{2-18}$$

n_W is the number of weather types for the selected demand pattern

n_{Inc} is the number of incident types for the selected demand pattern

Should the constraint in Equation (2-18) not be met, certain weather or incident events with high probabilities in category 4 need to occur more than once, and the probability of each occurrence is equal.

3) Calculate residual probabilities for category 2 and 3 probabilities

For weather and incident events that have different durations, the effect of the longer event will be modeled through the residual probabilities, which can be calculated using Equation (2-19) and (2-20).

π_i' is the residual probability for weather type *i* in category 2, can be calculated using Equation (2-19). For a scenario of weather type *i* and incident type *j*, if the duration of weather type *i* is longer than incident *j*, $\alpha_{ij} = 1$, else, $\alpha_{ij} = 0$.

$$\pi_i' = \sum_{j=1}^{n_{Inc}} \pi_{ij} \times \alpha_{ij} \times \frac{\Delta_{ij}}{SP} \tag{2-19}$$

π_j' is the residual probability for incident type *j* in category 3, can be calculated using Equation (2-20). For a scenario of weather type *i* and incident type *j*, if the duration of incident type *j* is longer than weather type *i*, $\beta_{ij} = 1$, else, $\beta_{ij} = 0$.

$$\pi_j' = \sum_{i=1}^{n_w} \pi_{ij} \times \beta_{ij} \times \frac{\Delta_{ij}}{SP} \tag{2-20}$$

Since the probabilities in category 4 may not only represent the category 4 base scenarios, but a portion of category 2 or 3 also. So the calculated residual probabilities should be taken out from the initial weather or incident probabilities.

Also, the residual probabilities should be lower than the category 2 and 3 initial base scenario's probabilities; if not, more than one event needs to be applied to solve the problem. And we need to restart from Stage 2 procedure 3).

4) Calculate the study period probabilities for category 2 and 3

The residual probabilities should be taken out from the initial weather and incident base scenario probabilities, using Equation (2-21) and (2-22), respectively:

$$\gamma_i = p_{i0} - \pi_i' \tag{2-21}$$

$$\gamma_j = p_{j0} - \pi_j' \tag{2-22}$$

The remainder probabilities for weather γ_i and incident γ_j are adjusted using Equation (2-23) and (2-24), respectively, to get the study period probabilities for category 2 and 3:

$$\pi_{i0} = \gamma_i \times \frac{SP}{Round(D_i^W)} \tag{2-23}$$

$$\pi_{j0} = \gamma_j \times \frac{SP}{Round\left(D_j^{Inc}\right)} \tag{2-24}$$

The sum of category 2, 3, and 4 study period probabilities should be lower than the sum of the base scenario probabilities of the selected demand pattern, if not, then some of the events in category 2 and 3 should occur more than once to solve the problem.

5) Calculate the study period probabilities for category 1

The study period probabilities for category 1 is the sum of base scenario probabilities of the selected demand pattern minus the sum of study period probabilities for category 2, 3, and 4.

Stage 3 Detailed scenario generation

Scenarios with probabilities and adjustment factors are assigned with detailed information such as start time, duration, and location for weather or incident. Each possible combination has equal probability to occur.

For weather events, there are two possible start times: beginning of SP, middle of the SP. For incident events, there are two possible start times: beginning of SP, and middle of the SP. The duration of an incident has three possibilities: 25th percentile incident duration, 50th percentile incident duration and 75th percentile incident duration. An incident has three possible locations: first basic segment, middle basic segment, and last basic segment.

Considering all the combinations of the detailed scenarios, the maximum number of scenarios is: N = 12 (DPs) + 12 (DPs) × 10 (weather types) × 2 (weather start times) + 12 (DPs) × 5 (incident types) × 2 (incident start times) × 3 (incident durations) × 3 (locations) + 12 (DPs) × 10 (weather types) × 5 (incident types) × 2 (incident start times) × 3 (incident durations) × 3 (locations)× 2 (weather start times) = 22,932.

With the detailed scenarios generated, analyst can use the HCM freeway facilities method to estimate the travel time for each scenario, and then all the travel times calculated can be compiled into a travel time distribution to evaluate the reliability of the facility.

HCM Methodology

The HCM methodology (HCM 6th Edition, TRB 2016) introduces some stochastic elements to the general procedure introduced through the SHRP2-L08 project. First, the number of scenarios with their probabilities are calculated, and the demand adjustment factors are calculated and assigned with the generated scenarios. Then, weather and incident events are generated and randomly assigned to the scenario.

Specific procedures for the HCM methodology (2) are explained as following:

Stage 1 Scenarios and DAFs

In this stage, the number of scenarios are generated based on demand patterns, and scenario probabilities are also calculated based on number of days associated with the scenario. Unlike the SHRP2-L08 method, the number of scenarios and their probabilities are fixed and will not change in the following calculations.

Step 1. Create the base file

Base file contains the basic facility information, such as facility geometry (such as segment type, number of lanes), terrain, jam density, capacity, demand entry flow rates, truck percentage, FFS, AP, SP, RRP, etc.

Step 2. Determine the number of demand patterns

For HCM method, by default, the number of demand pattern is: 5 (weekdays) × 12 (months) = 60 (demand patterns).

Step 3. Demand pattern scenario sets and the total number of scenarios

The scenario sets number could be 4 or 5, since each demand pattern usually consists of 4 or 5 calendar days, the default scenario sets number is 4.

Total number of scenarios: 4 (scenario sets) × 60 (demand patterns) = 240. These 240 scenarios are believed to represent the demand variability throughout the studied RRP.

Step 4. Calculate the DAF of the demand pattern using Equation (2-1).

Step 5. Calculate scenario probabilities

The probability of a scenario is the number of days for the demand pattern associated with the scenario divided by the product of number of days in the RRP and number of scenario sets, it can be calculated from the following:

$$P\{s\} = \frac{n_k}{4 \times \sum_{k=1}^{N_{DC}} n_k} \tag{2-25}$$

n_k is the number of days in demand pattern k

$\sum_{k=1}^{N_{DC}} n_k$ is the sum of number of days for all demand patterns or the number of days in RRP

Stage 2 Weather adjustment factors

In this stage, the calculations are on a monthly basis. Firstly, the expected weather event frequencies for a selected month are calculated. Secondly, the generated weather events are randomly assigned to the scenarios in the current month. Then, the start times are randomly assigned to the weather events.

Step 6. Group scenarios by month

Since the assigning of weather events to scenarios is on a monthly basis, the scenarios should be grouped by month.

Step 7. Expected frequency of weather events by month

The expected weather event frequency $E_{i,m}$ of weather type *i* in month *m* can be calculated using Equation (2-26).

$$E_{i,m} = Round(\frac{P_{i,m} \times D_{SP} \times N^m}{D_i}) \tag{2-26}$$

$P_{i,m}$ is the time-wise weather event probability of weather type *i* in month *m*

D_{SP} is the duration of study period in hours

N^m is the number of scenarios associated with month *m*

D_i is the expected duration of the weather type *i* rounded to the nearest 15 minutes and expressed in hours

Step 8. Update the list of weather events for the current month

Firstly, for the weather events generated in Step 7, associate them with their durations, SAFs and CAFs. Secondly, randomly assign the scenarios of the current month to the weather event list generated based on the scenario probabilities. Thirdly, randomly assign the start times (from the time periods in the study period) to the weather event list.

Step 9. Check for temporal overlap with other weather events

In one scenario, temporal overlap between weather events is not allowed, Equation (2-27) is the constraint for assigning weather start times, if the constraint is met, the weather events are not overlapping, if not, the weather events are overlapping, and a new start time should be assigned to the current weather event.

$$T_2^W - T_1^W > D_1^W \tag{2-27}$$

T_1^W is the weather event start time assigned with a smaller time period

T_2^W is the weather event start time assigned with a larger time period

D_1^W is the duration in time periods of the smaller time period weather event

When assigning scenario number and start time to a weather event, check the scenario number, start time and weather duration of all the former weather events. If there is overlap, undo the last weather event assignment; else move to Step 10. Do this until all weather events in the current month are associated with scenarios and start times.

Stage 3 Incident adjustment factors

In this stage, the calculations are on a monthly basis. Firstly, the expected incident frequencies of each month are calculated. Secondly, the incident frequencies for all scenarios in the current month are calculated. Thirdly, incident durations, incident start times and incident locations are randomly assigned to the scenarios generated.

Step 10. Expected frequency of incident events by month

Same as the SHRP2-L08 method, the expected frequency for each month can be calculated based on Equation (2-6) to Equation (2-10).

Step 11. Generate a set of incident frequencies for all scenarios in the current month

The number of incidents in a study period follows the Poisson distribution:

$$P(k) = \frac{{n_m}^k}{k!} e^{-n_m} \quad (2\text{-}28)$$

n_m is the expected incident frequency for month *m* from Equation (2-6)

The number of scenarios N_{Scen}^{k} that are assigned *k* incidents for month *m* can be calculated using the following:

$$N_{Scen}^{k} = Round\{N^m \times P(k)\} \quad (2\text{-}29)$$

Doing Step 10 and 11 for all the months and we can have all incident events generated throughout the months.

Step 12. Randomly assign each generated incident event to a scenario in current month

Randomly assign the scenarios of the current month to the incident event list generated based on the scenario probabilities.

Step 13. Generate incident severities for each incident event

Number of incidents with severity *i*:

$$N_{Inc}^{i} = N_{Inc}^{Tot} \times G(i) \tag{2-30}$$

N_{Inc}^{Tot} is the total number of incidents generated

Step 14. Randomly assign an incident severity to each incident

Randomly assign incident severity to the number of incidents generated based on the distribution of incident severities from Step 13.

Step 15. Generate incident durations by incident severity

The duration for each incident severity type follows a truncated lognormal distribution. For each incident type, a set of duration bins can be determined, usually with the bin interval of 15 minutes, then truncate the first and last bin interval depending on the range of the incident duration. For example, the duration of shoulder closure is from 8.7 to 52.5 min, the set of bin values can be 15, 30, 45, 60, the bin intervals are: (8.7, 22.5], (22.5, 37.5], (37.5, 52.5]. The probability of each bin can be calculated from Equation (2-31), and then normalize the probabilities to make the total to be 1.

$$P(d, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{(ln\ d-\mu)^2}{2\sigma^2}\right], d > 0 \tag{2-31}$$

d is the set of incident durations (bin values) in 15 minutes (15, 30, 45…), decided by the incident duration range

μ is the parameter converted by the mean incident duration *m*

σ is the parameter converted by the standard deviation of incident duration *v*

Since the incident duration sample is non-logarithmized, the mean incident duration and standard deviation need to be converted to μ and σ, respectively, using the following equations:

$$\mu = \ln\left(\frac{m}{\sqrt{1+\frac{v}{m^2}}}\right) \tag{2-32}$$

$$\sigma = \sqrt{\ln\left(1 + \frac{v}{m^2}\right)} \tag{2-33}$$

Step 16. Randomly assign incident durations by severity

Random assign incident durations to the incident events based on the probabilities from Step 15.

Step 17. Generate the distribution of incident start time and location

The distribution of incident start times will coincide with the distribution of facility VMT across the analysis periods. Also, the distribution of incident locations will be tied to the distribution of study period VMT across segments.

Distribution of the incident location:

$$P_1(seg) = \frac{VMT_{seg}}{VMT_{facility}} \tag{2-34}$$

VMT_{seg} is the VMT on a specific segment

$VMT_{facility}$ is the VMT on the whole facility

Distribution of the incident start time:

$$P_2(ap) = \frac{VMT_{ap}}{VMT_{st}} \tag{2-35}$$

VMT_{ap} is the VMT of the assigned analysis period for the incident start time

VMT_{st} is the VMT across all the analysis periods of the study period

Step 18. Generate incident start times and locations for all incidents

Number of incidents N_{Inc}^{x} assigned a location (segment) *x*:

$$N_{Inc}^{x} = N_{Inc}^{Tot} \times P_1(x) \tag{2-36}$$

Number of incidents assigned a starting time (analysis period) y:

$$N_{Inc}^{y} = N_{Inc}^{Tot} \times P_2(y) \tag{2-37}$$

Step 19. Random assign incident start time and location

From the list of events, select an incident whose start time and location have not been assigned, and randomly assign a start time and location based on the probabilities and numbers calculated from Step 17 and 18.

Step 20. Check spatial or temporal overlap with other incident events

Spatial or temporal overlap of incidents for the same scenario is not allowed: When assigning a location and start time to an incident event, check the scenario number, location and start time of all the former incident events. If there is overlap, undo the last start time and location assignment; if there is no overlap, move to the next assignment.

Stage 4 Overall scenarios

Now that all scenarios have the demand, weather and incident information assigned, these scenarios are believed to represent the demand, weather and incident variabilities. Same as the SHRP2-L08 method, analyst can use the HCM freeway facilities method to estimate the travel time for each scenario, and then all the travel times calculated can be compiled into a travel time distribution to evaluate the reliability of the facility.

Performance Measures

To evaluate the results and conduct the travel time reliability analysis of the facility, proper performance measures are needed. The following performance measures are commonly used in the TTR analysis:

- Travel time index (TTI), the ratio of the actual travel time on a facility to the theoretical travel time when traveling at free-flow speed.

- Planning time index (PTI), the 95th percentile travel time index (TTI) (95th percentile travel time divided by the free flow travel time).

- Misery index, the average of the highest five percent of travel times divided by the free flow travel time.

- Failure/On-time measures, such as the percent of trips completed exceed/within a defined travel time threshold.

- Semi-standard deviation, the standard deviation of travel time pegged to free flow travel time rather than the mean travel time.

- Reliability rating, the percent of trips serviced at or below a threshold travel time index (1.3 for freeways).

CHAPTER 3
SOFTWARE TOOL DEVELOPMENT

Brief Overview

The TTR software was built on the .NET Framework using the C# language. The TTR software program developed in this project is designed to utilize the Freeway Facility software module (of the HCM-CALC software suite) for setting up base facility network file and to perform the HCM freeway facilities analysis methodology calculations on each generated scenario (i.e., set of input conditions) from the TTR software program. The HCM-CALC: Freeway Facility software module was developed by Dr. Scott Washburn prior to the start of this project.

The basic procedure of TTR analysis via the software tool is: First, a base file that includes the basic facility information (facility geometry, demand entry flow rates, etc.) is generated through HCM-CALC: Freeway Facility software module. Second, additional data (demand, weather and incident variability information) are specified through the TTR user interface (UI). Third, the TTR software tool generates scenarios based on both the base file and the user-specified settings of demand, weather and incident inputs. Then, both the base file information and scenario information are passed in to the HCM-CALC: Freeway Facility software module for the core HCM freeway facilities analysis procedure calculation. Finally, in the TTR software tool, the scenario results obtained from the HCM-CALC: Freeway Facility software module are aggregated into travel time distribution and reliability MOEs are calculated. Figure 3-2 shows the basic process flow of the TTR analysis.

Overview of Software Screens

The following is an overview of the software screens. The guiding design principle for the software was to set up separate screens for each unique component of inputs (base file properties, demand inputs, weather inputs, etc.) and results, and to arrange them in a "left-to-right" workflow sequence.

The 'Project Properties' screen is used for the input of project description, analyst information, and base file. There are three scenario generation methodologies in this software. In addition to the SHRP2-L08 and HCM methods, the "Unrestricted" method is also included in this software tool. Unlike the other two methods, it allows users to specify any combination of demand, weather, incident, and work zone settings; thus, a very large number of input scenarios can be generated. While a detailed overview of the Unrestricted scenario generation methodology is beyond the scope of this project, guidance on its use is provided in the user guide.

Object 3-1. User Guide (.pdf file 12,396 KB)

The 'TTR Adjustment Factors' screen is where the user specifies the input settings for the generation of scenarios, it includes the demand patterns, weather events and incident events screens. The 'Demand' module in the 'TTR Adjustment Factors' screen is where users set the month and day groups for the demand patterns, specify the demand multipliers, ratio of base file demand to AADT, and number of scenario sets per demand pattern. The 'Weather' module in the 'TTR Adjustment Factors' screen is where users specify the time based weather probabilities for each month, weather durations and relative adjustment factors for each weather type. For SHRP2-L08 method, the results of this module are the weighted weather probabilities for each demand pattern, Figure 3-8. For HCM method, the results of this module are the expected weather events for each month, as shown in Figure 3-9 and Figure 3-10. Charts of weather events type, weather events by month and weather start times are also provided, Figure 3-11.

The ‘Incident’ module in the ‘TTR Adjustment Factors’ screen is where users specify the incident rate or crash rate or HERS model input and incident duration input. Incident adjustment factors can be specified in the form shown in Figure 3-13. Results of this module for SHRP2-L08 method are the incident probabilities by demand pattern, as shown in Figure 3-12. Results for HCM method are the incident events by month, as shown in Figure 3-14 and Figure 3-15. Charts of incident events are also provided, as shown in Figure 3-16. User can check the distribution of the generated incident severities, start times, locations and durations. Basic statistics for the charts of incident durations are also provided, so that users can check if the mean and standard deviation from the chart could match with the input of the ‘Incident’ module.

For SHRP2-L08 method, there is an ‘Overall’ module in the ‘TTR Adjustment Factors’ screen, which combines the demand pattern, weather and incident probabilities and convert the base probabilities to the study period probabilities. The user can set the probability threshold to remove scenarios with probabilities lower than the threshold. A summary table is provided to show the information of the generated scenarios with their probabilities.

The ‘TTR Scenarios Listing’ screen displays the list of scenarios generated. Click the ‘Run Analysis’ and results of each scenario will show up in the ‘Scenario Results’ screen. Time period results for an individual scenario can also be viewed, Figure 3-22. Overall results and charts are provided for analysis, as shown in Figure 3-23 and Figure 3-24.

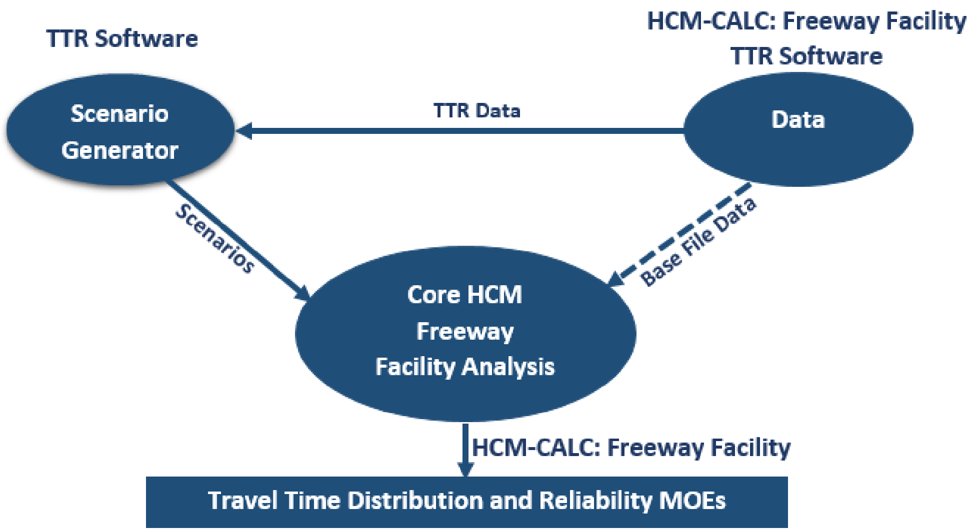


Figure 3-1. Software components and relationship

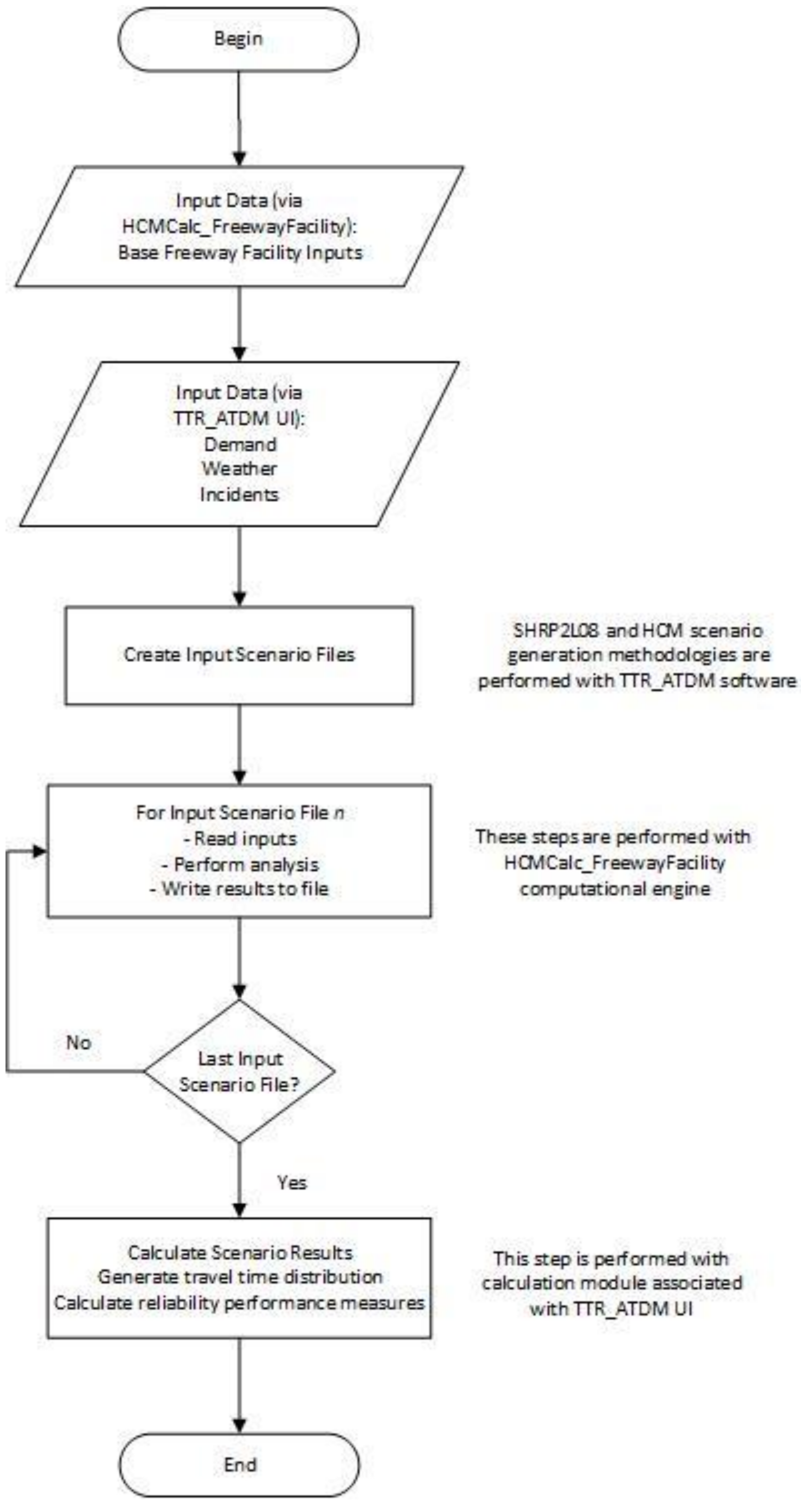


Figure 3-2. Process flow

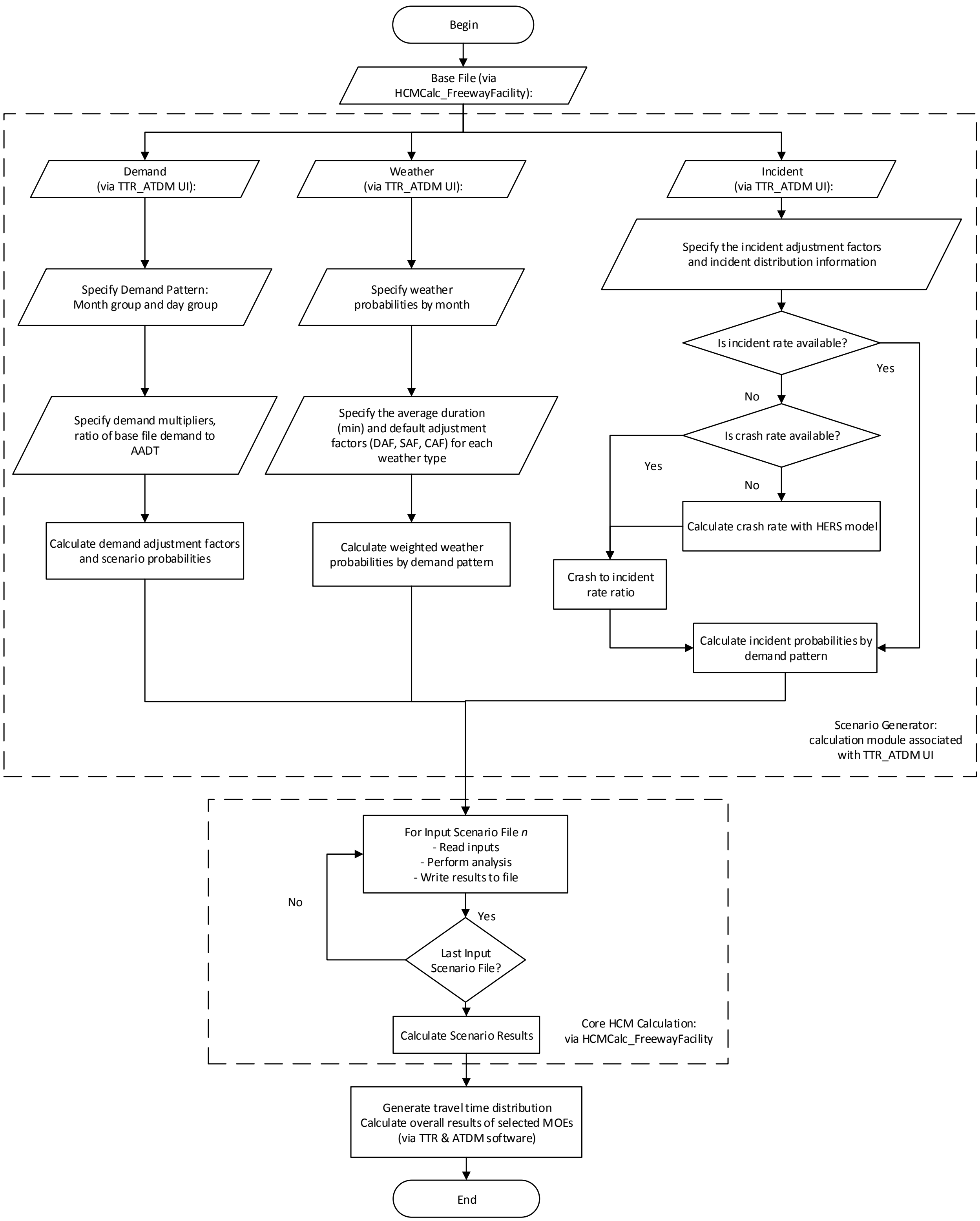


Figure 3-3. SHRP2-L08 scenario generation methodology

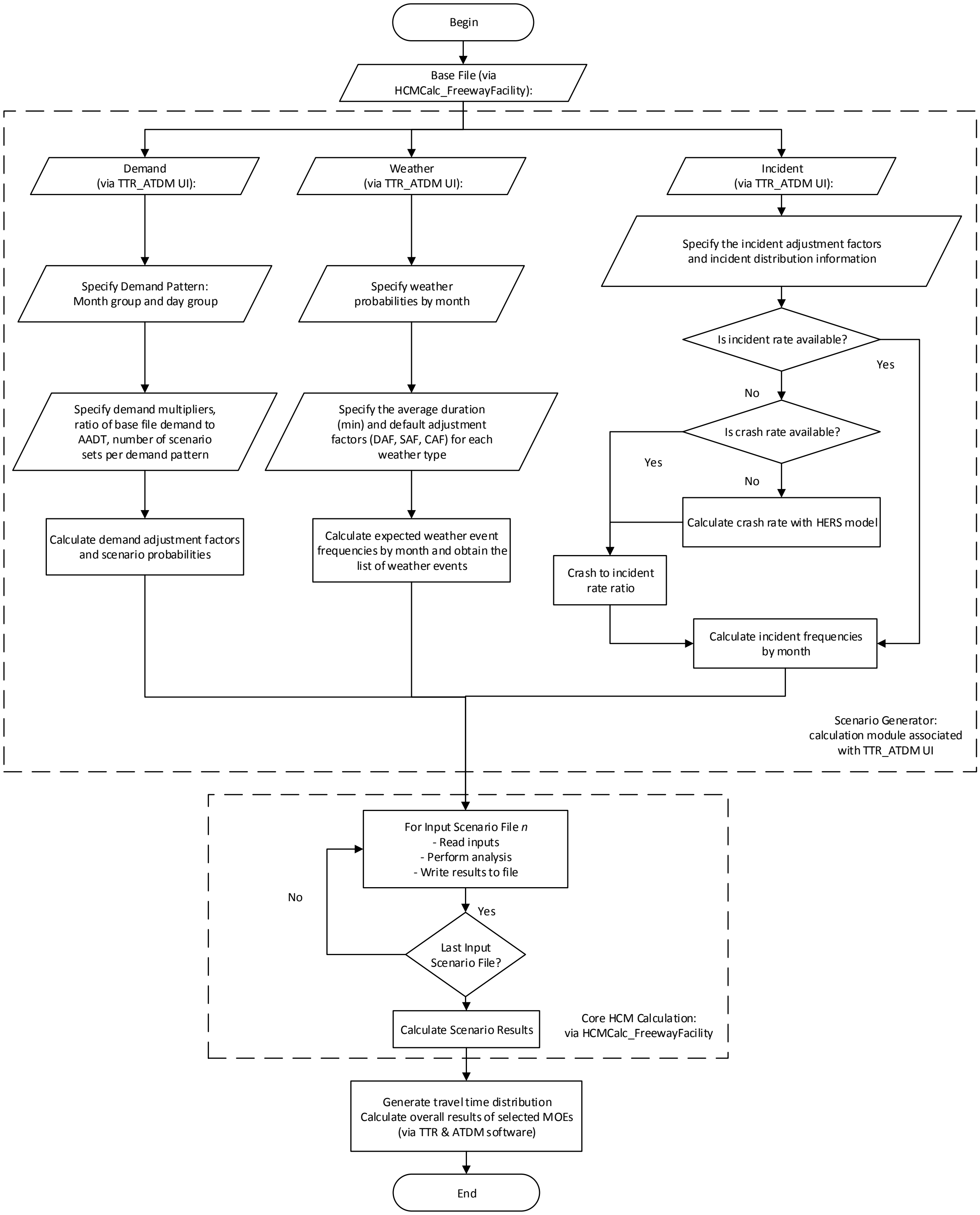


Figure 3-4. HCM scenario generation methodology

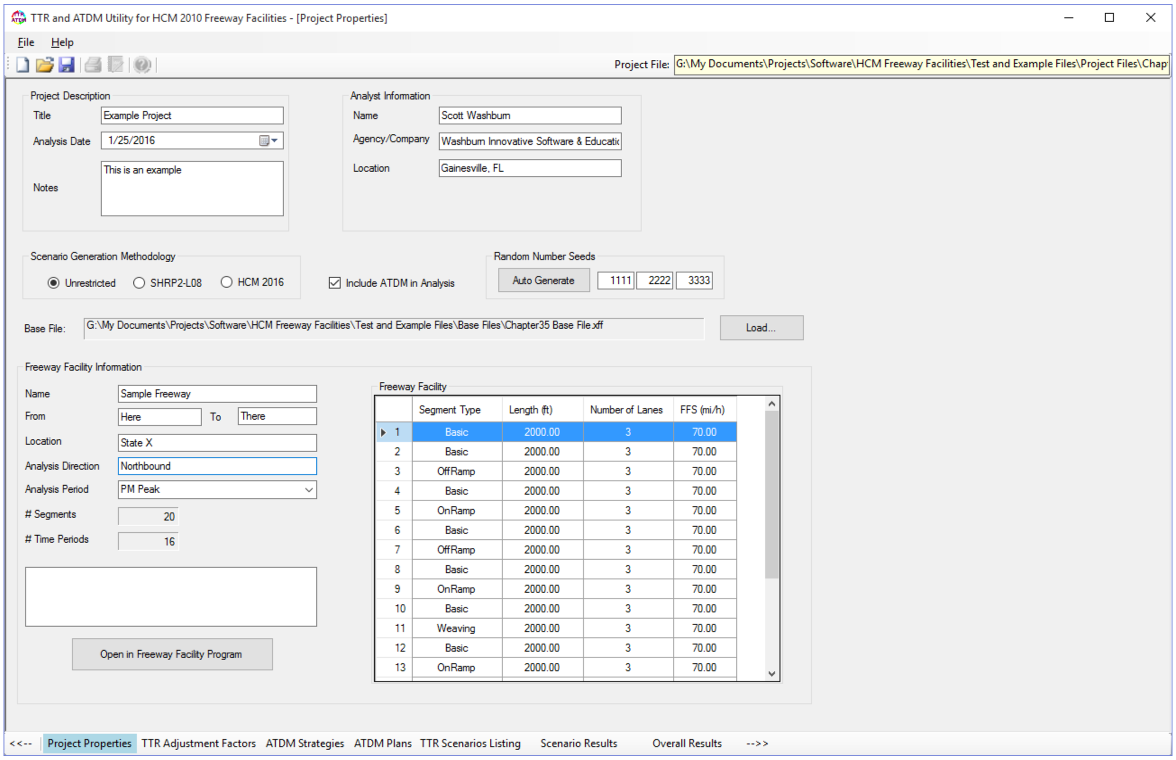


Figure 3-5. Project properties

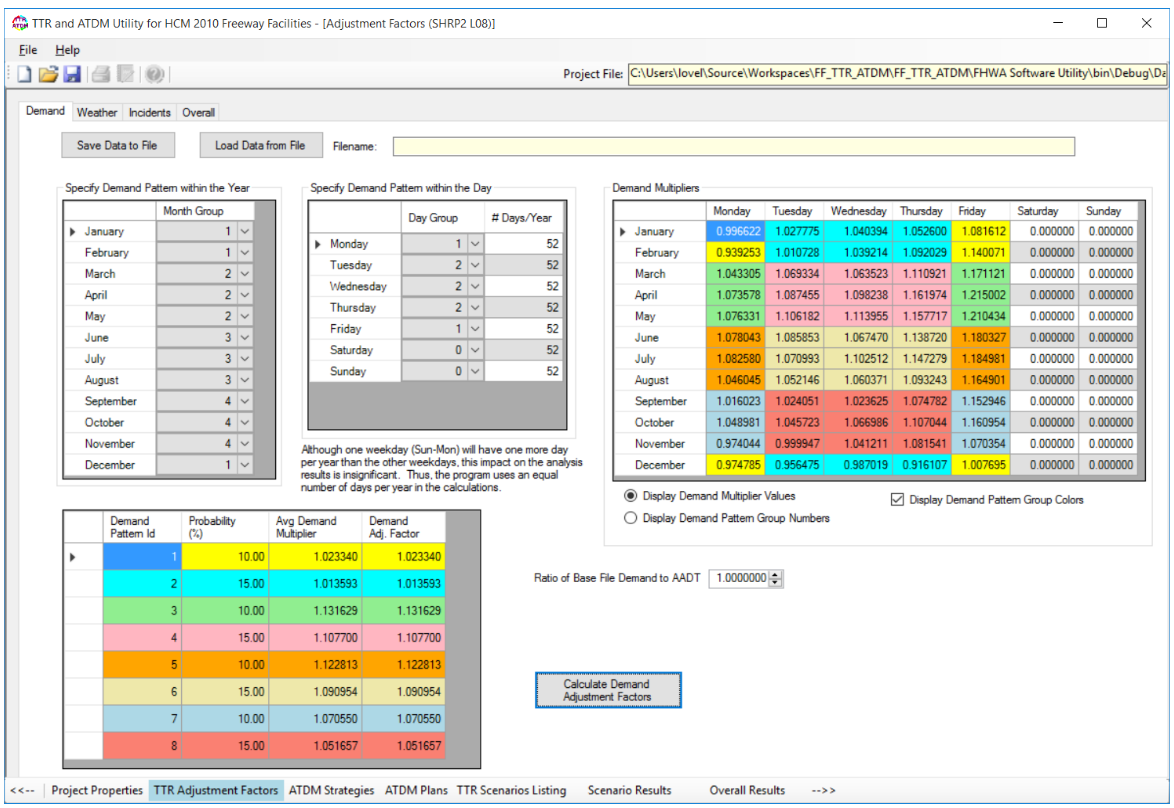


Figure 3-6. Demand settings

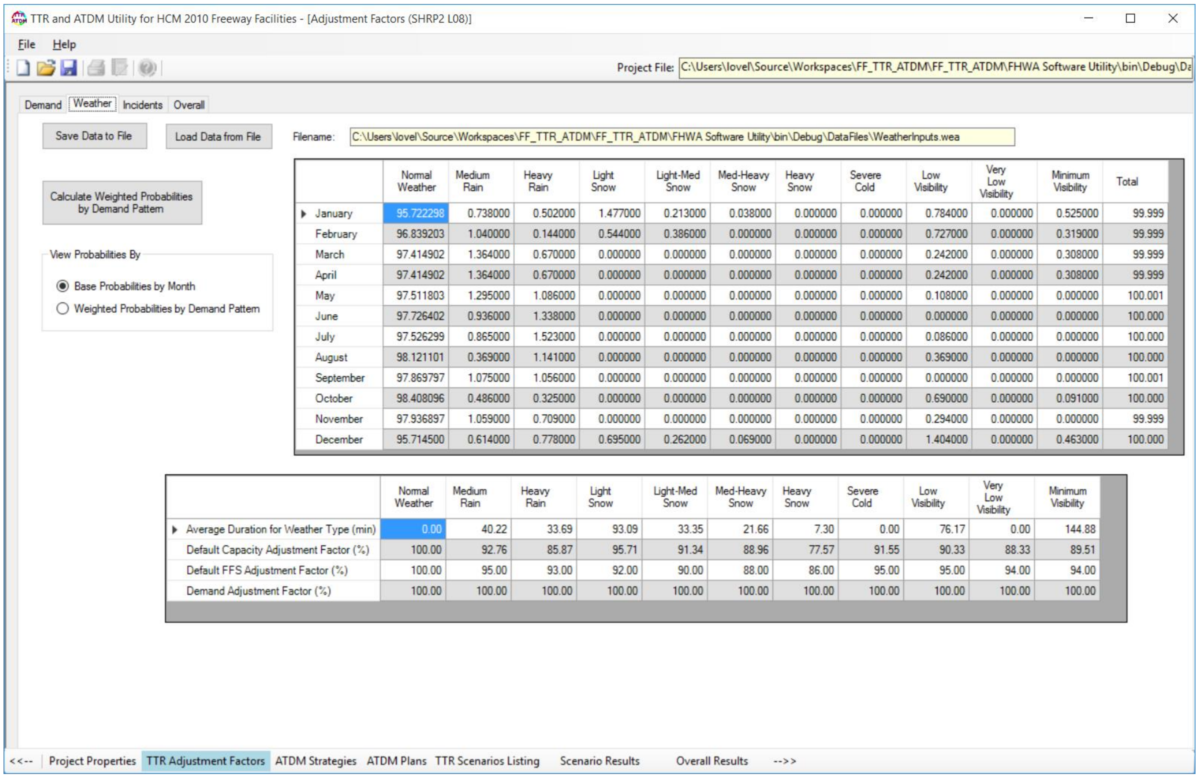


Figure 3-7. Weather settings

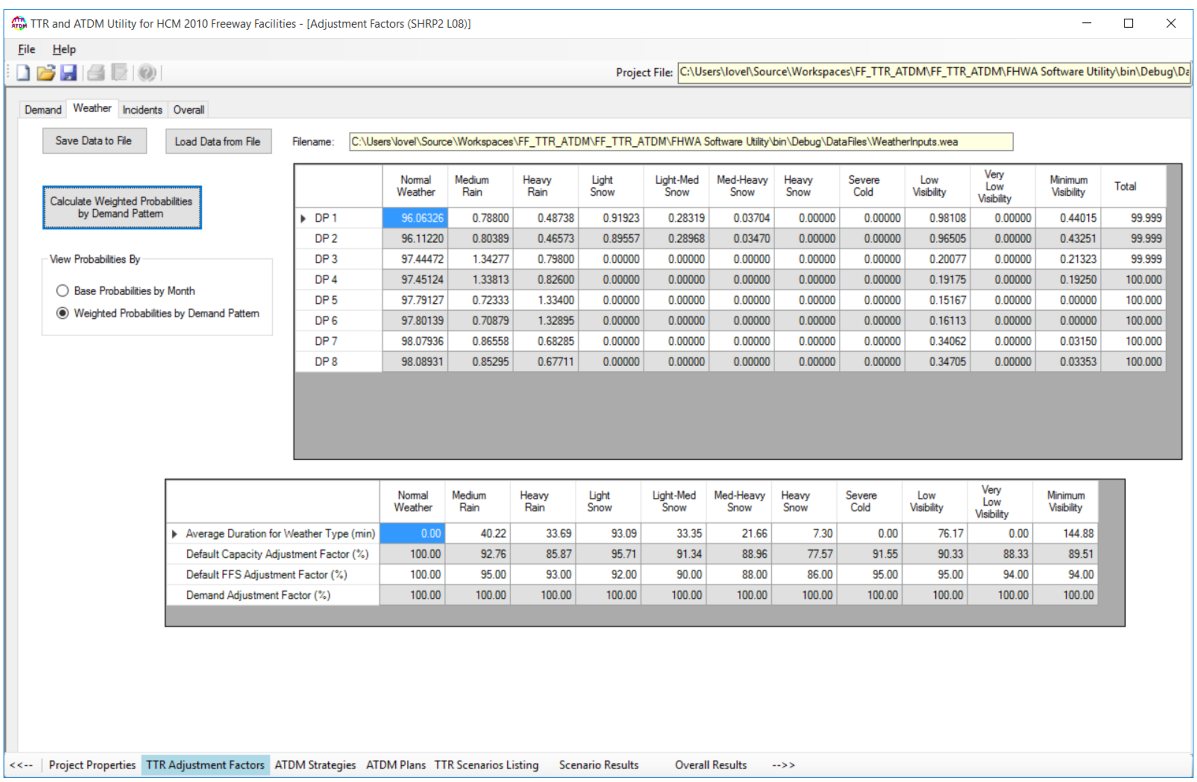
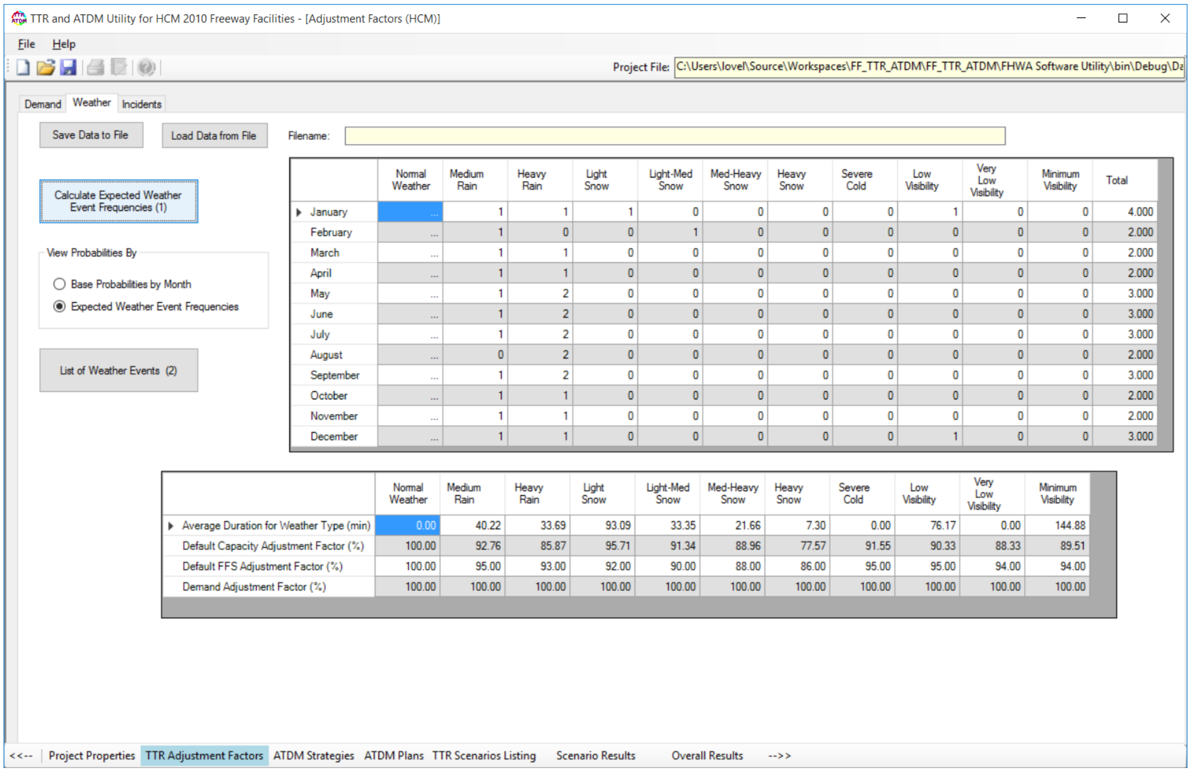


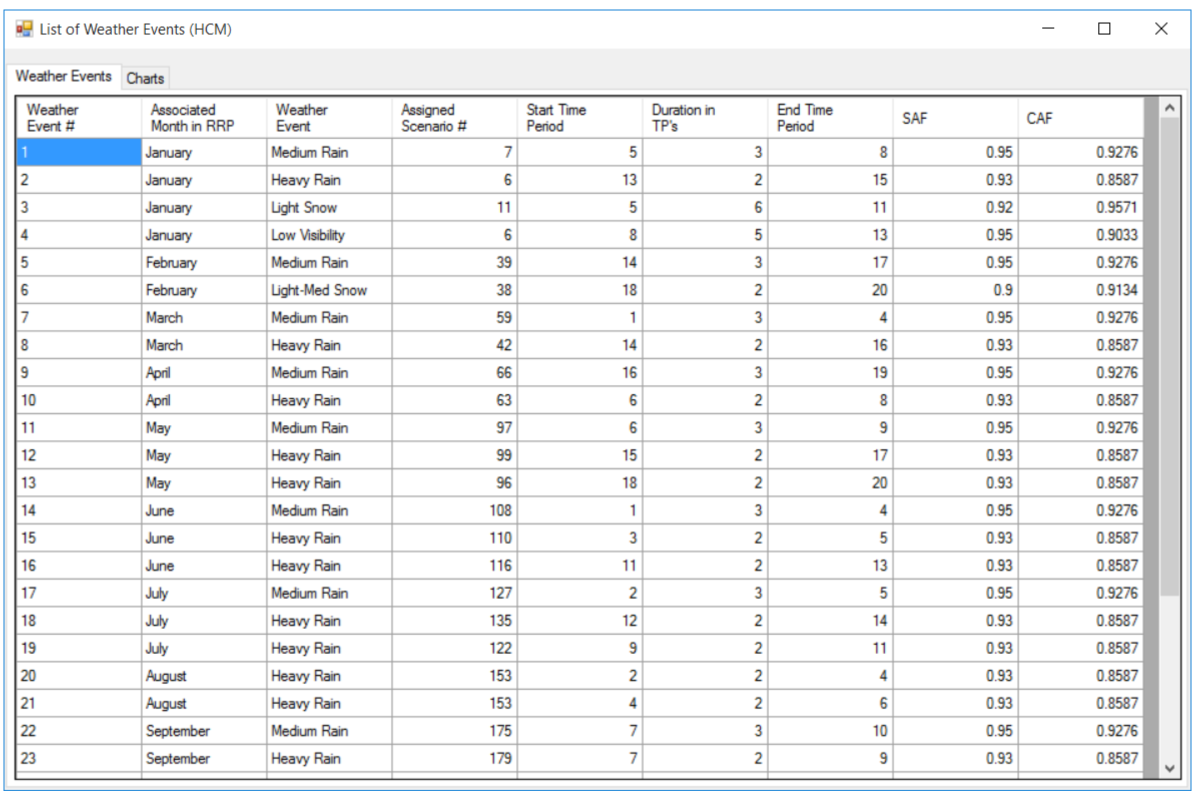
Figure 3-8. Weather probabilities by DP for SHRP2-L08



	Normal Weather	Medium Rain	Heavy Rain	Light Snow	Light-Med Snow	Med-Heavy Snow	Heavy Snow	Severe Cold	Low Visibility	Very Low Visibility	Minimum Visibility	Total
January	...	1	1	1	0	0	0	0	1	0	0	4.000
February	...	1	0	0	1	0	0	0	0	0	0	2.000
March	...	1	1	0	0	0	0	0	0	0	0	2.000
April	...	1	1	0	0	0	0	0	0	0	0	2.000
May	...	1	2	0	0	0	0	0	0	0	0	3.000
June	...	1	2	0	0	0	0	0	0	0	0	3.000
July	...	1	2	0	0	0	0	0	0	0	0	3.000
August	...	0	2	0	0	0	0	0	0	0	0	2.000
September	...	1	2	0	0	0	0	0	0	0	0	3.000
October	...	1	1	0	0	0	0	0	0	0	0	2.000
November	...	1	1	0	0	0	0	0	0	0	0	2.000
December	...	1	1	0	0	0	0	0	1	0	0	3.000

	Normal Weather	Medium Rain	Heavy Rain	Light Snow	Light-Med Snow	Med-Heavy Snow	Heavy Snow	Severe Cold	Low Visibility	Very Low Visibility	Minimum Visibility
Average Duration for Weather Type (min)	0.00	40.22	33.69	93.09	33.35	21.66	7.30	0.00	76.17	0.00	144.88
Default Capacity Adjustment Factor (%)	100.00	92.76	85.87	95.71	91.34	88.96	77.57	91.55	90.33	88.33	89.51
Default FFS Adjustment Factor (%)	100.00	95.00	93.00	92.00	90.00	88.00	86.00	95.00	95.00	94.00	94.00
Demand Adjustment Factor (%)	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Figure 3-9. Weather events by month for HCM



Weather Event #	Associated Month in RRP	Weather Event	Assigned Scenario #	Start Time Period	Duration in TP's	End Time Period	SAF	CAF
1	January	Medium Rain	7	5	3	8	0.95	0.9276
2	January	Heavy Rain	6	13	2	15	0.93	0.8587
3	January	Light Snow	11	5	6	11	0.92	0.9571
4	January	Low Visibility	6	8	5	13	0.95	0.9033
5	February	Medium Rain	39	14	3	17	0.95	0.9276
6	February	Light-Med Snow	38	18	2	20	0.9	0.9134
7	March	Medium Rain	59	1	3	4	0.95	0.9276
8	March	Heavy Rain	42	14	2	16	0.93	0.8587
9	April	Medium Rain	66	16	3	19	0.95	0.9276
10	April	Heavy Rain	63	6	2	8	0.93	0.8587
11	May	Medium Rain	97	6	3	9	0.95	0.9276
12	May	Heavy Rain	99	15	2	17	0.93	0.8587
13	May	Heavy Rain	96	18	2	20	0.93	0.8587
14	June	Medium Rain	108	1	3	4	0.95	0.9276
15	June	Heavy Rain	110	3	2	5	0.93	0.8587
16	June	Heavy Rain	116	11	2	13	0.93	0.8587
17	July	Medium Rain	127	2	3	5	0.95	0.9276
18	July	Heavy Rain	135	12	2	14	0.93	0.8587
19	July	Heavy Rain	122	9	2	11	0.93	0.8587
20	August	Heavy Rain	153	2	2	4	0.93	0.8587
21	August	Heavy Rain	153	4	2	6	0.93	0.8587
22	September	Medium Rain	175	7	3	10	0.95	0.9276
23	September	Heavy Rain	179	7	2	9	0.93	0.8587

Figure 3-10. Weather event list for HCM

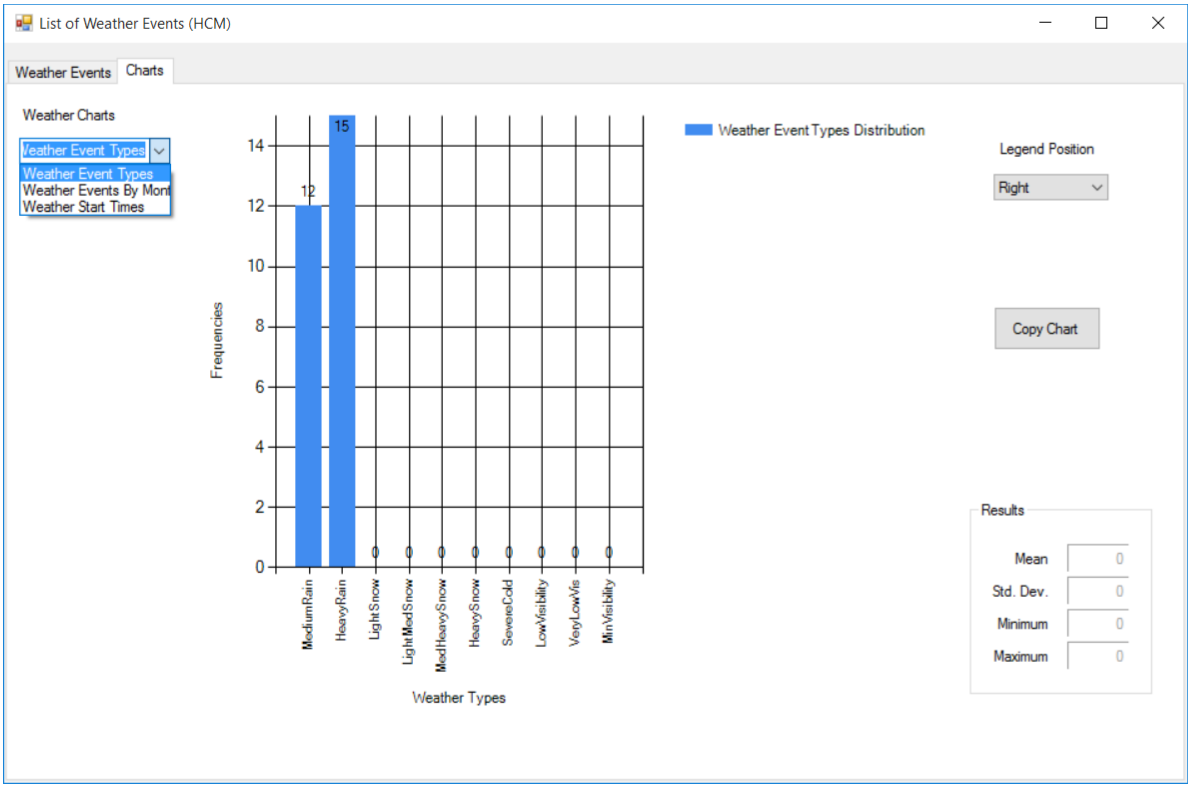


Figure 3-11. Weather event chart for HCM

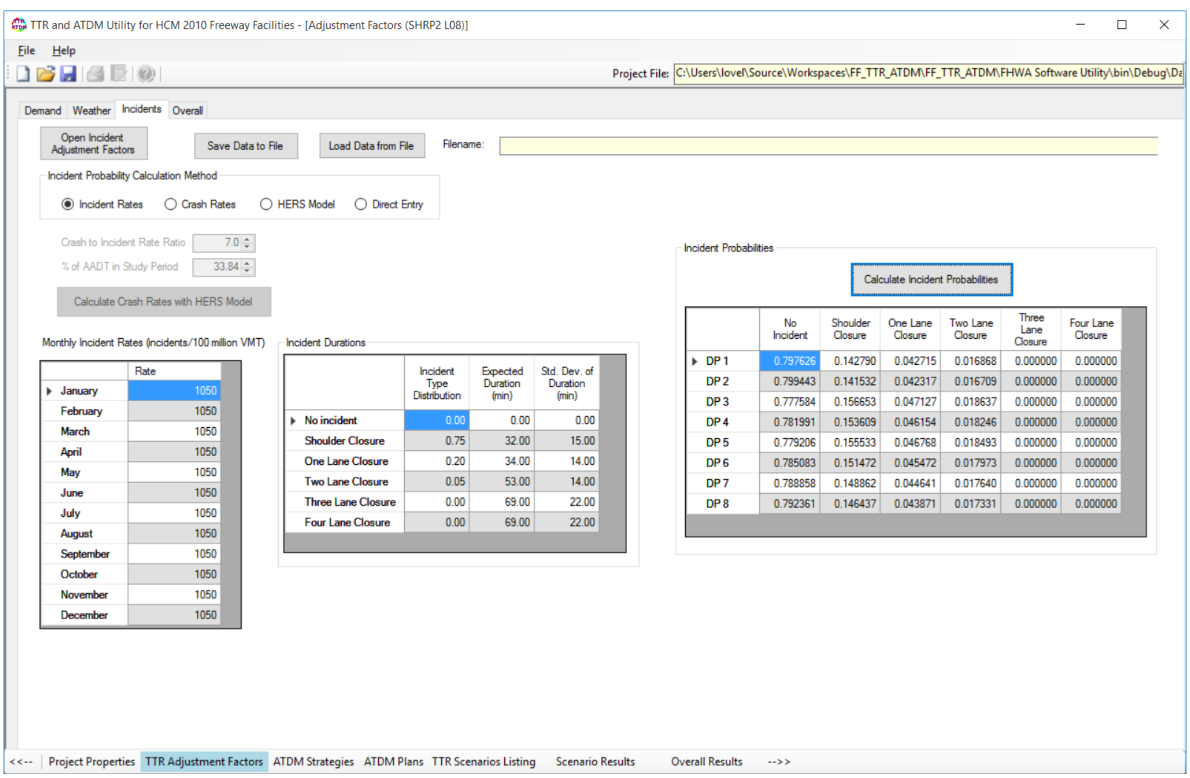
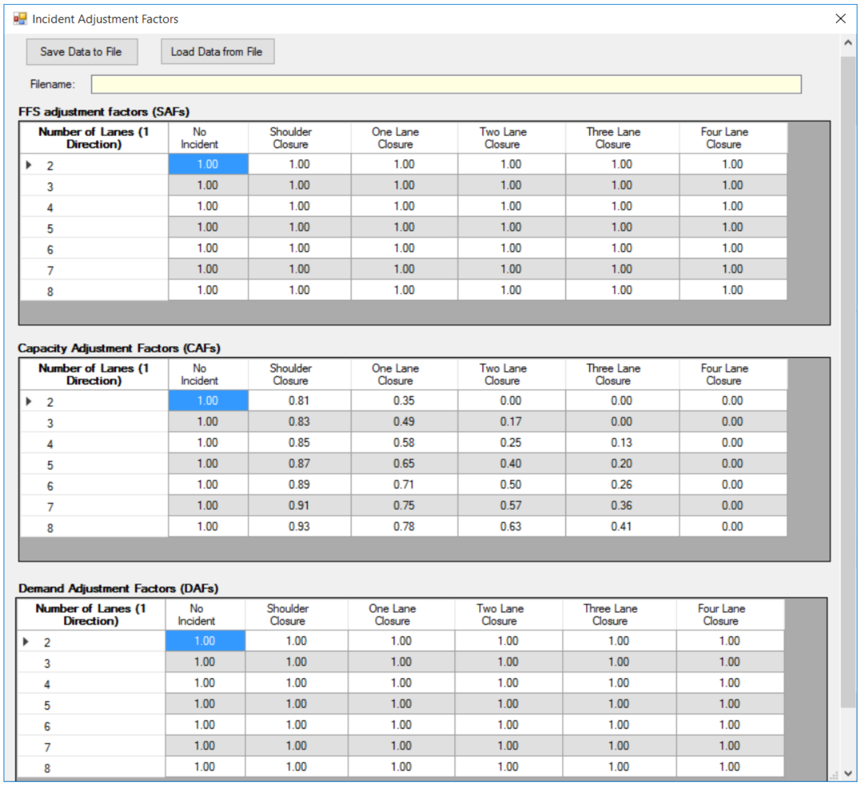


Figure 3-12. Incident settings



Incident Adjustment Factors

Save Data to File | Load Data from File

Filename:

FFS adjustment factors (SAFs)

Number of Lanes (1 Direction)	No Incident	Shoulder Closure	One Lane Closure	Two Lane Closure	Three Lane Closure	Four Lane Closure
2	1.00	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00	1.00
4	1.00	1.00	1.00	1.00	1.00	1.00
5	1.00	1.00	1.00	1.00	1.00	1.00
6	1.00	1.00	1.00	1.00	1.00	1.00
7	1.00	1.00	1.00	1.00	1.00	1.00
8	1.00	1.00	1.00	1.00	1.00	1.00

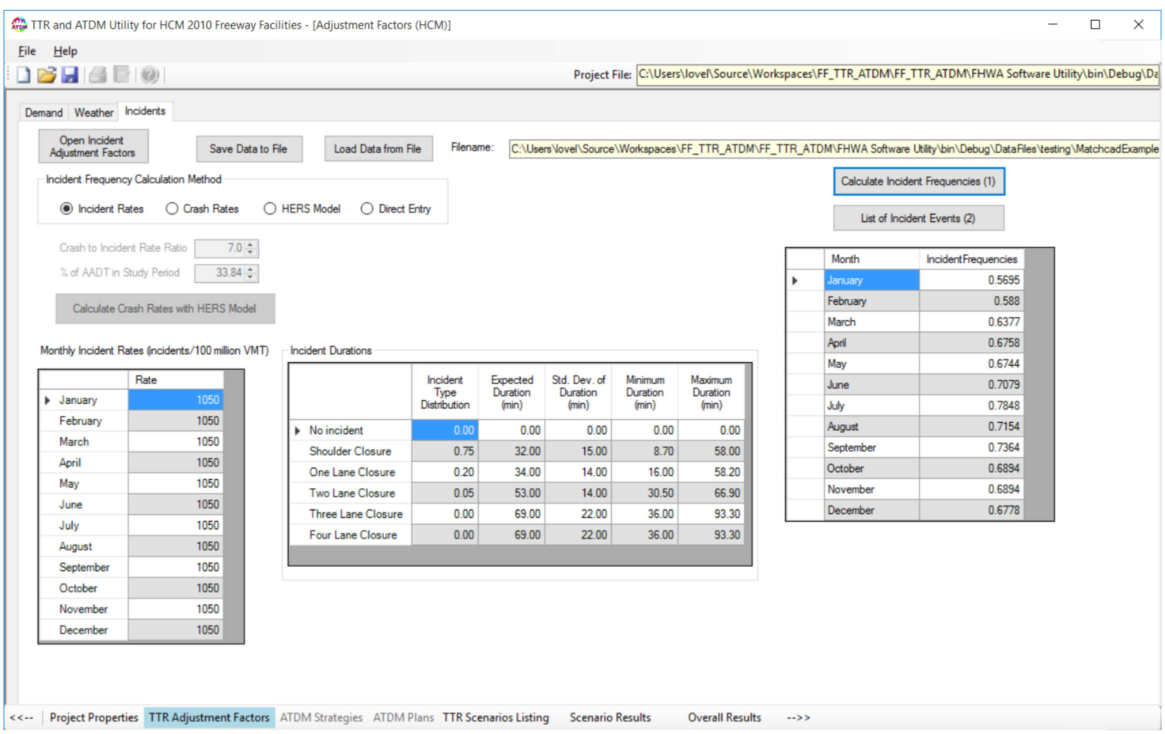
Capacity Adjustment Factors (CAFs)

Number of Lanes (1 Direction)	No Incident	Shoulder Closure	One Lane Closure	Two Lane Closure	Three Lane Closure	Four Lane Closure
2	1.00	0.81	0.35	0.00	0.00	0.00
3	1.00	0.83	0.49	0.17	0.00	0.00
4	1.00	0.85	0.58	0.25	0.13	0.00
5	1.00	0.87	0.65	0.40	0.20	0.00
6	1.00	0.89	0.71	0.50	0.26	0.00
7	1.00	0.91	0.75	0.57	0.36	0.00
8	1.00	0.93	0.78	0.63	0.41	0.00

Demand Adjustment Factors (DAFs)

Number of Lanes (1 Direction)	No Incident	Shoulder Closure	One Lane Closure	Two Lane Closure	Three Lane Closure	Four Lane Closure
2	1.00	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00	1.00
4	1.00	1.00	1.00	1.00	1.00	1.00
5	1.00	1.00	1.00	1.00	1.00	1.00
6	1.00	1.00	1.00	1.00	1.00	1.00
7	1.00	1.00	1.00	1.00	1.00	1.00
8	1.00	1.00	1.00	1.00	1.00	1.00

Figure 3-13. Incident adjustment factors form



TTR and ATDM Utility for HCM 2010 Freeway Facilities - [Adjustment Factors (HCM)]

File Help

Project File: C:\Users\lovel\Source\Workspaces\FF_TTR_ATDM\FF_TTR_ATDM\FHWA Software Utility\bin\Debug\Da

Demand | Weather | Incidents

Open Incident Adjustment Factors | Save Data to File | Load Data from File

Filename: C:\Users\lovel\Source\Workspaces\FF_TTR_ATDM\FF_TTR_ATDM\FHWA Software Utility\bin\Debug\DataFiles\testing\MatchcadExample

Incident Frequency Calculation Method

Incident Rates | Crash Rates | HERS Model | Direct Entry

Crash to Incident Rate Ratio 7.0

% of AADT in Study Period 33.84

Calculate Crash Rates with HERS Model

Calculate Incident Frequencies (1)

List of Incident Events (2)

Monthly Incident Rates (incidents/100 million VMT)

	Rate
January	1050
February	1050
March	1050
April	1050
May	1050
June	1050
July	1050
August	1050
September	1050
October	1050
November	1050
December	1050

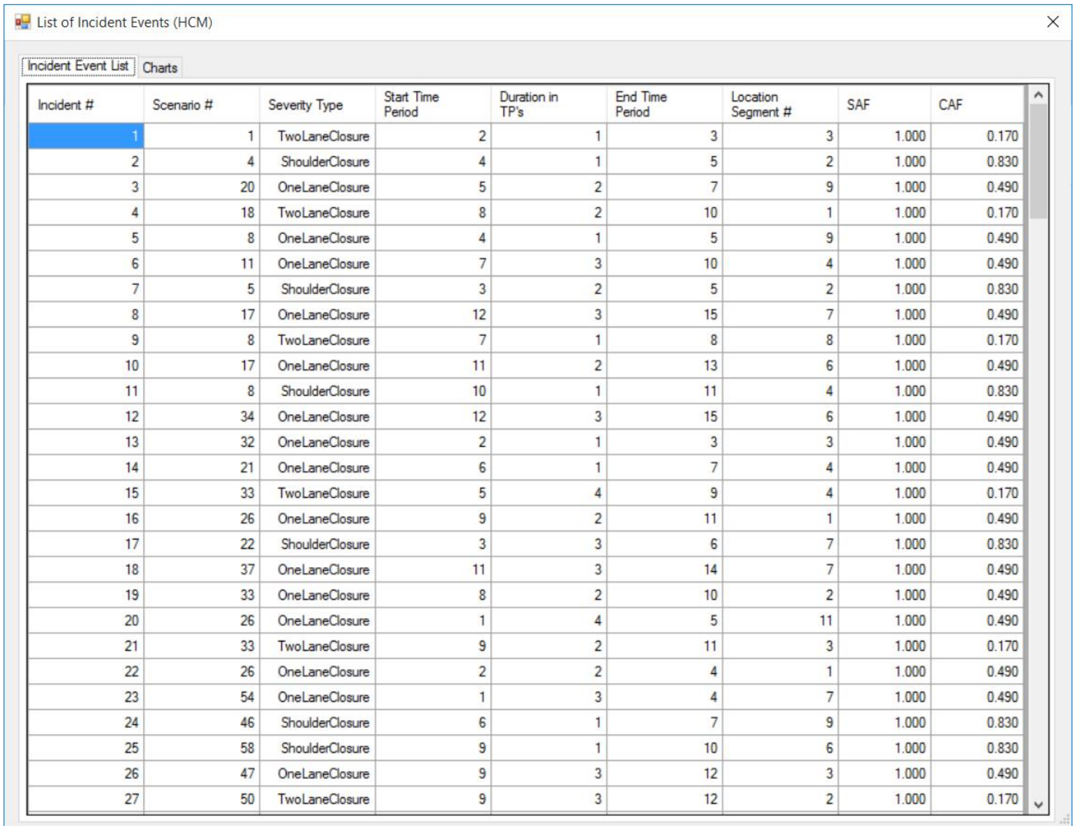
Incident Durations

	Incident Type Distribution	Expected Duration (min)	Std. Dev. of Duration (min)	Minimum Duration (min)	Maximum Duration (min)
No incident	0.00	0.00	0.00	0.00	0.00
Shoulder Closure	0.75	32.00	15.00	8.70	58.00
One Lane Closure	0.20	34.00	14.00	16.00	58.20
Two Lane Closure	0.05	53.00	14.00	30.50	66.90
Three Lane Closure	0.00	69.00	22.00	36.00	93.30
Four Lane Closure	0.00	69.00	22.00	36.00	93.30

Month	IncidentFrequencies
January	0.5695
February	0.588
March	0.6377
April	0.6758
May	0.6744
June	0.7079
July	0.7848
August	0.7154
September	0.7364
October	0.6894
November	0.6894
December	0.6778

<-- | Project Properties | TTR Adjustment Factors | ATDM Strategies | ATDM Plans | TTR Scenarios Listing | Scenario Results | Overall Results | -->

Figure 3-14. Incident adjustment factors for HCM



Incident #	Scenario #	Severity Type	Start Time Period	Duration in TP's	End Time Period	Location Segment #	SAF	CAF
1	1	TwoLaneClosure	2	1	3	3	1.000	0.170
2	4	ShoulderClosure	4	1	5	2	1.000	0.830
3	20	OneLaneClosure	5	2	7	9	1.000	0.490
4	18	TwoLaneClosure	8	2	10	1	1.000	0.170
5	8	OneLaneClosure	4	1	5	9	1.000	0.490
6	11	OneLaneClosure	7	3	10	4	1.000	0.490
7	5	ShoulderClosure	3	2	5	2	1.000	0.830
8	17	OneLaneClosure	12	3	15	7	1.000	0.490
9	8	TwoLaneClosure	7	1	8	8	1.000	0.170
10	17	OneLaneClosure	11	2	13	6	1.000	0.490
11	8	ShoulderClosure	10	1	11	4	1.000	0.830
12	34	OneLaneClosure	12	3	15	6	1.000	0.490
13	32	OneLaneClosure	2	1	3	3	1.000	0.490
14	21	OneLaneClosure	6	1	7	4	1.000	0.490
15	33	TwoLaneClosure	5	4	9	4	1.000	0.170
16	26	OneLaneClosure	9	2	11	1	1.000	0.490
17	22	ShoulderClosure	3	3	6	7	1.000	0.830
18	37	OneLaneClosure	11	3	14	7	1.000	0.490
19	33	OneLaneClosure	8	2	10	2	1.000	0.490
20	26	OneLaneClosure	1	4	5	11	1.000	0.490
21	33	TwoLaneClosure	9	2	11	3	1.000	0.170
22	26	OneLaneClosure	2	2	4	1	1.000	0.490
23	54	OneLaneClosure	1	3	4	7	1.000	0.490
24	46	ShoulderClosure	6	1	7	9	1.000	0.830
25	58	ShoulderClosure	9	1	10	6	1.000	0.830
26	47	OneLaneClosure	9	3	12	3	1.000	0.490
27	50	TwoLaneClosure	9	3	12	2	1.000	0.170

Figure 3-15. HCM incident event list

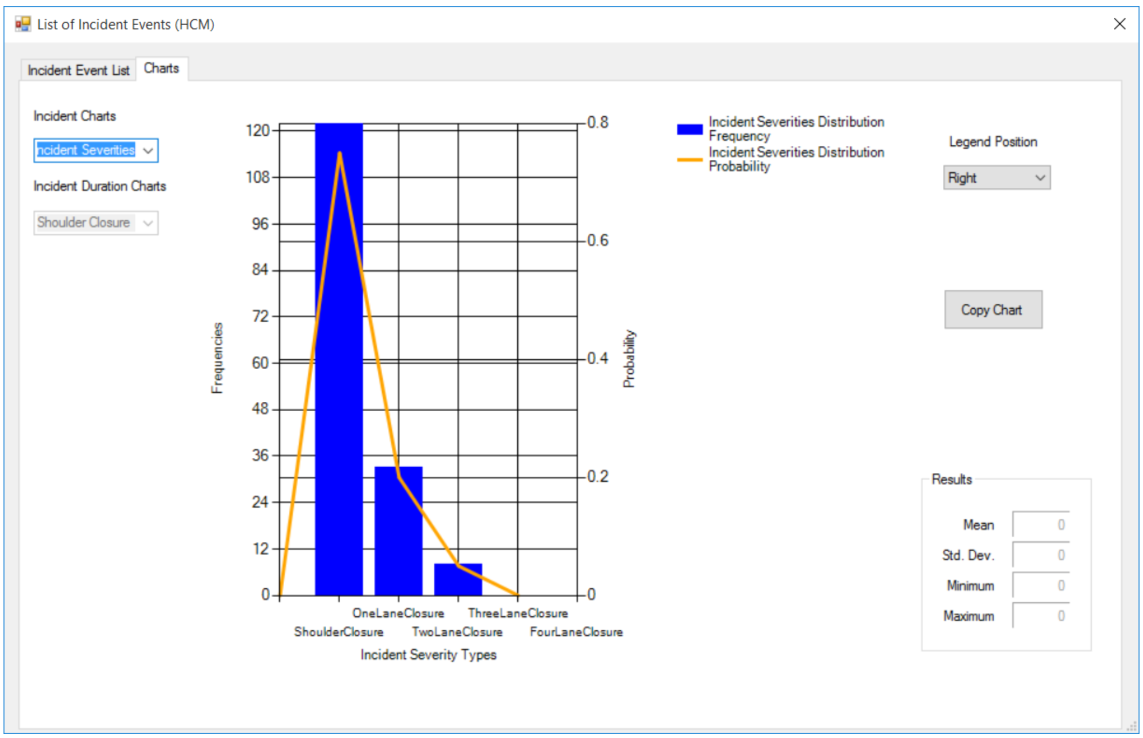


Figure 3-16. HCM incident event chart

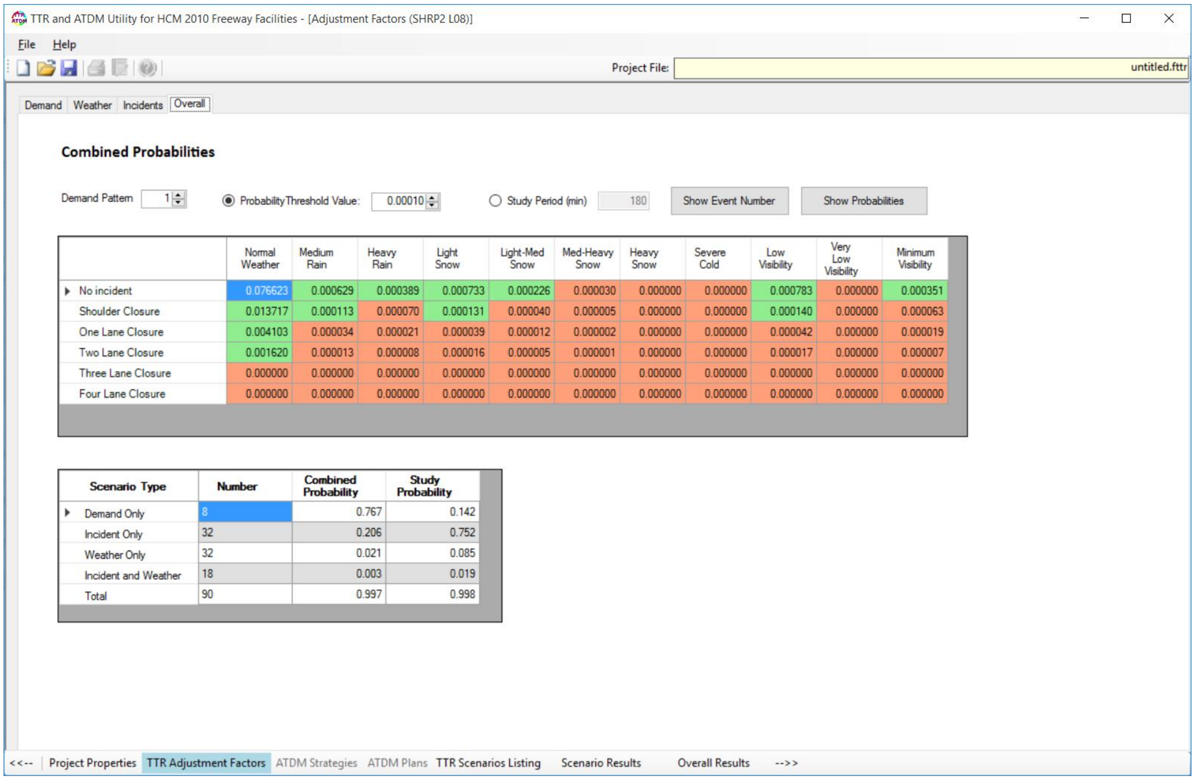


Figure 3-17. Base probabilities for SHRP2-L08

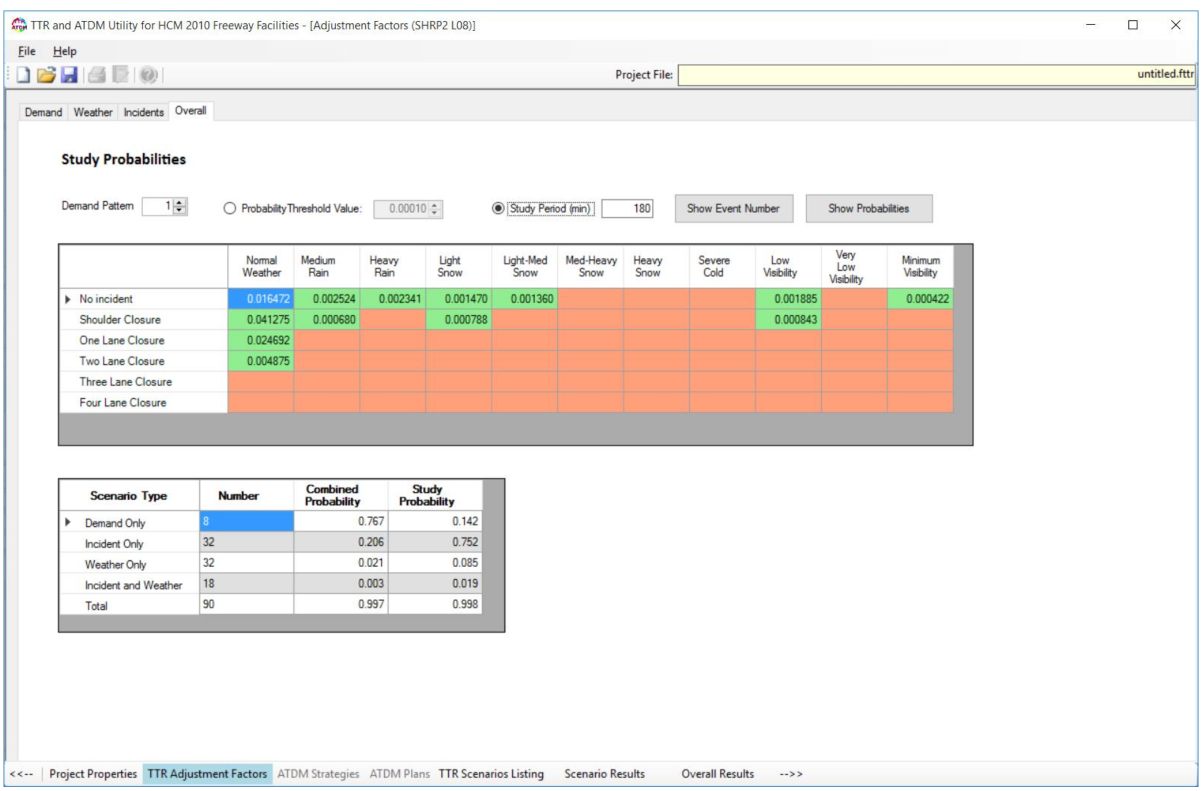


Figure 3-18. Study period probabilities for SHRP2-L08

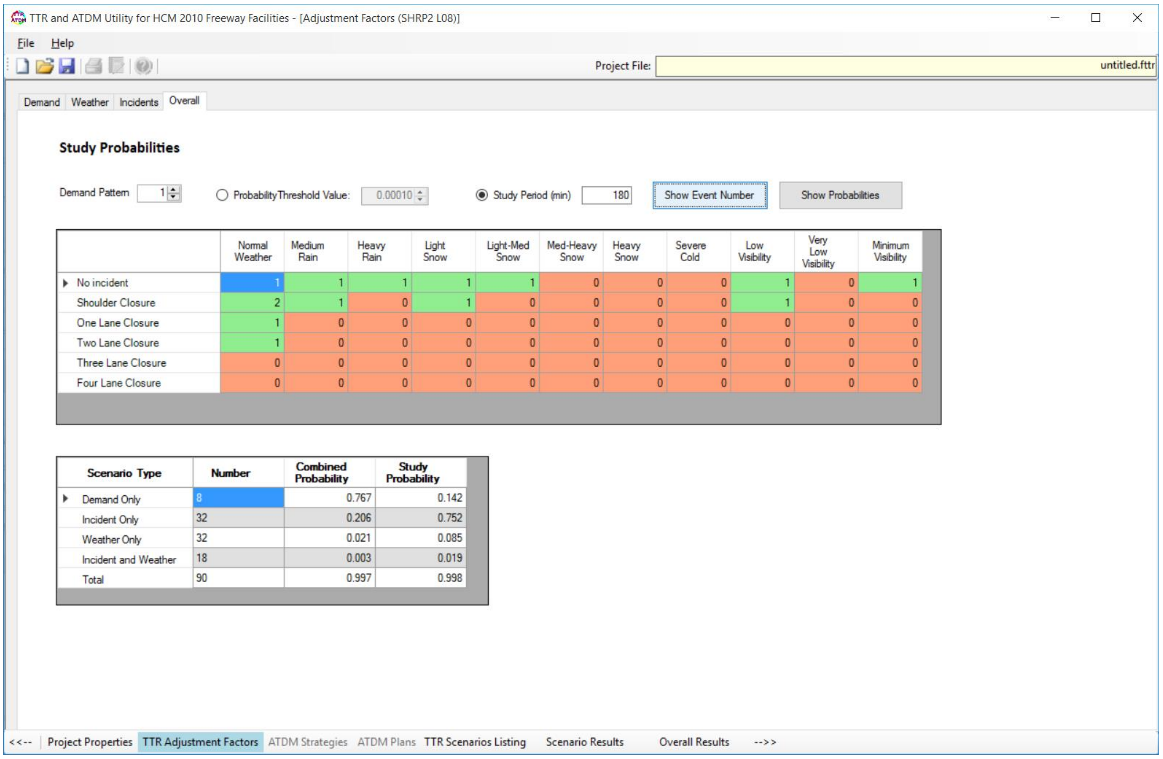


Figure 3-19. Scenario event numbers for SHRP2-L08

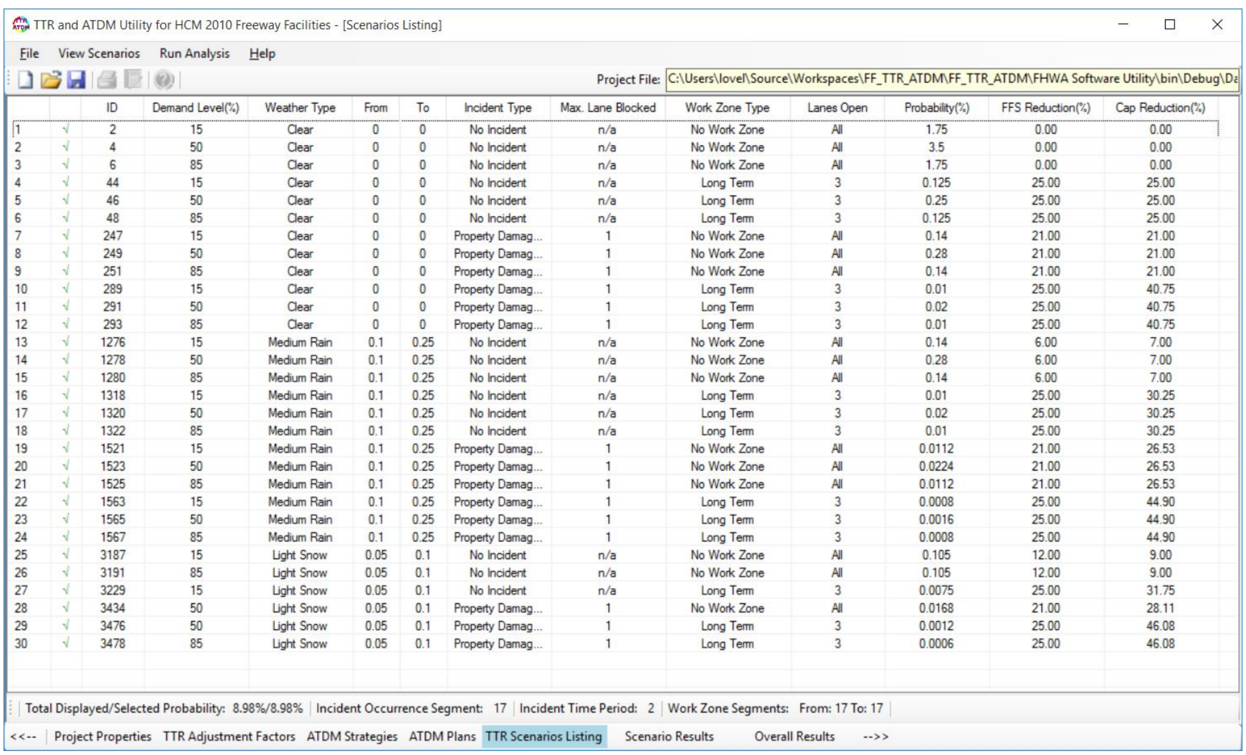
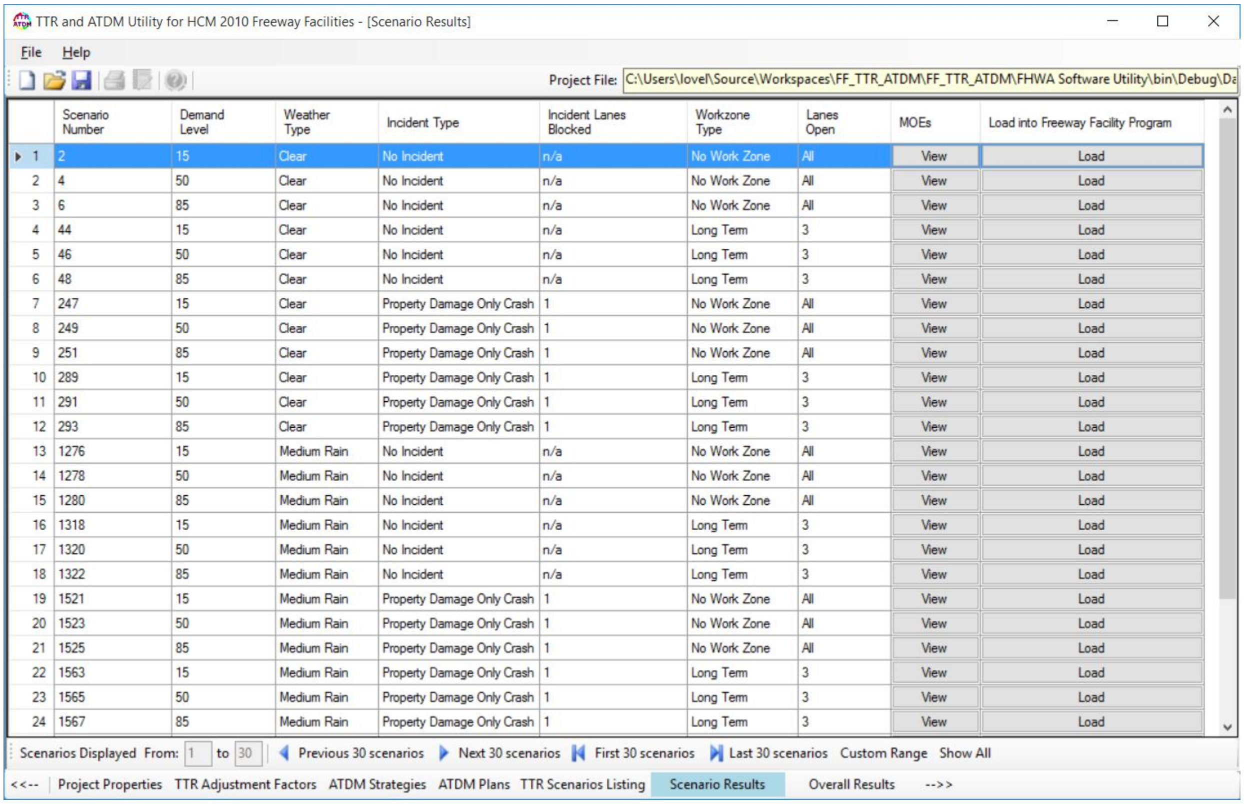
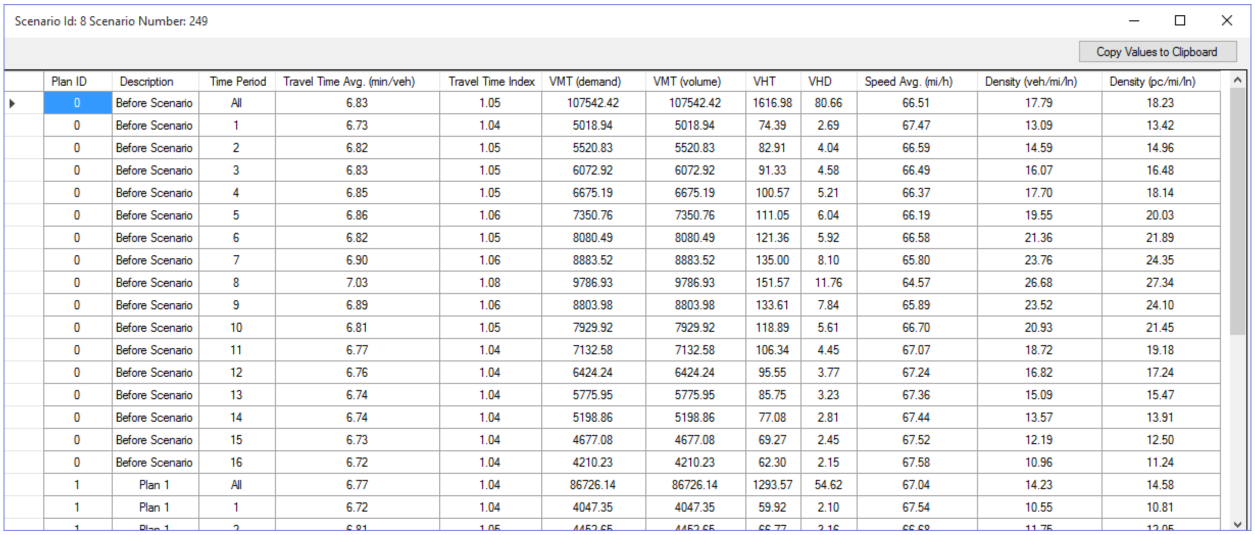


Figure 3-20. TTR scenarios listing



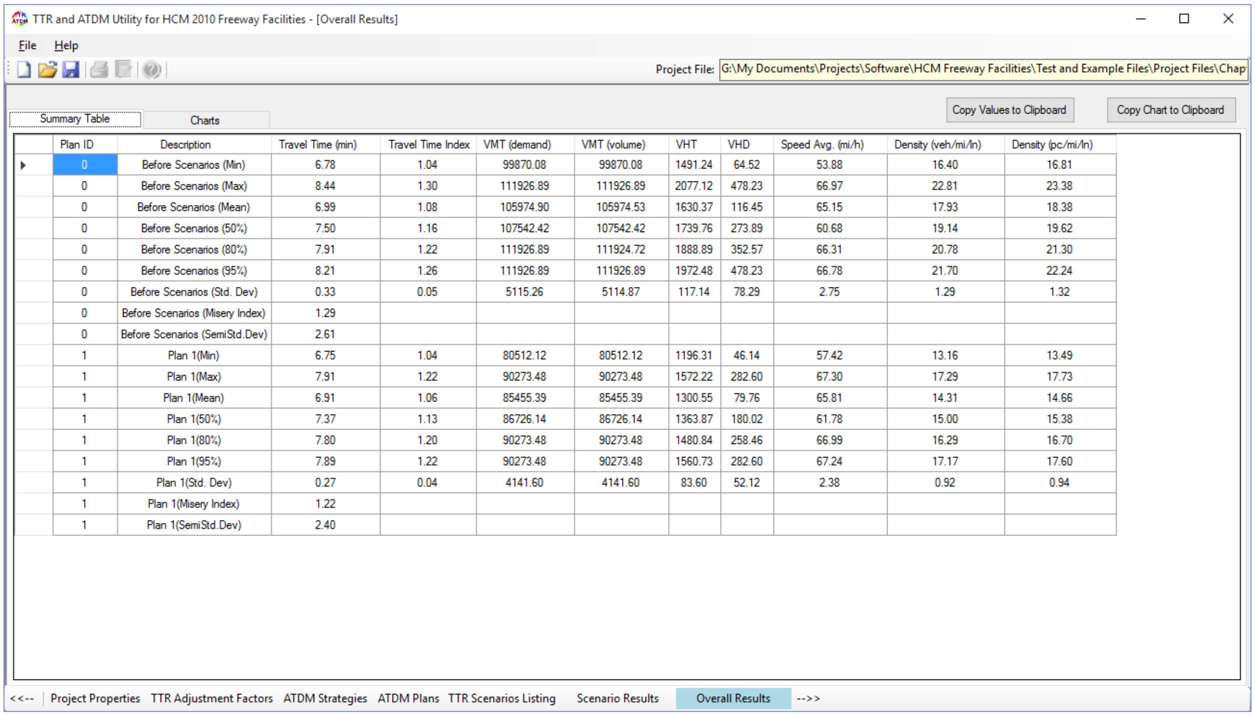
	Scenario Number	Demand Level	Weather Type	Incident Type	Incident Lanes Blocked	Workzone Type	Lanes Open	MOEs	Load into Freeway Facility Program
1	2	15	Clear	No Incident	n/a	No Work Zone	All	View	Load
2	4	50	Clear	No Incident	n/a	No Work Zone	All	View	Load
3	6	85	Clear	No Incident	n/a	No Work Zone	All	View	Load
4	44	15	Clear	No Incident	n/a	Long Term	3	View	Load
5	46	50	Clear	No Incident	n/a	Long Term	3	View	Load
6	48	85	Clear	No Incident	n/a	Long Term	3	View	Load
7	247	15	Clear	Property Damage Only Crash	1	No Work Zone	All	View	Load
8	249	50	Clear	Property Damage Only Crash	1	No Work Zone	All	View	Load
9	251	85	Clear	Property Damage Only Crash	1	No Work Zone	All	View	Load
10	289	15	Clear	Property Damage Only Crash	1	Long Term	3	View	Load
11	291	50	Clear	Property Damage Only Crash	1	Long Term	3	View	Load
12	293	85	Clear	Property Damage Only Crash	1	Long Term	3	View	Load
13	1276	15	Medium Rain	No Incident	n/a	No Work Zone	All	View	Load
14	1278	50	Medium Rain	No Incident	n/a	No Work Zone	All	View	Load
15	1280	85	Medium Rain	No Incident	n/a	No Work Zone	All	View	Load
16	1318	15	Medium Rain	No Incident	n/a	Long Term	3	View	Load
17	1320	50	Medium Rain	No Incident	n/a	Long Term	3	View	Load
18	1322	85	Medium Rain	No Incident	n/a	Long Term	3	View	Load
19	1521	15	Medium Rain	Property Damage Only Crash	1	No Work Zone	All	View	Load
20	1523	50	Medium Rain	Property Damage Only Crash	1	No Work Zone	All	View	Load
21	1525	85	Medium Rain	Property Damage Only Crash	1	No Work Zone	All	View	Load
22	1563	15	Medium Rain	Property Damage Only Crash	1	Long Term	3	View	Load
23	1565	50	Medium Rain	Property Damage Only Crash	1	Long Term	3	View	Load
24	1567	85	Medium Rain	Property Damage Only Crash	1	Long Term	3	View	Load

Figure 3-21. TTR scenarios results



Plan ID	Description	Time Period	Travel Time Avg. (min/veh)	Travel Time Index	VMT (demand)	VMT (volume)	VHT	VHD	Speed Avg. (mi/h)	Density (veh/mi/ln)	Density (pc/mi/ln)
0	Before Scenario	All	6.83	1.05	107542.42	107542.42	1616.98	80.66	66.51	17.79	18.23
0	Before Scenario	1	6.73	1.04	5018.94	5018.94	74.39	2.69	67.47	13.09	13.42
0	Before Scenario	2	6.82	1.05	5520.83	5520.83	82.91	4.04	66.59	14.59	14.96
0	Before Scenario	3	6.83	1.05	6072.92	6072.92	91.33	4.58	66.49	16.07	16.48
0	Before Scenario	4	6.85	1.05	6675.19	6675.19	100.57	5.21	66.37	17.70	18.14
0	Before Scenario	5	6.86	1.06	7350.76	7350.76	111.05	6.04	66.19	19.55	20.03
0	Before Scenario	6	6.82	1.05	8080.49	8080.49	121.36	5.92	66.58	21.36	21.89
0	Before Scenario	7	6.90	1.06	8883.52	8883.52	135.00	8.10	65.80	23.76	24.35
0	Before Scenario	8	7.03	1.08	9786.93	9786.93	151.57	11.76	64.57	26.68	27.34
0	Before Scenario	9	6.89	1.06	8803.98	8803.98	133.61	7.84	65.89	23.52	24.10
0	Before Scenario	10	6.81	1.05	7929.92	7929.92	118.89	5.61	66.70	20.93	21.45
0	Before Scenario	11	6.77	1.04	7132.58	7132.58	106.34	4.45	67.07	18.72	19.18
0	Before Scenario	12	6.76	1.04	6424.24	6424.24	95.55	3.77	67.24	16.82	17.24
0	Before Scenario	13	6.74	1.04	5775.95	5775.95	85.75	3.23	67.36	15.09	15.47
0	Before Scenario	14	6.74	1.04	5198.86	5198.86	77.08	2.81	67.44	13.57	13.91
0	Before Scenario	15	6.73	1.04	4677.08	4677.08	69.27	2.45	67.52	12.19	12.50
0	Before Scenario	16	6.72	1.04	4210.23	4210.23	62.30	2.15	67.58	10.96	11.24
1	Plan 1	All	6.77	1.04	86726.14	86726.14	1293.57	54.62	67.04	14.23	14.58
1	Plan 1	1	6.72	1.04	4047.35	4047.35	59.92	2.10	67.54	10.55	10.81

Figure 3-22. Individual scenario results viewer



Plan ID	Description	Travel Time (min)	Travel Time Index	VMT (demand)	VMT (volume)	VHT	VHD	Speed Avg. (mi/h)	Density (veh/mi/ln)	Density (pc/mi/ln)
0	Before Scenarios (Min)	6.78	1.04	99870.08	99870.08	1491.24	64.52	53.88	16.40	16.81
0	Before Scenarios (Max)	8.44	1.30	111926.89	111926.89	2077.12	478.23	66.97	22.81	23.38
0	Before Scenarios (Mean)	6.99	1.08	105974.90	105974.53	1630.37	116.45	65.15	17.93	18.38
0	Before Scenarios (50%)	7.50	1.16	107542.42	107542.42	1739.76	273.89	60.68	19.14	19.62
0	Before Scenarios (80%)	7.91	1.22	111926.89	111924.72	1888.89	352.57	66.31	20.78	21.30
0	Before Scenarios (95%)	8.21	1.26	111926.89	111926.89	1972.48	478.23	66.78	21.70	22.24
0	Before Scenarios (Std. Dev)	0.33	0.05	5115.26	5114.87	117.14	78.29	2.75	1.29	1.32
0	Before Scenarios (Misery Index)	1.29								
0	Before Scenarios (SemiStd.Dev)	2.61								
1	Plan 1(Min)	6.75	1.04	80512.12	80512.12	1196.31	46.14	57.42	13.16	13.49
1	Plan 1(Max)	7.91	1.22	90273.48	90273.48	1572.22	282.60	67.30	17.29	17.73
1	Plan 1(Mean)	6.91	1.06	85455.39	85455.39	1300.55	79.76	65.81	14.31	14.66
1	Plan 1(50%)	7.37	1.13	86726.14	86726.14	1363.87	180.02	61.78	15.00	15.38
1	Plan 1(80%)	7.80	1.20	90273.48	90273.48	1480.84	258.46	66.99	16.29	16.70
1	Plan 1(95%)	7.89	1.22	90273.48	90273.48	1560.73	282.60	67.24	17.17	17.60
1	Plan 1(Std. Dev)	0.27	0.04	4141.60	4141.60	83.60	52.12	2.38	0.92	0.94
1	Plan 1(Misery Index)	1.22								
1	Plan 1(SemiStd.Dev)	2.40								

Figure 3-23. TTR overall results

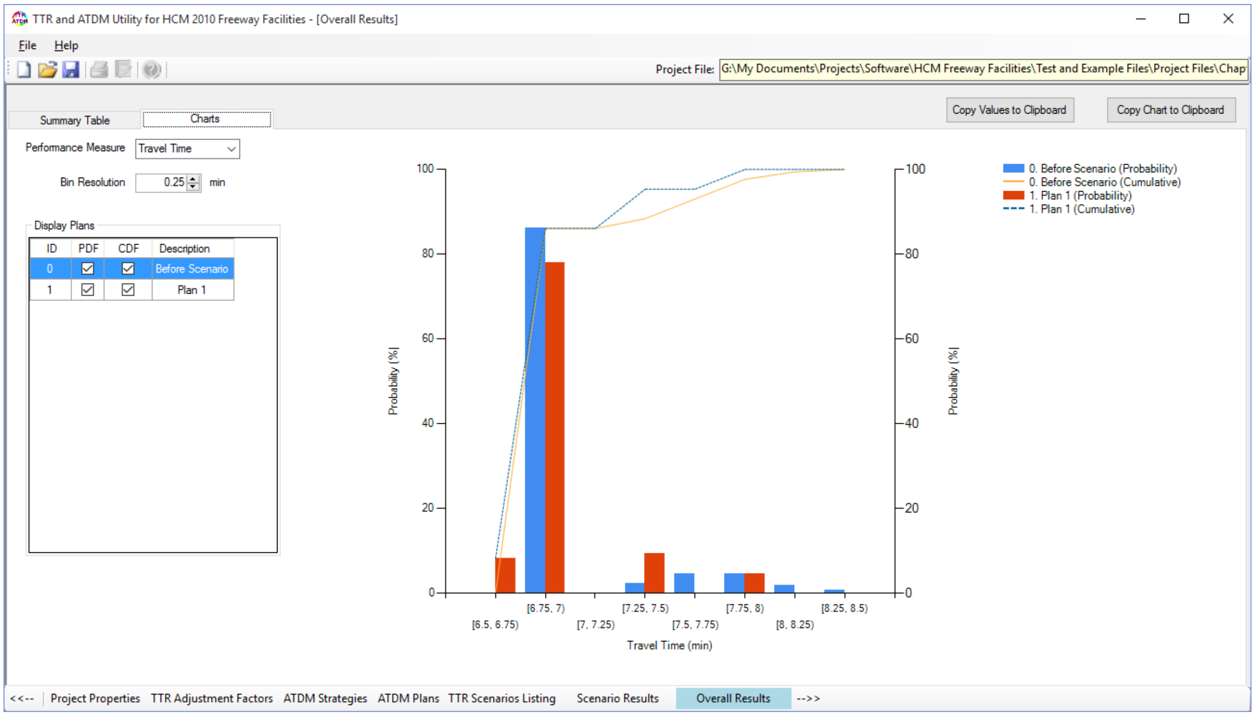


Figure 3-24. TTR overall results charts

CHAPTER 4
VERIFICATION

Overview

This chapter documents the efforts performed to verify the accuracy of the implementation of the SHRP2-L08 and HCM TTR analysis methodologies into the TTR software tool. An example freeway facility is created for TTR analysis. Computational documentation for the two reliability scenario generation methods are provided. Calculated results from both the computational documentation and the software tool are used to verify the accuracy of the software tool.

Input Data

The studied freeway facility contains 11 segments, detailed geometry of the facility are given in Table 4-1 and Table 4-2.

Other facts of the example includes:

- Study period is from 4 to 7 p.m., with a duration of 3 hours
- Analysis period is 15 min
- RRP are all weekdays in the calendar year
- Mainline segments FFS = 60 mi/h, ramp segments FFS = 40 mi/h
- Acceleration and deceleration lane length = 500 ft
- Jam density is 190 pc/mi/ln
- Capacity is 2,300 pc/h/ln
- Short length of the weaving segment is 1640 ft
- Total ramp density is 1.0 ramp/mi
- Terrain is level for all segments
- Percent of truck on the facility is 5%
- Incident rate is 1050 incidents per 100 million VMT

Computational Documentation

This chapter provides computational documentation via Mathcad (Appendix A) regarding the step-by-step calculations in the SHRP2-L08 and HCM methods, as wells as the overall results calculation. The computational documentation serve as a verification of the software tool, in the documentation, besides the calculation results from the functions, there will be screen shots from the software tool for comparison.

Verification of Software Tool for SHRP2-L08 Methodology

Following are the results from the TTR software tool for the TTR analysis using SHRP2-L08 method on the example facility specified above. The SHRP2-L08 method is a deterministic approach, and for this case a total of 604 scenarios will be generated. The overall results from the software considering all the time period results in each scenario are in
Table 4-3.

Verification of Software Tool for HCM Methodology

The following are the results from the TTR software conducting the TTR analysis using the HCM method on the example facility specified previously. The HCM method involves the generation of random numbers in weather event generation and incident event generation part, the software has random number seeds settings for the HCM method, same random number seeds setting will output the same results.

To verify the weather event and incident event generation, the average weather events information (weather start times) and incident events information (incident severities, incident start times, incident locations and incident durations) are collected from 100 sets of random seeds runs. For all the incident verification figures, the blue bar is the frequency of the incidents generated from the software, the orange line is the probability based on the user input. The blue bars' trend should match with the orange line.

The incident severity distribution specified in this example is: 0.75, 0.20, 0.05, 0, 0 for shoulder closure, one-lane closure, two-lane closure, three-lane closure and four or more lane closure, respectively. From Figure 4-3 we can see that the generated incident severity distribution matches with the input.

The incident start time distribution is based on the VMT by time period, in this example, the probability of VMT in each of the 12 time periods is: 0.068, 0.08, 0.09, 0.10, 0.11, 0.12, 0.10, 0.08, 0.07, 0.06, 0.05, and 0.05. From Figure 4-4 we can see that the generated incident start time distribution matches with the user input.

The incident location distribution is based on the VMT by segment, in this example, the probability of VMT in each of the 11 segment is: 0.16, 0.05, 0.07, 0.05, 0.16, 0.09, 0.16, 0.04, 0.01, 0.04 and 0.17. From Figure 4-5 we can see that the generated incident location distribution matches with the user input.

The shoulder closure duration distribution follows a truncated lognormal distribution based on the mean duration, duration range and standard deviation of the duration for shoulder closure. The shoulder closure duration distribution probabilities based on the user input should be: 0.239, 0.483, 0.238 and 0.041 for 15, 30, 45 and 60 min duration, respectively.

Figure 4-6 shows that the frequencies of the shoulder closure durations generated match with the shoulder closure duration distribution based on the user input. Statistics from

Table 4-4 shows that the durations generated from the software match with the user input, the truncation of the distribution due to duration range may cause certain loss of the standard deviation.

The one-lane closure duration distribution follows a truncated lognormal distribution based on the mean duration, duration range and standard deviation of the duration for one-lane closure. The one-lane closure duration distribution probabilities based on the user input should be: 0.188, 0.511, 0.259 and 0.042 for 15, 30, 45 and 60 min duration, respectively.

Figure 4-7 shows that the frequencies of the one-lane closure durations generated match with the one-lane closure duration distribution based on the user input. Statistics from

Table 4-5 shows that the durations generated from the software match with the user input, the truncation of the distribution due to duration range may cause certain loss of the standard deviation.

The two-lane closure duration distribution follows a truncated lognormal distribution based on the mean duration, duration range and standard deviation of the duration for two-lane closure. The two-lane closure duration distribution probabilities based on the user input should be: 0.121, 0.496 and 0.383 for 30, 45 and 60 min duration, respectively.

Figure 4-8 shows that the frequencies of the two-lane closure durations generated match with the two-lane closure duration distribution based on the user input. Statistics from
Table 4-6 shows that the durations generated from the software match with the user input, the truncation of the distribution due to duration range may cause certain loss of the standard deviation.

For each weather event, the start time is randomly assigned from the 12 time periods in the study periods, so the weather start time distribution should be uniformly distributed, as shown in Figure 4-9.

The overall results for the HCM method are from the average of 20 sets of random seeds runs, as shown in
Table 4-7.

Comparison

A detailed comparison of the differences between the results produced by the two methods is beyond the scope of the project. However, a brief summary will be provided in this section.

From the output results in Chapter 4, the following reliability performance measures for SHRP2-L08 and HCM methods can be obtained.

From
Table 4-8 we can see that, for the example facility, the mean TTI of SHRP2-L08 method is greater than HCM method. The 50^{th} % TTI of the two methods are the same, as the percentile goes up, the relative percentile TTI for HCM method tend to be smaller than the SHRP2-L08 method. This means that the HCM method has less extreme TTI values than SHRP2-L08

method, which is further backed up by the fact that the misery index and semi-standard deviation of HCM method are both smaller than SHRP2-L08 method.

The reason for the difference of extreme TTI values between the SHRP2-L08 method and HCM methods lies in the assignment of weather and incident events, which is also the major difference between the two scenario generation methods. For SHRP2-L08 method, a weather event can only start at either the beginning or middle of the study period, and an incident event can only start at either the beginning or middle of the study period, only on the first, middle or last basic segment. For the HCM method, however, the start times of weather and incident events are randomly assigned based on the proportion of VMT of each time period in the study period, and the locations of the incident events are randomly assigned based on the proportion of VMT of each segment of the facility. In this case, the limitations of start times and locations for weather and incident events of the SHRP2-L08 method may result in severe conditions for certain time period and segment, which lead to long travel times.

In this case, the more weather and incident events generated, the more likely severe conditions for certain time periods and segments would happen for the SHRP2-L08 method, which will lead to the increase of difference between the extreme travel time values of the two methods. To demonstrate this, a set of travel time reliability runs have been conducted to the same example facility through the software by increasing the incident rate. For the HCM method, increase of incident rate will lead to the increase of incident frequencies generated. For SHRP2-L08 method, increase of incident rate will increase the probabilities of scenarios that involve incidents. For the example problem, the incident rate for each month is 1050 per million VMT, a set of runs are conducted by increasing the incident rate by 50 per million VMT at a time.

Figure 4-11 shows that as the incident rate increases, the difference of the 95th % TTI between the two methods also increases, which means that the effect of extreme travel times will be more significant for SHRP2-L08 method as the number of incidents generated increases.

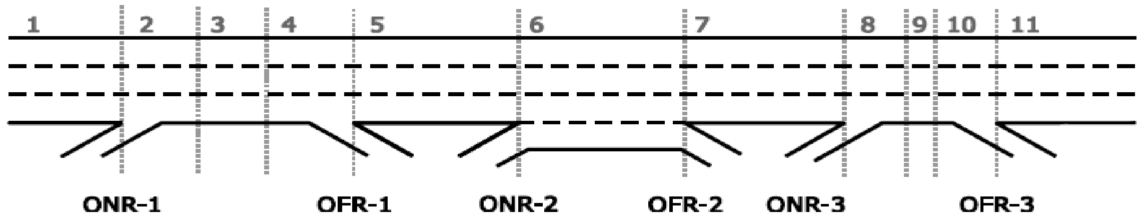


Figure 4-1. Example freeway facility

Source: Highway Capacity Manual 2010
Note: ONR = on-ramp segment, OFR = off-ramp segment

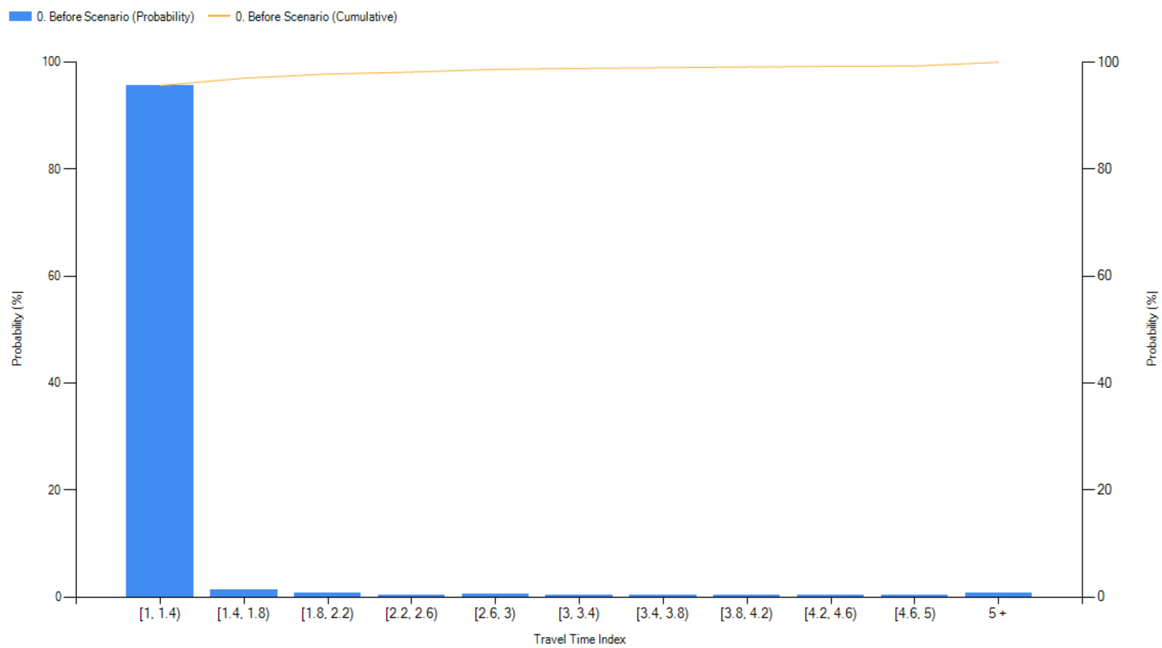


Figure 4-2. TTI distribution of SHRP2-L08 method

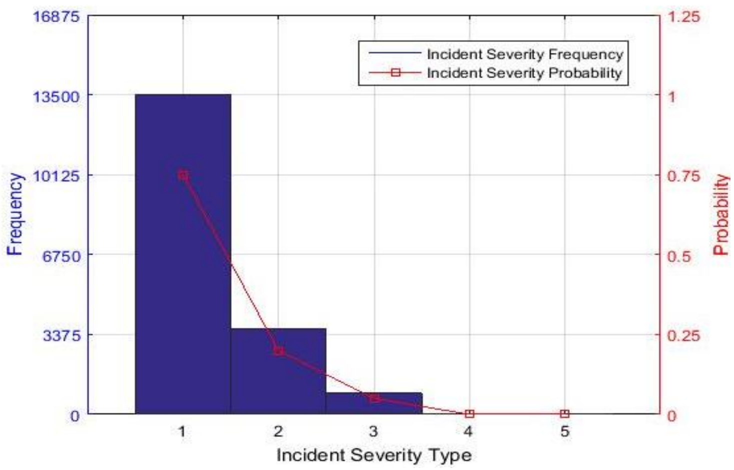


Figure 4-3. Incident severity distribution

Note: 1 = shoulder closure, 2 = one-lane closure, 3 = two-lane closure, 4 = three-lane closure, 5 = four or more lane closure

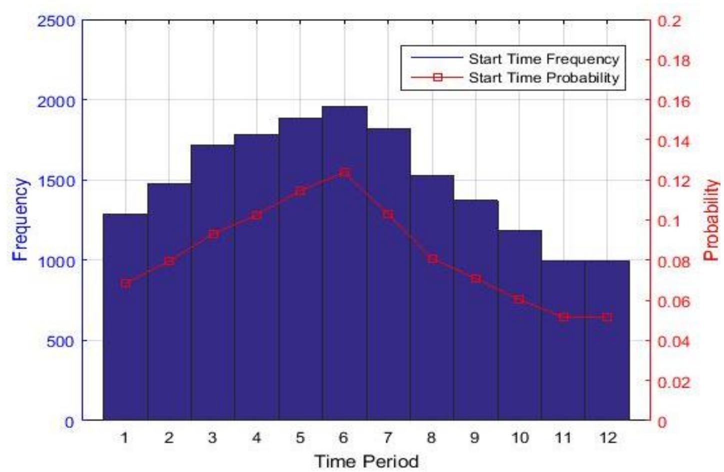


Figure 4-4. Incident start time distribution

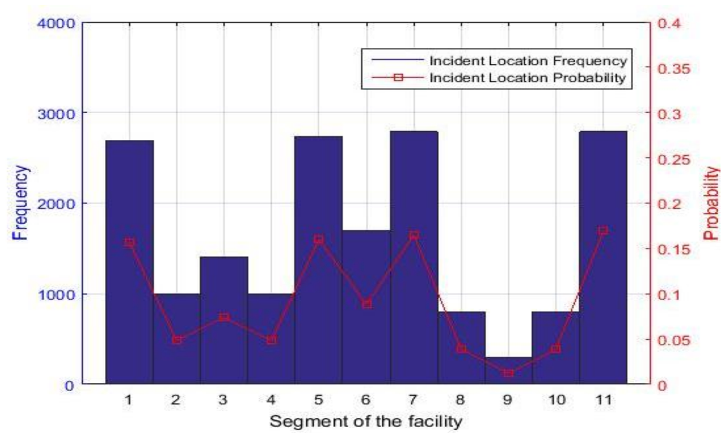


Figure 4-5. Incident location distribution

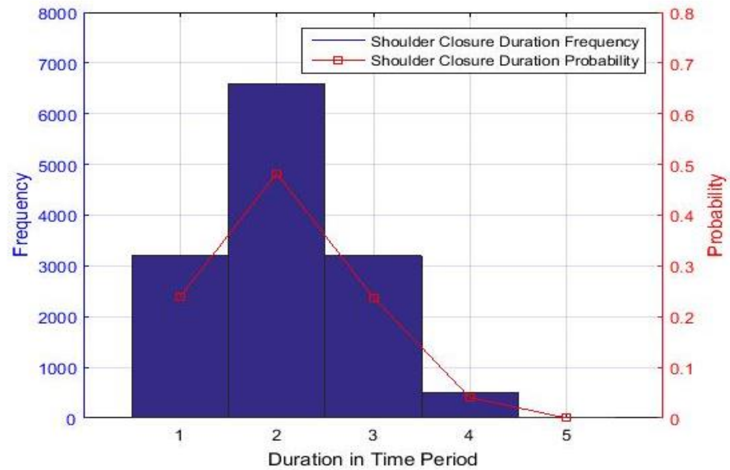


Figure 4-6. Shoulder closure duration distribution

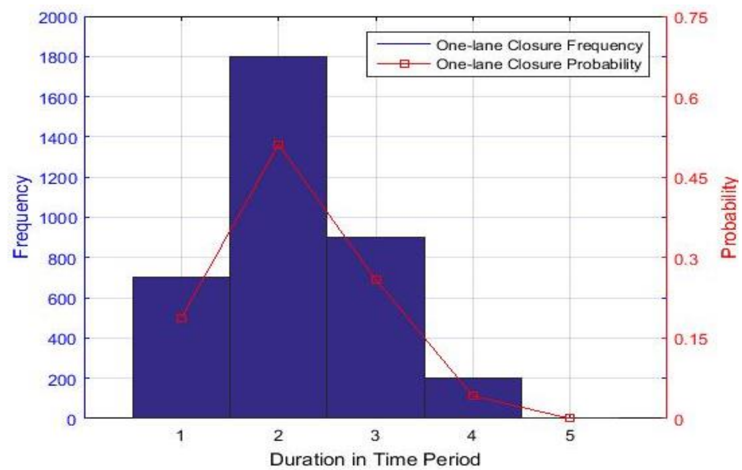


Figure 4-7. One-lane closure duration distribution

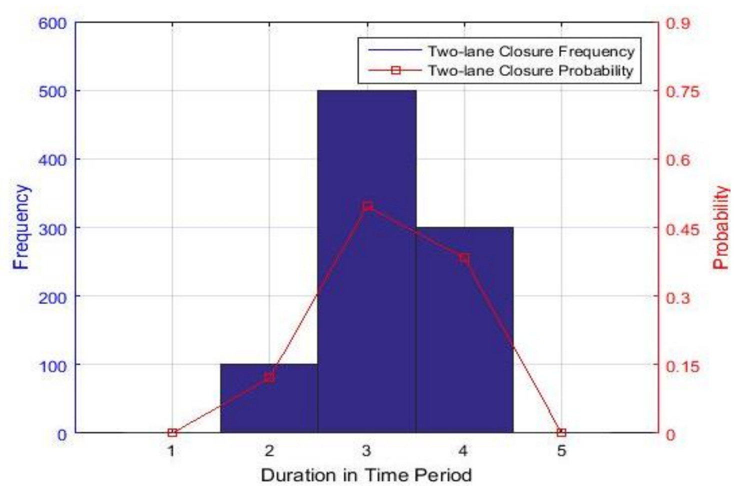


Figure 4-8. Two-lane closure duration distribution

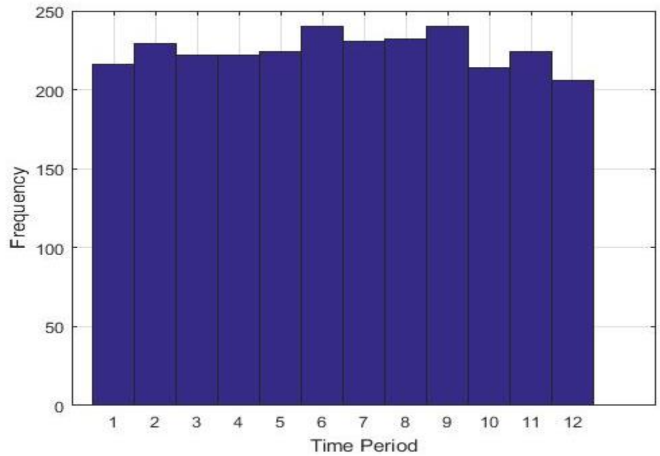


Figure 4-9. Weather start time distribution

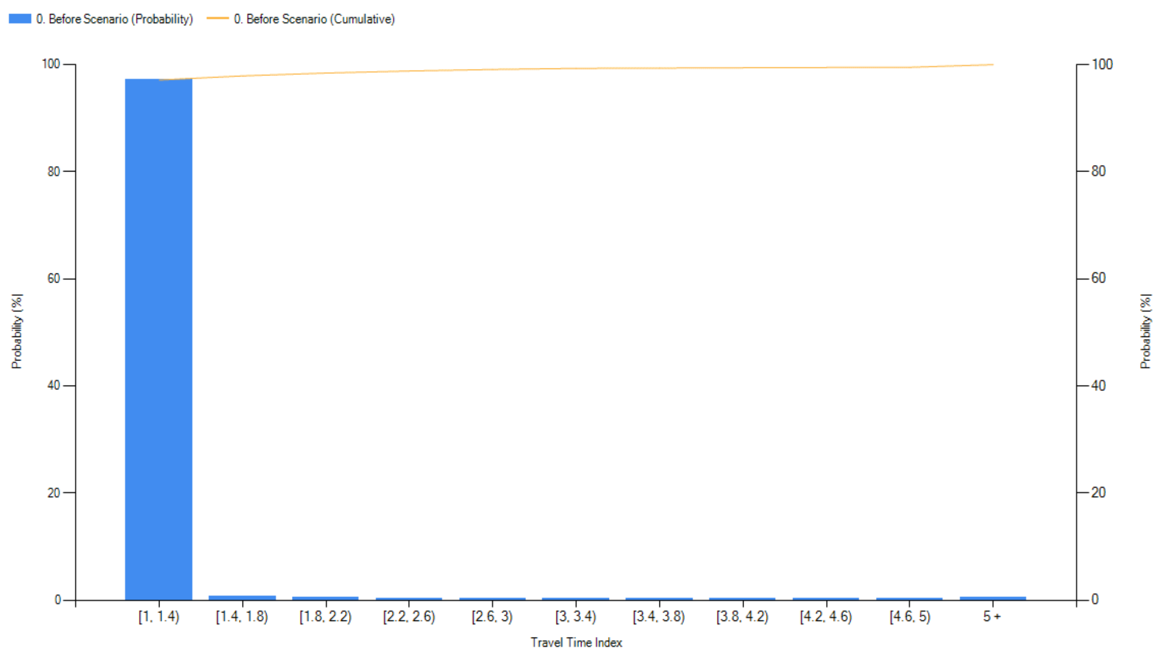


Figure 4-10. TTI distribution of HCM method

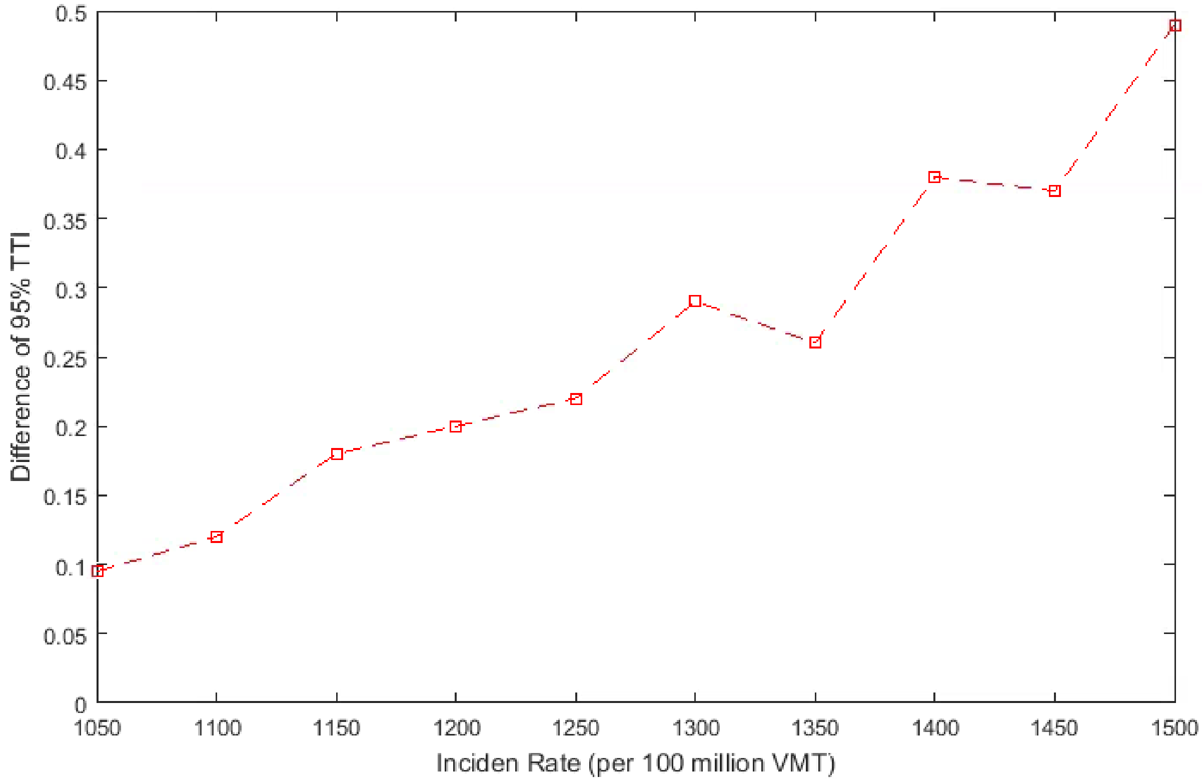


Figure 4-11. Difference of 95th % TTI values between two methods

Table 4-1. Detailed geometry

Segment	Type	Length (ft)	Number of Lanes	FFS (mi/h)
1	Basic	5280	3	60
2	On-Ramp	1500	3	60
3	Basic	2280	3	60
4	Off-Ramp	1500	3	60
5	Basic	5280	3	60
6	Weaving	2640	4	60
7	Basic	5280	3	60
8	On-Ramp	1140	3	60
9	Ramp Overlap	360	3	60
10	Off-Ramp	1140	3	60
11	Basic	5280	3	60

Following are the base demand entry flow rate for each analysis period in the study period:

Table 4-2. Demand entry flow rate

Analysis Period	Demand Flow Rate	ONR 1	ONR 2	ONR 3	OFR 1	OFR 2	OFR 3
1	3,095	270	270	270	180	270	180
2	3,595	360	360	360	270	360	270
3	4,175	360	450	450	270	360	270
4	4,505	450	540	450	270	360	270
5	4,955	540	720	540	360	360	270
6	5,225	630	810	630	270	360	450
7	4,685	360	360	450	270	360	270
8	3,785	180	270	270	270	180	180
9	3,305	180	270	270	270	180	180
10	2,805	180	270	270	270	180	180
11	2,455	180	180	180	270	180	180
12	2,405	180	180	180	180	180	180

Table 4-3. Overall results for SHRP2-L08 method

	TT (min)	TTI	VHT	VHD	Speed Avg. (mi/h)	Density (pc/mi/ln)
Mean	7.07	1.18	110.82	13.48	55.86	24.49
Min	6.1	1.02	54.04	1.19	1.81	11.98
Max	212.84	35.47	746.45	723.94	59.03	161.58
50%	6.20	1.03	99.85	3.41	57.96	22.13
80%	6.37	1.06	134.97	8.43	58.51	29.91
95%	7.89	1.31	183.12	39.69	58.66	40.12
Standard Deviation	7.21	1.20	58.33	48.19	7.20	12.64
Misery Index			4.88			
Semi-standard Deviation			8.12			

Table 4-4. Shoulder closure duration (min) statistics

Statistics	User Input	Generated Shoulder Closure Durations
Mean	32.0	31.1
Standard deviation	15.0	11.8
Range	8.7-58.0	15-60

Table 4-5. One-lane closure duration (min) statistics

Statistics	User Input	Generated One-lane Closure Durations
Mean	34.0	32.5
Standard deviation	14.0	12.0
Range	16.0-58.2	15-60

Table 4-6. Two-lane closure duration (min) statistics

Statistics	User Input	Generated Two-lane Closure Durations
Mean	53.0	49.6
Standard deviation	14.0	10.5
Range	30.5-66.9	30-60

Table 4-7. Overall results HCM

	TT (min)	TTI	VHT	VHD	Speed Avg. (mi/h)	Density (pc/mi/ln)
Mean	6.85	1.14	108.08	9.85	56.35	23.92
Min	6.13	1.02	50.92	1.18	2.29	11.28
Max	168.72	28.12	620.18	591.79	58.62	134.25
50%	6.20	1.03	102.18	3.77	57.89	22.65
80%	6.29	1.05	133.79	6.45	58.51	29.64
95%	7.29	1.22	169.19	27.06	58.58	37.33
Standard Deviation	5.47	0.91	43.66	32.52	6.36	9.53
Misery Index	3.05					
Semi-standard Deviation	6.39					

Table 4-8. Reliability performance measure of two methods

Reliability Performance Measure	SHRP2-L08 Scenarios	HCM Scenarios
Mean TTI	1.18	1.14
50th % TTI	1.03	1.03
80th % TTI	1.06	1.05
95th % TTI (PTI)	1.31	1.22
Misery Index	4.88	3.05
Semi-standard Deviation	8.12	6.39

CHAPTER 5
SUMMARY

In this project, a software tool was developed that implements the large scale and highly iterative calculation processes of the SHRP2-L08 and HCM TTR analysis methodologies, specific to freeway facilities. After studying the SHRP2-L08 and HCM methodologies, they were implemented into a commercial-grade software tool using the .NET Framework and C# programming language. The software tool focuses on the scenario generation for the two methods, and utilizes the HCM-CALC: Freeway Facility software module to create the facility base file and perform the HCM freeway facility analysis methodology calculations on the scenarios generated from the TTR software tool. During the development process, besides addressing the functional requirements, user friendliness also had to be taken into consideration due to the volume and complexity of the required inputs, so that users can conduct the reliability methodologies efficiently. Also, feedback on the software design features were obtained from stakeholders during this process.

To test if the TTR methodologies had been correctly implemented in the software, a verification process was conducted. From the demand pattern groupings, weather events generation, incident events generation to the adjustment factors calculation and overall results calculation, each major step of the two TTR methodologies were included in the verification. To better present the verification calculations and show the completeness of the verification process, computational documentation was developed in Mathcad, which can both show the functions and calculate the results. The Mathcad documents present the full travel time reliability methods and corresponding calculations based on an example problem run with the software tool. The results of each major step in the computational documents were compared to the corresponding results in the software tool. The verification process demonstrated that the two TTR analysis methodologies were correctly implemented in the software tool. Additionally, a brief comparison was made between the relative results generated by the two TTR analysis methodologies, which showed that the SHRP2-L08 method tends to generate more extreme travel times than the HCM method when the number of incident events increased. This is likely because the SHRP2-L08 method limits the start times and locations of the events, which may result in extreme travel times within certain time periods and segments. A user guide was also developed to help guide the transportation practitioner on how to operate the software tool to perform the TTR analysis methodologies.

APPENDIX
COMPUTATIONAL DOCUMENTATION

SHRP2-L08 METHOD

Stage 1 Demand Adjustment Factors

Demand Patterns:

$\text{MonthGroupNum} := 4 \qquad\qquad \text{DayGroupNum} := 2$

$\text{DemandPatternNum} := \text{MonthGroupNum} \cdot \text{DayGroupNum} = 8$

Figures (captions and numbers) in this document are screen shots from the TTR&ATDM software:

Specify Demand Pattern within the Year

	Month Group
January	1
February	1
March	2
April	2
May	2
June	3
July	3
August	3
September	4
October	4
November	4
December	1

Specify Demand Pattern within the Day

	Day Group	# Days/Year
Monday	1	52
Tuesday	2	52
Wednesday	2	52
Thursday	2	52
Friday	1	52
Saturday	0	52
Sunday	0	52

Although one weekday (Sun-Mon) will have one more day per year than the other weekdays, this impact on the analysis results is insignificant. Thus, the program uses an equal number of days per year in the calculations.

Figure1. Demand Patterns

$$\text{DP\_Groups} := \begin{pmatrix} 1 & 2 & 2 & 2 & 1 \\ 1 & 2 & 2 & 2 & 1 \\ 3 & 4 & 4 & 4 & 3 \\ 3 & 4 & 4 & 4 & 3 \\ 3 & 4 & 4 & 4 & 3 \\ 5 & 6 & 6 & 6 & 5 \\ 5 & 6 & 6 & 6 & 5 \\ 5 & 6 & 6 & 6 & 5 \\ 7 & 8 & 8 & 8 & 7 \\ 7 & 8 & 8 & 8 & 7 \\ 7 & 8 & 8 & 8 & 7 \\ 1 & 2 & 2 & 2 & 1 \end{pmatrix}$$

In this example, Saturday and Sunday are not involved in the calculation, so their group numbers are 0.

Column headers are weekdays:
Monday, Tuesday, Wednesday, Thursday and Friday.
Row headers are months:
Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec.

Default Adjustment Factors:

CAF := 1   SAF := 1   DAF := 1

Demand Multipliers:

$$\text{DemandMultipliers} := \begin{pmatrix} 0.8220 & 0.8220 & 0.8390 & 0.8640 & 0.9650 \\ 0.8490 & 0.8490 & 0.8660 & 0.8920 & 0.9960 \\ 0.9210 & 0.9210 & 0.9390 & 0.9670 & 1.0800 \\ 0.9760 & 0.9760 & 0.9950 & 1.0250 & 1.1450 \\ 0.9740 & 0.9740 & 0.9930 & 1.0230 & 1.1420 \\ 1.0220 & 1.0220 & 1.0430 & 1.0740 & 1.1990 \\ 1.1330 & 1.1330 & 1.1560 & 1.1910 & 1.3290 \\ 1.0330 & 1.0330 & 1.0540 & 1.0850 & 1.2120 \\ 1.0630 & 1.0630 & 1.0850 & 1.1170 & 1.2480 \\ 0.9950 & 0.9950 & 1.0160 & 1.0460 & 1.1680 \\ 0.9950 & 0.9950 & 1.0160 & 1.0460 & 1.1680 \\ 0.9790 & 0.9790 & 0.9980 & 1.0280 & 1.1480 \end{pmatrix} \qquad \text{DemandMultiplierSeed} := 1.05$$

Column headers are weekdays:
Monday, Tuesday, Wednesday, Thursday and Friday.
Row headers are months:
Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec.

Demand Adjustment Factors (Demand Pattern):

Demand adjustment factor (DAF) for one demand pattern is calculated as the average demand multiplier of the days involved in the demand pattern.

```
DAFs := | for DemandPattern ∈ 1..8
        |   | Sum ← 0
        |   | n ← 0
        |   | for Month ∈ 1..12
        |   |   for Weekday ∈ 1..5
        |   |     | if DP_Groups(Month−1, Weekday−1) = DemandPattern
        |   |     |   | n ← n + 1
        |   |     |   | Sum ← Sum + DemandMultipliers(Month−1, Weekday−1) / DemandMultiplierSeed
        |   |     | SumDAF_DemandPattern ← Sum
        |   |     | N_DemandPattern ← n
        |   | DAF_(DemandPattern−1) ← SumDAF_DemandPattern / N_DemandPattern
        | DAF
```

	0
0	0.914
1	0.861
2	0.990
3	0.933
4	1.100
5	1.036
6	1.053
7	0.992

DAFs =

Row headers are Demand Patterns:
DP1, DP2, DP3, DP4, DP5, DP6, DP7, DP8.

Demand Pattern Probabilities:

Although one weekday (Sun-Mon) will have one more day per year than the other weekdays, this impact on the analysis results is insignificant. Thus, the program uses an equal number of days per year in the calculations: 52 days for each weekday.

Scenario probability is the number of days in DC divided by the product of scenarios sets number and number of days in RRP:

$$
\begin{aligned}
\text{DP\_Prob} := \;& \text{for } \text{DemandPattern} \in 1..8 \\
& \quad n \leftarrow 0 \\
& \quad \text{for } \text{Month} \in 1..12 \\
& \quad\quad \text{for } \text{Weekday} \in 1..5 \\
& \quad\quad\quad n \leftarrow n + 1 \text{ if } \text{DP\_Groups}_{(\text{Month}-1,\,\text{Weekday}-1)} = \text{DemandPattern} \\
& \quad N_{\text{DemandPattern}} \leftarrow n \\
& \quad \text{Sum} \leftarrow \text{Sum} + N_{\text{DemandPattern}} \\
& \text{for } \text{DemandPattern} \in 1..8 \\
& \quad \text{probabilities}_{\text{DemandPattern}-1} \leftarrow \frac{N_{\text{DemandPattern}}}{\text{Sum}} \\
& \text{probabilities}
\end{aligned}
$$

	0
0	0.10
1	0.15
2	0.10
3	0.15
4	0.10
5	0.15
6	0.10
7	0.15

DP_Prob =

Row headers are Demand Patterns:
DP1, DP2, DP3, DP4, DP5, DP6, DP7, DP8.

	Demand Pattern Id	Probability (%)	Avg Demand Multiplier	Demand Adj. Factor
▸	1	10.00	0.959833	0.914127
	2	15.00	0.904111	0.861058
	3	10.00	1.039667	0.990159
	4	15.00	0.979222	0.932593
	5	10.00	1.154667	1.099683
	6	15.00	1.087889	1.036085
	7	10.00	1.106167	1.053492
	8	15.00	1.042111	0.992487

Figure 2. Probabilities and Calculated DAFs

Stage 2 Weather Adjustment Factors

Weather Probability (Month, Weather Category):

$$\mathrm{WeatherProbability} := \begin{pmatrix} 0.0080 & 0.0047 & 0.0091 & 0.0029 & 0.0004 & 0.0000 & 0.0000 & 0.0097 & 0.0000 & 0.0044 \\ 0.0080 & 0.0047 & 0.0091 & 0.0029 & 0.0004 & 0.0000 & 0.0000 & 0.0097 & 0.0000 & 0.0044 \\ 0.0101 & 0.0081 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0012 & 0.0000 & 0.0010 \\ 0.0101 & 0.0081 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0012 & 0.0000 & 0.0010 \\ 0.0101 & 0.0081 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0012 & 0.0000 & 0.0010 \\ 0.0071 & 0.0133 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0016 & 0.0000 & 0.0000 \\ 0.0071 & 0.0133 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0016 & 0.0000 & 0.0000 \\ 0.0071 & 0.0133 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0016 & 0.0000 & 0.0000 \\ 0.0086 & 0.0068 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0034 & 0.0000 & 0.0003 \\ 0.0086 & 0.0068 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0034 & 0.0000 & 0.0003 \\ 0.0086 & 0.0068 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0034 & 0.0000 & 0.0003 \\ 0.0080 & 0.0047 & 0.0091 & 0.0029 & 0.0004 & 0.0000 & 0.0000 & 0.0097 & 0.0000 & 0.0044 \end{pmatrix}$$

Column headers are weather categories:
Med Rain, Heavy Rain, Light Snow, Light Medium Snow, Medium Heavy Snow, Heavy Snow, Severe Cold, Low Visibility, Very Low Visibility, Min Visibility.
Row headers are months:
Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec.

Weather duration, adjustment factors by weather category:

$$\mathrm{DurationWea0} := \begin{pmatrix} 42.2 & 33.7 & 93.1 & 33.4 & 21.7 & 7.3 & 0.00 & 76.2 & 0.00 & 145 \end{pmatrix} \ \mathrm{min}$$

Rounded into the nearest 15s:

$$\mathrm{DurationWea} := \begin{pmatrix} 45 & 30 & 90 & 30 & 15 & 15 & 0.00 & 75 & 0.00 & 150 \end{pmatrix} \ \mathrm{min}$$

$$WeatherCaf := (0.93\ \ 0.86\ \ 0.96\ \ 0.94\ \ 0.91\ \ 0.78\ \ 0.92\ \ 0.90\ \ 0.88\ \ 0.90)$$

$$WeatherSaf := (0.95\ \ 0.93\ \ 0.92\ \ 0.90\ \ 0.88\ \ 0.86\ \ 0.95\ \ 0.95\ \ 0.94\ \ 0.9)$$

$$WeatherDaf := (1\ \ 1\ \ 1\ \ 1\ \ 1\ \ 1\ \ 1\ \ 1\ \ 1\ \ 1)$$

Column headers are weather categories:
Med Rain, Heavy Rain, Light Snow, Light Medium Snow, Medium Heavy Snow, Heavy Snow, Severe Cold, Low Visibility, Very Low Visibility, Min Visibility.

Weighted Weather Probabilities by Demand Pattern:

Group the months by demand patterns:

$$Month\_DP(DP) := \left| \begin{array}{l} \begin{pmatrix} 1 \\ 2 \\ 12 \end{pmatrix} \text{ if } DP = 1 \vee DP = 2 \\ \begin{pmatrix} 3 \\ 4 \\ 5 \end{pmatrix} \text{ if } DP = 3 \vee DP = 4 \\ \begin{pmatrix} 6 \\ 7 \\ 8 \end{pmatrix} \text{ if } DP = 5 \vee DP = 6 \\ \begin{pmatrix} 9 \\ 10 \\ 11 \end{pmatrix} \text{ if } DP = 7 \vee DP = 8 \end{array} \right.$$

Calculate the weighted probabilities of each demand pattern:

$$Prob := \left| \begin{array}{l} \text{for } DP \in 1..8 \\ \quad \text{for } WeatherType \in 1..10 \\ \qquad \left| \begin{array}{l} Sum \leftarrow 0 \\ n \leftarrow 0 \\ \text{for } Month \in Month\_DP(DP)_0, Month\_DP(DP)_1, Month\_DP(DP)_2 \\ \quad \left| \begin{array}{l} n \leftarrow n + 1 \\ Sum \leftarrow Sum + WeatherProbability_{Month-1,\, WeatherType-1} \end{array} \right. \\ DAF_{DP-1,\, WeatherType} \leftarrow \dfrac{Sum}{n} \end{array} \right. \\ DAF \end{array} \right.$$

Row headers are Demand Patterns:
DP1, DP2, DP3, DP4, DP5, DP6, DP7, DP8.
Column headers are weather categories:
Normal Weather, Med Rain, Heavy Rain, Light Snow, Light Medium Snow, Medium Heavy Snow, Heavy Snow, Severe Cold, Low Visibility, Very Low Visibility, Min Visibility.

Prob =

	0	1	2	3	4	5	6	7	8	9	10
0	0.0000	0.0080	0.0047	0.0091	0.0029	0.0004	0.0000	0.0000	0.0097	0.0000	0.0044
1	0.0000	0.0080	0.0047	0.0091	0.0029	0.0004	0.0000	0.0000	0.0097	0.0000	0.0044
2	0.0000	0.0101	0.0081	0.0000	0.0000	0.0000	0.0000	0.0000	0.0012	0.0000	0.0010
3	0.0000	0.0101	0.0081	0.0000	0.0000	0.0000	0.0000	0.0000	0.0012	0.0000	0.0010
4	0.0000	0.0071	0.0133	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000
5	0.0000	0.0071	0.0133	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000
6	0.0000	0.0086	0.0068	0.0000	0.0000	0.0000	0.0000	0.0000	0.0034	0.0000	0.0003
7	0.0000	0.0086	0.0068	0.0000	0.0000	0.0000	0.0000	0.0000	0.0034	0.0000	0.0003

Add the normal weather probabilities (1 - sum of all weather event probabilities) for each demand pattern, then we can get the weather probabilities by demand pattern:

```
P_W := | for DP ∈ 1..8
       |    | sum ← 0
       |    | for WeatherType ∈ 1..10
       |    |    sum ← sum + Prob_{DP−1, WeatherType}
       |    | Prob_{DP−1, 0} ← 1 − sum
       | Prob
```

P_W =

	0	1	2	3	4	5	6	7	8	9	10
0	0.9608	0.0080	0.0047	0.0091	0.0029	0.0004	0.0000	0.0000	0.0097	0.0000	0.0044
1	0.9608	0.0080	0.0047	0.0091	0.0029	0.0004	0.0000	0.0000	0.0097	0.0000	0.0044
2	0.9796	0.0101	0.0081	0.0000	0.0000	0.0000	0.0000	0.0000	0.0012	0.0000	0.0010
3	0.9796	0.0101	0.0081	0.0000	0.0000	0.0000	0.0000	0.0000	0.0012	0.0000	0.0010
4	0.9780	0.0071	0.0133	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000
5	0.9780	0.0071	0.0133	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000
6	0.9809	0.0086	0.0068	0.0000	0.0000	0.0000	0.0000	0.0000	0.0034	0.0000	0.0003
7	0.9809	0.0086	0.0068	0.0000	0.0000	0.0000	0.0000	0.0000	0.0034	0.0000	0.0003

	Normal Weather	Medium Rain	Heavy Rain	Light Snow	Light-Med Snow	Med-Heavy Snow	Heavy Snow	Severe Cold	Low Visibility	Very Low Visibility	Minimum Visibility
DP 1	96.08000	0.80000	0.47000	0.91000	0.29000	0.04000	0.00000	0.00000	0.97000	0.00000	0.44000
DP 2	96.08000	0.80000	0.47000	0.91000	0.29000	0.04000	0.00000	0.00000	0.97000	0.00000	0.44000
DP 3	97.96000	1.01000	0.81000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12000	0.00000	0.10000
DP 4	97.96000	1.01000	0.81000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12000	0.00000	0.10000
DP 5	97.80000	0.71000	1.33000	0.00000	0.00000	0.00000	0.00000	0.00000	0.16000	0.00000	0.00000
DP 6	97.80000	0.71000	1.33000	0.00000	0.00000	0.00000	0.00000	0.00000	0.16000	0.00000	0.00000
DP 7	98.09000	0.86000	0.68000	0.00000	0.00000	0.00000	0.00000	0.00000	0.34000	0.00000	0.03000
DP 8	98.09000	0.86000	0.68000	0.00000	0.00000	0.00000	0.00000	0.00000	0.34000	0.00000	0.03000

Figure 3. Weighted Weather Probabilities by Demand Pattern

Stage 3 Incident Adjustment Factors

Incident Severities Information:

$\text{Shoulder} := 0 \quad \text{OneLane} := 1 \quad \text{TwoLane} := 2 \quad \text{ThreeLane} := 3 \quad \text{FourOrMoreLanes} := 4$

Incident severities distribution probabilities:

$$D(\text{IncidentType}) := \begin{cases} 0.75 & \text{if IncidentType} = 0 \\ 0.20 & \text{if IncidentType} = 1 \\ 0.05 & \text{if IncidentType} = 2 \\ 0 & \text{if IncidentType} = 3 \\ 0 & \text{if IncidentType} = 4 \end{cases}$$

(The example facility has three lanes in one direction, so the incident type is not feasible to be more than two lane closure)

Incident duration distribution parameters:

$$\text{DurationInc0}(\text{IncidentType}) := \begin{cases} 34 & \text{if IncidentType} = 0 \\ 34.6 & \text{if IncidentType} = 1 \\ 53.6 & \text{if IncidentType} = 2 \\ 69.6 & \text{if IncidentType} = 3 \\ 69.6 & \text{if IncidentType} = 4 \end{cases}$$

Rounded into the nearest 15s:

$$\text{DurationInc}(\text{IncidentType}) := \begin{cases} 30 & \text{if IncidentType} = 0 \\ 30 & \text{if IncidentType} = 1 \\ 60 & \text{if IncidentType} = 2 \\ 75 & \text{if IncidentType} = 3 \\ 75 & \text{if IncidentType} = 4 \end{cases}$$

$$\text{StdDev}(\text{IncidentType}) := \begin{cases} 15.1 & \text{if IncidentType} = 0 \\ 13.8 & \text{if IncidentType} = 1 \\ 13.9 & \text{if IncidentType} = 2 \\ 21.9 & \text{if IncidentType} = 3 \\ 21.9 & \text{if IncidentType} = 4 \end{cases}$$

Default adjustment factors (two lanes one direction):

$\text{IncidentCaf} := (0.81 \;\; 0.35 \;\; 0.00 \;\; 0.00 \;\; 0.00) \qquad \text{IncidentSaf} := (1.00 \;\; 1.00 \;\; 1.00 \;\; 1.00 \;\; 1.00)$

$\text{IncidentDaf} := (1.00 \;\; 1.00 \;\; 1.00 \;\; 1.00 \;\; 1.00)$

Expected number of incidents (demand pattern 1):

$\text{IncidentRate} := 1050$ (default: per 100 MVMT for each demand pattern)

$\text{VMTseed} := 71501$ (Vehicle miles traveled) $\qquad \text{StudyPeriod} := 3 \;\; \text{h}$

Demand adjustment factor (DAF) of demand pattern 1: $\text{DAF\_DP1} := \text{DAFs}_0 = 0.914$

Expected number of incidents is the product of the incident rate of the demand pattern, DAF for the demand pattern and the VMT from seed file:

$$n := \text{IncidentRate} \cdot 10^{-8} \cdot \text{DAF\_DP1} \cdot \text{VMTseed} = 0.6863$$

Time based incident probabilities per study period for each demand pattern:

The probabilities for incident severities by demand pattern are calculated as following, firstly, calculate the expected number of incident of the demand pattern, then use in a function below to obtain the probability:

$$\text{Probability} := \left| \begin{array}{l} \text{for } DP \in 1..8 \\ \quad \left| \begin{array}{l} N \leftarrow \text{IncidentRate} \cdot 10^{-8} \cdot \text{DAFs}_{DP-1} \cdot \text{VMTseed} \\ \text{for } Inc \in 1..5 \\ \quad \text{Prob}_{DP-1,Inc} \leftarrow 1 - e^{\left[\frac{(-N \cdot D(Inc-1)) \cdot (\text{DurationInc0}(Inc-1))}{\text{StudyPeriod} \cdot 60}\right]} \end{array} \right. \\ \text{Prob} \end{array} \right.$$

Probability =

	0	1	2	3	4	5
0	0.0000	0.0926	0.0260	0.0102	0.0000	0.0000
1	0.0000	0.0875	0.0245	0.0096	0.0000	0.0000
2	0.0000	0.1000	0.0282	0.0110	0.0000	0.0000
3	0.0000	0.0944	0.0266	0.0104	0.0000	0.0000
4	0.0000	0.1104	0.0312	0.0122	0.0000	0.0000
5	0.0000	0.1043	0.0295	0.0115	0.0000	0.0000
6	0.0000	0.1060	0.0299	0.0117	0.0000	0.0000
7	0.0000	0.1002	0.0282	0.0110	0.0000	0.0000

Column headers are incident sevirities:
Shoulder closure, one-lane closure, two-lane closure, three-lane closure.
Row headers are:
DP1, DP2, DP3, DP4, DP5, DP6, DP7, DP8.

Add no incident probabilities (1 - sum of all incident event probabilities) to each demand pattern, and then we can get the incident probabilities by demand pattern:

$$\text{P\_I} := \left| \begin{array}{l} \text{for } DP \in 1..8 \\ \quad \left| \begin{array}{l} \text{sum} \leftarrow 0 \\ \text{for IncidentType} \in 1..4 \\ \quad \text{sum} \leftarrow \text{sum} + \text{Probability}_{DP-1,\text{IncidentType}} \\ \text{Probability}_{DP-1,0} \leftarrow 1 - \text{sum} \end{array} \right. \\ \text{Probability} \end{array} \right.$$

P_I =

	0	1	2	3	4	5
0	0.8711	0.0926	0.0260	0.0102	0.0000	0.0000
1	0.8784	0.0875	0.0245	0.0096	0.0000	0.0000
2	0.8609	0.1000	0.0282	0.0110	0.0000	0.0000
3	0.8686	0.0944	0.0266	0.0104	0.0000	0.0000
4	0.8462	0.1104	0.0312	0.0122	0.0000	0.0000
5	0.8547	0.1043	0.0295	0.0115	0.0000	0.0000
6	0.8523	0.1060	0.0299	0.0117	0.0000	0.0000
7	0.8605	0.1002	0.0282	0.0110	0.0000	0.0000

	No Incident	Shoulder Closure	One Lane Closure	Two Lane Closure	Three Lane Closure	Four Lane Closure
DP 1	0.871147	0.092648	0.026039	0.010166	0.000000	0.000000
DP 2	0.878363	0.087512	0.024546	0.009579	0.000000	0.000000
DP 3	0.860864	0.099955	0.028174	0.011007	0.000000	0.000000
DP 4	0.868644	0.094428	0.026558	0.010370	0.000000	0.000000
DP 5	0.846163	0.110379	0.031241	0.012217	0.000000	0.000000
DP 6	0.854683	0.104341	0.029461	0.011515	0.000000	0.000000
DP 7	0.852346	0.105998	0.029949	0.011707	0.000000	0.000000
DP 8	0.860550	0.100178	0.028239	0.011033	0.000000	0.000000

Figure 4. Calculated Incident Probabilities

Stage 4 Base Scenarios and Probabilities

Base scenario probabilities (example calculation based just on demand pattern 2):

The base scenarios are combinations of all demand patterns, weather events and incidents, the base scenario probability is the product of the demand pattern probability, weather event probability and incident probability of that scenario.

$$
P2 := \left|\begin{array}{l}
\text{for } DP \in 2 \\
\quad \text{for } Wea \in 1..11 \\
\quad\quad \text{for } Inc \in 1..5 \\
\quad\quad\quad p_{Inc-1,\,Wea-1} \leftarrow DP\_Prob_{DP-1} \cdot P\_W_{DP-1,\,Wea-1} \cdot P\_I_{DP-1,\,Inc-1} \\
p
\end{array}\right.
$$

P2 =

	0	1	2	3	4	5	6	7	8	9	10
0	0.1266	0.0011	0.0006	0.0012	0.0004	0.0001	0	0	0.0013	0	0.0006
1	0.0126	0.0001	0.0001	0.0001	0	0	0	0	0.0001	0	0.0001
2	0.0035	0	0	0	0	0	0	0	0	0	0
3	0.0014	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0

	Normal Weather	Medium Rain	Heavy Rain	Light Snow	Light-Med Snow	Med-Heavy Snow	Heavy Snow	Severe Cold	Low Visibility	Very Low Visibility	Minimum Visibility
No incident	0.126590	0.001054	0.000619	0.001199	0.000382	0.000053	0.000000	0.000000	0.001278	0.000000	0.000580
Shoulder Closure	0.012612	0.000105	0.000062	0.000119	0.000038	0.000005	0.000000	0.000000	0.000127	0.000000	0.000058
One Lane Closure	0.003538	0.000029	0.000017	0.000034	0.000011	0.000001	0.000000	0.000000	0.000036	0.000000	0.000016
Two Lane Closure	0.001380	0.000011	0.000007	0.000013	0.000004	0.000001	0.000000	0.000000	0.000014	0.000000	0.000006
Three Lane Closure	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Four Lane Closure	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Figure 5. Overall Probabilities

Stage 5 Study Period Probabilities

Probability Threshold:

A threshold is set to remove base scenarios with very low probabilities. A base scenario with a probability lower than the threshold is removed and its probability is assigned to the remainder ("rem") of the scenarios proportionally.

Probability threshold value: $PTV := 0.00010$

$$
P\_rem := \left| \begin{array}{l}
\text{for } Wea \in 1..11 \\
\quad \text{for } Inc \in 1..5 \\
\quad\quad sum1 \leftarrow sum1 + P2_{Inc-1,\,Wea-1} \\
\text{for } Wea \in 1..11 \\
\quad \text{for } Inc \in 1..5 \\
\quad\quad \left| \begin{array}{l} P2_{Inc-1,\,Wea-1} \leftarrow 0 \ \text{ if } P2_{Inc-1,\,Wea-1} < PTV \\ sum2 \leftarrow sum2 + P2_{Inc-1,\,Wea-1} \end{array} \right. \\
\text{for } Wea \in 1..11 \\
\quad \text{for } Inc \in 1..5 \\
\quad\quad P2_{Inc-1,\,Wea-1} \leftarrow \dfrac{P2_{Inc-1,\,Wea-1} \cdot sum1}{sum2} \\
P2
\end{array} \right.
$$

Base scenario probabilities remaining for demand pattern 2:

P_rem =

	0	1	2	3	4	5	6	7	8	9	10
0	0.1269	0.0011	0.0006	0.0012	0.0004	0	0	0	0.0013	0	0.0006
1	0.0126	0.0001	0	0.0001	0	0	0	0	0.0001	0	0
2	0.0035	0	0	0	0	0	0	0	0	0	0
3	0.0014	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0

Row headers are incident severities, column headers are weather types.

For the selected demand pattern, the base sceanrio probabilities are classified into four categories:
Category 1, demand only;
Category 2, demand and weather;
Category 3, demand and incident;
Category 4, demand, weather and incident.
The sum of probabilities of all scenarios in this demand pattern remains the same after the following adjustments.

Category 4 probabilities and residual probabilities (demand pattern 2):

Compare the weather durations and incident durations, pick the smaller duation:

$$\text{Duration} := \left| \begin{array}{l} \text{for } W \in 1..10 \\ \quad \text{for } I \in 1..4 \\ \quad\quad \left| \begin{array}{l} D_{I-1,W-1} \leftarrow \text{DurationWea}_{0,W-1} \ \text{ if } \text{DurationWea}_{0,W-1} < \text{DurationInc}(I-1) \\ D_{I-1,W-1} \leftarrow \text{DurationInc}(I-1) \ \text{ if } \text{DurationWea}_{0,W-1} \geq \text{DurationInc}(I-1) \end{array} \right. \\ D \end{array} \right.$$

$$\text{Duration} = \begin{pmatrix} 30 & 30 & 30 & 30 & 15 & 15 & 0 & 30 & 0 & 30 \\ 30 & 30 & 30 & 30 & 15 & 15 & 0 & 30 & 0 & 30 \\ 45 & 30 & 60 & 30 & 15 & 15 & 0 & 60 & 0 & 60 \\ 45 & 30 & 75 & 30 & 15 & 15 & 0 & 75 & 0 & 75 \end{pmatrix}$$

$$\text{Diff} := \left| \begin{array}{l} \text{for } \text{Wea} \in 1..10 \\ \quad \text{for } \text{Inc} \in 1..4 \\ \quad\quad d_{\text{Inc}-1,\text{Wea}-1} \leftarrow \left| \text{DurationWea}_{0,\text{Wea}-1} - \text{DurationInc}(\text{Inc}-1) \right| \\ d \end{array} \right.$$

$$\text{Diff} = \begin{pmatrix} 15 & 0 & 60 & 0 & 15 & 15 & 30 & 45 & 30 & 120 \\ 15 & 0 & 60 & 0 & 15 & 15 & 30 & 45 & 30 & 120 \\ 15 & 30 & 30 & 30 & 45 & 45 & 60 & 15 & 60 & 90 \\ 30 & 45 & 15 & 45 & 60 & 60 & 75 & 0 & 75 & 75 \end{pmatrix}$$

The Category 4 study period probability is the base scenario probability multiplied by study period devided by the smaller duration of the weather and incident.

$$\text{SP4} := \left| \begin{array}{l} \text{for } \text{Wea} \in 1..10 \\ \quad \text{for } \text{Inc} \in 1..4 \\ \quad\quad \left| \begin{array}{l} sp_{\text{Inc},\text{Wea}} \leftarrow \dfrac{\text{P\_rem}_{\text{Inc},\text{Wea}} \cdot \text{StudyPeriod} \cdot 60}{\text{Duration}_{\text{Inc}-1,\text{Wea}-1}} \ \text{ if } \text{Duration}_{\text{Inc}-1,\text{Wea}-1} > 0 \\ sp_{\text{Inc},\text{Wea}} \leftarrow 0 \ \text{ if } \text{Duration}_{\text{Inc}-1,\text{Wea}-1} = 0 \end{array} \right. \\ sp \end{array} \right.$$

SP4 =	0	1	2	3	4	5	6	7	8	9	10
0	0	0	0	0	0	0	0	0	0	0	0
1	0	0.0006	0	0.0007	0	0	0	0	0.0008	0	0
2	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0

Row headers are incident severities:
No incident, shoulder closure, one-lane closure, two-lane closure, three-lane closure.
Column headers are weather types:
Normal Weather, Med Rain, Heavy Rain, Light Snow, Light Medium Snow, Medium Heavy Snow, Heavy Snow, Severe Cold, Low Visibility, Very Low Visibility, Min Visibility.

Residual probabilities for Category 2 and 3 probabilities (demand pattern 2):

$$\text{Residuals} := \left| \begin{array}{l} \text{for } \ \text{Wea} \in 1..10 \\ \quad \text{for } \ \text{Inc} \in 1..4 \\ \quad\quad \text{residuals}_{\text{Inc},\text{Wea}} \leftarrow \dfrac{\text{SP4}_{\text{Inc},\text{Wea}} \cdot \text{Diff}_{\text{Inc}-1,\text{Wea}-1}}{\text{StudyPeriod} \cdot 60} \\ \text{residuals} \end{array} \right.$$

Residuals =	0	1	2	3	4	5	6	7	8	9	10
0	0	0	0	0	0	0	0	0	0	0	0
1	0	0.0001	0	0.0002	0	0	0	0	0.0002	0	0
2	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0

Category 2 and Category 3 probabilities (demand pattern 2):

Remove the residual probabilities from incident only or weather only base scenario probabilities:
From incident only probabilities, if incident duration is greater than weather duration;
From weather only probabilities, if weather duration is greater than incident duration

$$\text{P} := \left| \begin{array}{l} \text{for } \ \text{W} \in 1..10 \\ \quad \text{for } \ \text{I} \in 1..4 \\ \quad\quad \left| \begin{array}{l} \text{P\_rem}_{\text{I},0} \leftarrow \left(\text{P\_rem}_{\text{I},0} - \text{Residuals}_{\text{I},\text{W}}\right) \ \text{ if } \ \text{DurationWea}_{0,\text{W}-1} < \text{DurationInc}(\text{I}-1) \\ \text{P\_rem}_{0,\text{W}} \leftarrow \left(\text{P\_rem}_{0,\text{W}} - \text{Residuals}_{\text{I},\text{W}}\right) \ \text{ if } \ \text{DurationWea}_{0,\text{W}-1} \geq \text{DurationInc}(\text{I}-1) \end{array} \right. \\ \text{P\_rem} \end{array} \right.$$

P =	0	1	2	3	4	5	6	7	8	9	10
0	0.1269	0.001	0.0006	0.001	0.0004	0	0	0	0.0011	0	0.0006
1	0.0126	0.0001	0	0.0001	0	0	0	0	0.0001	0	0
2	0.0035	0	0	0	0	0	0	0	0	0	0
3	0.0014	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0

$$
SP23 := \left|
\begin{array}{l}
\text{for } Wea \in 1..10 \\
\quad \left|
\begin{array}{l}
sp_{0,Wea} \leftarrow \dfrac{P_{0,Wea} \cdot StudyPeriod \cdot 60}{DurationWea_{0,Wea-1}} \;\; \text{if } DurationWea_{0,Wea-1} > 0 \\
sp_{0,Wea} \leftarrow 0 \;\; \text{if } DurationWea_{0,Wea-1} = 0
\end{array}
\right. \\
\text{for } Inc \in 1..4 \\
\quad \left|
\begin{array}{l}
sp_{Inc,0} \leftarrow \dfrac{P_{Inc,0} \cdot StudyPeriod \cdot 60}{DurationInc(Inc-1)} \;\; \text{if } DurationInc(Inc-1) > 0 \\
sp_{Inc,0} \leftarrow 0 \;\; \text{if } DurationInc(Inc-1) = 0
\end{array}
\right. \\
sp
\end{array}
\right.
$$

SP23 =

	0	1	2	3	4	5	6	7	8	9	10
0	0	0.004	0.0037	0.0019	0.0023	0	0	0	0.0026	0	0.0007
1	0.0759	0	0	0	0	0	0	0	0	0	0
2	0.0213	0	0	0	0	0	0	0	0	0	0
3	0.0042	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0

Category 1 probability (demand pattern 2):

The Category 1 probability is sum of the base probabilities of the demand pattern minus the sum of Category 2,3, and 4 study period probabilities for the selected demand pattern, and the we can get the study period probabilities for demand pattern 2:

$$
SP := \left|
\begin{array}{l}
\text{for } Wea \in 1..10 \\
\quad sp_{0,Wea} \leftarrow SP23_{0,Wea} \\
\text{for } Inc \in 1..4 \\
\quad sp_{Inc,0} \leftarrow SP23_{Inc,0} \\
\text{for } Wea \in 1..10 \\
\quad \text{for } Inc \in 1..4 \\
\qquad sp_{Inc,Wea} \leftarrow SP4_{Inc,Wea} \\
\text{for } Wea \in 1..11 \\
\quad \text{for } Inc \in 1..5 \\
\qquad sum1 \leftarrow sum1 + P\_rem_{Inc-1,Wea-1} \\
sp_{0,0} \leftarrow 0 \\
\text{for } Wea \in 1..11 \\
\quad \text{for } Inc \in 1..5 \\
\qquad sum2 \leftarrow sum2 + sp_{Inc-1,Wea-1} \\
sp_{0,0} \leftarrow sum1 - sum2 \\
sp
\end{array}
\right.
$$

SP =

	0	1	2	3	4	5	6	7	8	9	10
0	0.0313	0.004	0.0037	0.0019	0.0023	0	0	0	0.0026	0	0.0007
1	0.0759	0.0006	0	0.0007	0	0	0	0	0.0008	0	0
2	0.0213	0	0	0	0	0	0	0	0	0	0
3	0.0042	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0

	Normal Weather	Medium Rain	Heavy Rain	Light Snow	Light-Med Snow	Med-Heavy Snow	Heavy Snow	Severe Cold	Low Visibility	Very Low Visibility	Minimum Visibility
No incident	0.030535	0.004020	0.003720	0.001928	0.002304				0.002618		0.000697
Shoulder Closure	0.075996	0.000631		0.000715					0.000764		
One Lane Closure	0.021318										
Two Lane Closure	0.002502										
Three Lane Closure	0.001733										
Four Lane Closure											

Figure 6. Study Period Probabilities

Stage 6 Scenario List

Scenario list generation (example calculation based only on demand pattern 2):

In Stage 5, after the probability threshold and adjusting the base scenario probabilities to study period probabilities, for demand pattern 2, the number of scenarios for each categoty are:

$N1 := 1$ Category 1 (no incident, normal weather) $N2 := 4$ Category 2 (incident only)

$N3 := 6$ Category 3 (weather only) $N4 := 2$ Category 4 (weather and incident)

Detailed scenario generation:

Assign the scenarios above with detailed information, such as start time, duration and location. Each possible combination has equal probability to occur.

For no incident and normal weather (Category 1):

$n1 := N1 = 1$

For incident only (Category 2):

For each incident event, there are 2 possible start times: beginning of the SP, middle of the SP; 3 possible durations: 25th percentile incident duration, 50th percentile incident duration and 75th percentile incident duration; and 3 possible locations: first basic segment, middle basic segment, and last basic segment.

Number of detailed scenarios for category 2 scenarios (demand pattern 2):

$n2 := N2 \cdot 2 \cdot 3 \cdot 3 = 72$

For weather only (Category 3):

For each weather event, there are 2 possible start times: beginning of the SP, middle of the SP.

Number of detailed scenarios for category 3 scenarios (demand pattern 2):

$n3 := N3 \cdot 2 = 12$

For weather and incident (Category 4):

$n4 := N4 \cdot (2) \cdot (2 \cdot 3 \cdot 3) = 72$

So, the number of detailed scenarios in demand pattern 2:

$NumDP2 := n1 + n2 + n3 + n4 = 157$

Assign detailed information to scenarios in each category in each demand pattern, then we will obtain the scenario list.

Assign information to the list of scenarios (exmaple calculation of no incident and medium rain in demand pattern 2):

Assign the relative demand information (probability and DAF), weather event information (weather type, duration, SAF, CAF and startAP), incident event information (severity type, duration, SAF, CAF, startAP, and location) to each scenario.

For no incident and medium rain (Category 3), we will have 2 detailed scenarios, each will carry the same probability:

$$\frac{SP_{0,1}}{2} = 2.009 \times 10^{-3}$$

Demand information (same for the 2 detailed scenarios):

$$Daf := \frac{DemandMultipliers_{0,0}}{DemandMultiplierSeed} = 0.7829$$

Weather event information:

$\mathrm{MediumRain} := 0$ $\mathrm{DurationWea}_{0,\,\mathrm{MediumRain}} = 45$ min

$\mathrm{WeatherCaf}_{0,\,\mathrm{MediumRain}} = 0.93$ $\mathrm{WeatherSaf}_{0,\,\mathrm{MediumRain}} = 0.95$

In this case, there are 12 time periods in the study period of 3 h.

Weather start time for the first detailed scenario:

$\mathrm{WeatherStartAP1} := 1$

Weather start time for the secoind detailed scenario:

$\mathrm{WeatherStartAP2} := 6$

HCM METHOD

Stage 1 Demand Adjustment Factors

Number of Scenarios:

$\text{DemandCombinationNum} := 60 \quad \text{ScenarioSetsNum} := 4$

$\text{TotalScenarioNum} := \text{DemandCombinationNum} \cdot \text{ScenarioSetsNum} = 240$

Figures (captions and numbers) in this document are screen shots from the TTR&ATDM software:

Specify Demand Pattern within the Year

	Month Group
January	1
February	2
March	3
April	4
May	5
June	6
July	7
August	8
September	9
October	10
November	11
December	12

Specify Demand Pattern within the Day

	Day Group	# Days/Year
Monday	1	52
Tuesday	2	52
Wednesday	3	52
Thursday	4	52
Friday	5	52
Saturday	0	52
Sunday	0	52

Although one weekday (Sun-Mon) will have one more day per year than the other weekdays, this impact on the analysis results is insignificant. Thus, the program uses an equal number of days per year in the calculations.

Figure 1. Demand Combination

Default Adjustment Factors:

$\text{CAF} := 1 \quad \text{SAF} := 1 \quad \text{DAF} := 1$

In this example, Saturday and Sunday are not involved in the calculation, so their group numbers are 0.

Demand Multipliers:

Column headers are weekdays:
Monday, Tuesday, Wednesday, Thursday and Friday.
Row headers are months:
Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec.

$$\text{DemandMultipliers} := \begin{pmatrix} 0.8220 & 0.8220 & 0.8390 & 0.8640 & 0.9650 \\ 0.8490 & 0.8490 & 0.8660 & 0.8920 & 0.9960 \\ 0.9210 & 0.9210 & 0.9390 & 0.9670 & 1.0800 \\ 0.9760 & 0.9760 & 0.9950 & 1.0250 & 1.1450 \\ 0.9740 & 0.9740 & 0.9930 & 1.0230 & 1.1420 \\ 1.0220 & 1.0220 & 1.0430 & 1.0740 & 1.1990 \\ 1.1330 & 1.1330 & 1.1560 & 1.1910 & 1.3290 \\ 1.0330 & 1.0330 & 1.0540 & 1.0850 & 1.2120 \\ 1.0630 & 1.0630 & 1.0850 & 1.1170 & 1.2480 \\ 0.9950 & 0.9950 & 1.0160 & 1.0460 & 1.1680 \\ 0.9950 & 0.9950 & 1.0160 & 1.0460 & 1.1680 \\ 0.9790 & 0.9790 & 0.9980 & 1.0280 & 1.1480 \end{pmatrix}$$

$\text{DemandMultiplierSeed} := 1.05$

Demand Adjustment Factors (Month, Weekday):

Column headers are weekdays:
Monday, Tuesday, Wednesday, Thursday and Friday.
Row headers are months:
Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec.

$$\text{DAFs} := \frac{\text{DemandMultipliers}}{\text{DemandMultiplierSeed}} =$$

	0	1	2	3	4
0	0.7829	0.7829	0.7990	0.8229	0.9190
1	0.8086	0.8086	0.8248	0.8495	0.9486
2	0.8771	0.8771	0.8943	0.9210	1.0286
3	0.9295	0.9295	0.9476	0.9762	1.0905
4	0.9276	0.9276	0.9457	0.9743	1.0876
5	0.9733	0.9733	0.9933	1.0229	1.1419
6	1.0790	1.0790	1.1010	1.1343	1.2657
7	0.9838	0.9838	1.0038	1.0333	1.1543
8	1.0124	1.0124	1.0333	1.0638	1.1886
9	0.9476	0.9476	0.9676	0.9962	1.1124
10	0.9476	0.9476	0.9676	0.9962	1.1124
11	0.9324	0.9324	0.9505	0.9790	1.0933

Scenario Probabilities:

Although one weekday (Sun-Mon) will have one more day per year than the other weekdays, this impact on the analysis results is insignificant. Thus, the program uses an equal number of days per year in the calculations.

$\text{NumOfDaysInDC} := 4$ $\qquad$ $\text{NumOfDaysInRRP} := 52 \cdot 5 = 260$

Scenario probability is the number of days in DC divided by the product of scenarios sets number and number of days in RRP:

$$\text{ScenarioProbability} := \frac{\text{NumOfDaysInDC}}{\text{ScenarioSetsNum} \cdot \text{NumOfDaysInRRP}} = 3.846 \times 10^{-3}$$

$$\text{DemandPatternProbability} := \frac{\text{NumOfDaysInDC}}{\text{NumOfDaysInRRP}} = 0.0154$$

	Demand Pattern Id	Probability (%)	Avg Demand Multiplier	Demand Adj. Factor
▸	1	1.54	0.822000	0.782857
	2	1.54	0.822000	0.782857
	3	1.54	0.839000	0.799048
	4	1.54	0.864000	0.822857
	5	1.54	0.965000	0.919048
	6	1.54	0.849000	0.808571
	7	1.54	0.849000	0.808571
	8	1.54	0.866000	0.824762

Figure 2. Probabilities and Calculated DAFs

Stage 2 Weather Adjustment Factors

Weather Probability (Month, Weather Category):

Column headers are weather categories:
Med Rain, Heavy Rain, Light Snow, Light Medium Snow, Medium Heavy Snow, Heavy Snow, Severe Cold, Low Visibility, Very Low Visibility, Min Visibility .
Row headers are months:
Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec.

$$\text{WeatherProbability} := \begin{pmatrix} 0.0080 & 0.0047 & 0.0091 & 0.0029 & 0.0004 & 0.0000 & 0.0000 & 0.0097 & 0.0000 & 0.0044 \\ 0.0080 & 0.0047 & 0.0091 & 0.0029 & 0.0004 & 0.0000 & 0.0000 & 0.0097 & 0.0000 & 0.0044 \\ 0.0101 & 0.0081 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0012 & 0.0000 & 0.0010 \\ 0.0101 & 0.0081 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0012 & 0.0000 & 0.0010 \\ 0.0101 & 0.0081 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0012 & 0.0000 & 0.0010 \\ 0.0071 & 0.0133 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0016 & 0.0000 & 0.0000 \\ 0.0071 & 0.0133 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0016 & 0.0000 & 0.0000 \\ 0.0071 & 0.0133 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0016 & 0.0000 & 0.0000 \\ 0.0086 & 0.0068 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0034 & 0.0000 & 0.0003 \\ 0.0086 & 0.0068 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0034 & 0.0000 & 0.0003 \\ 0.0086 & 0.0068 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0034 & 0.0000 & 0.0003 \\ 0.0080 & 0.0047 & 0.0091 & 0.0029 & 0.0004 & 0.0000 & 0.0000 & 0.0097 & 0.0000 & 0.0044 \end{pmatrix}$$

Weather duration, adjustment factors by weather category:

Column headers are weather categories:
Med Rain, Heavy Rain, Light Snow, Light Medium Snow, Medium Heavy Snow, Heavy Snow, Severe Cold, Low Visibility, Very Low Visibility, Min Visibility .

$$\text{DurationWea0} := (42.2 \;\; 33.7 \;\; 93.1 \;\; 33.4 \;\; 21.7 \;\; 7.3 \;\; 0.00 \;\; 76.2 \;\; 0.00 \;\; 145)\ \text{min}$$

Rounded into the nearest 15s:

$$\text{DurationWea} := (45 \;\; 30 \;\; 90 \;\; 30 \;\; 15 \;\; 15 \;\; 0.00 \;\; 75 \;\; 0.00 \;\; 150)\ \ \text{min}$$

$$\text{WeatherCaf} := (0.93 \;\; 0.86 \;\; 0.96 \;\; 0.94 \;\; 0.91 \;\; 0.78 \;\; 0.92 \;\; 0.90 \;\; 0.88 \;\; 0.90)$$

$$\text{WeatherSaf} := (0.95 \;\; 0.93 \;\; 0.92 \;\; 0.90 \;\; 0.88 \;\; 0.86 \;\; 0.95 \;\; 0.95 \;\; 0.94 \;\; 0.9)$$

$$\text{WeatherDaf} := (1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1)$$

Expected frequencies of each weather category by month:

$\text{SP} := 3\ \text{h}$ (Study Period) $\qquad$ $\text{Ns} := 20$ (Number of scenarios per month)

Expected frequencies are the product of weather probabilities of each month, study period and number of scenarios each month divided by the rounded weather duration:

$$\text{Nw} := \left| \begin{array}{l} \text{for } m \in 1..12 \\ \quad \text{for } w \in 1..10 \\ \quad \left| \begin{array}{l} F_{m-1,w-1} \leftarrow \text{round}\left(\dfrac{\text{WeatherProbability}_{m-1,w-1} \cdot \text{SP} \cdot \text{Ns}}{\dfrac{\text{DurationWea}_{0,w-1}}{60}}, 0 \right) \text{ if } \text{DurationWea}_{0,w-1} > 0 \\ F_{m-1,w-1} \leftarrow 0 \text{ if } \text{DurationWea}_{0,w-1} = 0 \end{array} \right. \\ F \end{array} \right.$$

Nw =

	0	1	2	3	4	5	6	7	8	9
0	1	1	0	0	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	0	0
4	1	1	0	0	0	0	0	0	0	0
5	1	2	0	0	0	0	0	0	0	0
6	1	2	0	0	0	0	0	0	0	0
7	1	2	0	0	0	0	0	0	0	0
8	1	1	0	0	0	0	0	0	0	0
9	1	1	0	0	0	0	0	0	0	0
10	1	1	0	0	0	0	0	0	0	0
11	1	1	0	0	0	0	0	0	0	0

	Normal Weather	Medium Rain	Heavy Rain	Light Snow	Light-Med Snow	Med-Heavy Snow	Heavy Snow	Severe Cold	Low Visibility	Very Low Visibility	Minimum Visibility	Total
January	...	1	1	0	0	0	0	0	0	0	0	2.000
February	...	1	1	0	0	0	0	0	0	0	0	2.000
March	...	1	1	0	0	0	0	0	0	0	0	2.000
April	...	1	1	0	0	0	0	0	0	0	0	2.000
May	...	1	1	0	0	0	0	0	0	0	0	2.000
June	...	1	2	0	0	0	0	0	0	0	0	3.000
July	...	1	2	0	0	0	0	0	0	0	0	3.000
August	...	1	2	0	0	0	0	0	0	0	0	3.000
September	...	1	1	0	0	0	0	0	0	0	0	2.000
October	...	1	1	0	0	0	0	0	0	0	0	2.000
November	...	1	1	0	0	0	0	0	0	0	0	2.000
December	...	1	1	0	0	0	0	0	0	0	0	2.000

Figure 3. Calculated Weather Frequencies

Group scenarios by month:

$$
\mathrm{ScenarioNumber(Month)} := \left|\begin{array}{l} \text{for } \mathrm{Month} \in 1..12 \\ \quad \left|\begin{array}{l} \mathrm{n0} \leftarrow 1 + (\mathrm{Month} - 1) \cdot 20 \\ \mathrm{n1} \leftarrow \mathrm{Month} \cdot 20 \\ \text{for } \mathrm{scenario} \in \mathrm{n0}..\mathrm{n1} \\ \quad s_{\mathrm{scenario}-1} \leftarrow \mathrm{scenario} \\ \mathrm{ScenarioGroup} \leftarrow s \end{array}\right. \\ \mathrm{ScenarioGroup} \end{array}\right.
$$

In this case, each month has 20 scenarios, with a total of 240 scenarios.

Random assign scenario number and start time to weather events on a monthly basis:

Example Calculation (January, 8 weather events calculated above):

$\mathrm{NumEvents} := 8 \qquad \mathrm{Month} := 1$

$\mathrm{FirstScenarioNum} := \mathrm{ScenarioNumber(Month)}_0 = 1$

$\mathrm{LastScenarioNum} := \mathrm{ScenarioNumber(Month)}_{19} = 20$

$\mathrm{RndScenarioNumbers(NumEvents)} := \mathrm{round(runif(NumEvents, FirstScenarioNum, LastScenarioNum), 0)}$

$\mathrm{RndScenarioNumbers(NumEvents)}^T = (1 \ \ 5 \ \ 12 \ \ 8 \ \ 17 \ \ 4 \ \ 14 \ \ 7)$

$\mathrm{FirstTimePeriod} := 1 \qquad \mathrm{LastTimePeriod} := 12$ (In this example we have 12 analysis periods)

$\mathrm{RndStartTime(NumEvents)} := \mathrm{round(runif(NumEvents, FirstTimePeriod, LastTimePeriod), 0)}$

$\mathrm{RndStartTime(NumEvents)}^T = (2 \ \ 3 \ \ 12 \ \ 2 \ \ 1 \ \ 7 \ \ 8 \ \ 3)$

Check overlap (example calculation):

WeatherEvent #	Month	WeatherType	Duration (h)	SAF	CAF	AssignedScenario #	StartAP
1	January	Med Rain	0.75	1	1	9	17
2	January	Med Rain	0.75	1	1	5	11
3	January	Med Rain	0.75	1	1	2	8
4	January	Light Snow	1.5	1	1	19	2
5	January	Light Snow	1.5	1	1	7	1
6	January	Light Snow	1.5	1	1	11	6
7	January	Light Snow	1.5	1	1	3	11
8	January	Light Snow	1.5	1	1	11	11

Weather event 6 and weather event 8 are assigned with the same scenario number, we need to check if there is any temporal overlap for these two events. If there is overlap, reassign the scenario number and startAP to the current event; else, move on assigning the next weather event.

$\mathrm{WeatherStartAP6} := 6 \qquad \mathrm{WeatherStartAP8} := 11 \qquad \mathrm{WeatherDuration} := 1.5$ h (Light Snow)

$$\mathrm{TimePeriendDifference} := \left|\mathrm{WeatherStartAP6} - \mathrm{WeatherStartAP8}\right| \cdot \frac{15}{60} = 1.25$$

$$\mathrm{IfOverlap} := \left| \begin{array}{l} \mathrm{out} \leftarrow 0 \ \ \text{if } \ \mathrm{TimePeriendDifference} \geq \mathrm{WeatherDuration} \\ \mathrm{out} \leftarrow 1 \ \ \text{if } \ \mathrm{TimePeriendDifference} < \mathrm{WeatherDuration} \end{array} \right.$$

$\mathrm{IfOverlap} = 1$ (0 = No, 1 = Yes) Reassign scenario number and startAP to weather event 8.

List of Weather Events (HCM)

Weather Event #	Associated Month in RRP	Weather Event	Assigned Scenario #	Start Time Period	Duration in TP's	End Time Period	SAF	CAF
1	January	Medium Rain	5	2	3	5	0.95	0.9300
2	January	Heavy Rain	10	11	2	13	0.93	0.8600
3	February	Medium Rain	34	6	3	9	0.95	0.9300
4	February	Heavy Rain	28	13	2	15	0.93	0.8600
5	March	Medium Rain	43	9	3	12	0.95	0.9300
6	March	Heavy Rain	41	4	2	6	0.93	0.8600
7	April	Medium Rain	67	13	3	16	0.95	0.9300
8	April	Heavy Rain	74	9	2	11	0.93	0.8600
9	May	Medium Rain	86	8	3	11	0.95	0.9300
10	May	Heavy Rain	95	10	2	12	0.93	0.8600
11	June	Medium Rain	119	2	3	5	0.95	0.9300
12	June	Heavy Rain	104	5	2	7	0.93	0.8600
13	June	Heavy Rain	116	3	2	5	0.93	0.8600
14	July	Medium Rain	136	4	3	7	0.95	0.9300
15	July	Heavy Rain	137	12	2	14	0.93	0.8600
16	July	Heavy Rain	132	10	2	12	0.93	0.8600
17	August	Medium Rain	154	1	3	4	0.95	0.9300
18	August	Heavy Rain	160	11	2	13	0.93	0.8600
19	August	Heavy Rain	158	1	2	3	0.93	0.8600
20	September	Medium Rain	171	7	3	10	0.95	0.9300
21	September	Heavy Rain	166	13	2	15	0.93	0.8600
22	October	Medium Rain	194	6	3	9	0.95	0.9300
23	October	Heavy Rain	189	9	2	11	0.93	0.8600
24	November	Medium Rain	214	7	3	10	0.95	0.9300
25	November	Heavy Rain	205	5	2	7	0.93	0.8600
26	December	Medium Rain	231	3	3	6	0.95	0.9300
27	December	Heavy Rain	227	9	2	11	0.93	0.8600

Figure 4. Weather Event List

Stage 3 Incident Adjustment Factors

Expected incident frequencies per study period for each month:

$IncidentRate := 1050$ (per 100 MVMT for month j) $VMTseed := 71501$ (Vehicle miles traveled)

Incident frequency is the product of incident rate of that month, average demand multiplier for that month, and the seed file VMT:

$$
N\_I := \left|
\begin{array}{l}
\text{for } month \in 1..12 \\
\quad \left|
\begin{array}{l}
SumDM \leftarrow 0 \\
\text{for } day \in 1..5 \\
\quad SumDM \leftarrow SumDM + DAFs_{month-1,\,day-1} \\
n_{month-1} \leftarrow IncidentRate \cdot 10^{-8} \dfrac{SumDM}{5} \cdot VMTseed
\end{array}
\right. \\
n
\end{array}
\right.
$$

	Month	IncidentFrequencies
▶	January	0.6166
	February	0.6366
	March	0.6904
	April	0.7317
	May	0.7302
	June	0.7665
	July	0.8497
	August	0.7746
	September	0.7974
	October	0.7465
	November	0.7465
	December	0.7339

$N\_I =$

	0
0	0.6166
1	0.6366
2	0.6904
3	0.7317
4	0.7302
5	0.7665
6	0.8497
7	0.7746
8	0.7974
9	0.7465
10	0.7465
11	0.7339

Row headers are months: Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec.

Figure 5. Calculated Incident Frequencies

Number of scenarios with k incidents (example calculation for January):

$NumOfScenariosJanuary := 20$

Incident Frequency of January: $N\_I_0 = 0.6166$

The frequency of incidents for a set of monthly scenarios can be computed that follows the Poisson distribution:

$$P(k) := \frac{(N\_I_0)^k}{k!} \cdot e^{-N\_I_0} \qquad k := 0..8 \qquad P(k) =$$

0.5398
0.3328
0.1026
0.0211
0.0033
0.0004
0.0000
0.0000
0.0000

Row headers are the number of incidents k: from 0 to 8.

Specify a rounding parameter δ to make the sum to be exactly 20 (the number of scenarios for January):

$$\delta := 1.005 \qquad \text{Sum} := \left| \begin{array}{l} \text{for } k \in 0..8 \\ \quad \text{sum} \leftarrow \text{sum} + \text{round}(\delta \cdot P(k) \cdot \text{NumOfScenariosJanuary}, 0) \\ \text{sum} \end{array} \right. \qquad \text{Sum} = 20$$

The number of scenarios that are assigned with k incidents for January:

$$\text{round}(\delta \cdot P(k) \cdot \text{NumOfScenariosJanuary}, 0) =$$

11
7
2
0
0
0
0
0
0

(Row headers are the number of incidents k: from 0 to 8)

Generate total number of incidents:

$$\text{SumOfIncidentsJanuary} := \left| \begin{array}{l} \text{for } k \in 0..8 \\ \quad \text{sum} \leftarrow \text{sum} + k \cdot \text{round}(\delta \cdot P(k) \cdot \text{NumOfScenariosJanuary}, 0) \\ \text{sum} \end{array} \right.$$

$$\text{SumOfIncidentsJanuary} = 11$$

Randomly assign scenario numbers to the generated incident frequencies:

$$\text{Month} = 1$$

Scenario numbers with 1 incident: Scenario numbers with 2 incident:

$$\mathrm{RndScenarioNumbers}(7) = \begin{pmatrix} 10 \\ 2 \\ 16 \\ 11 \\ 18 \\ 19 \\ 11 \end{pmatrix} \qquad \mathrm{RndScenarioNumbers}(2) = \begin{pmatrix} 10 \\ 17 \end{pmatrix}$$

Do this for every month, then we will have a list of incident events generated (in this example we have a total number of 180 incident events with randomly assigned sceanrio numbers):

List of Incident Events (HCM)

Incident #	Scenario #	Severity Type	Start Time Period	Duration in TP's	End Time Period	Location Segment #	SAF	CAF
1	7	OneLaneClosure	5	3	8	7	1.000	0.490
2	8	ShoulderClosure	10	1	11	9	1.000	0.830
3	13	TwoLaneClosure	7	3	10	4	1.000	0.170
4	20	TwoLaneClosure	12	4	16	10	1.000	0.170
5	15	OneLaneClosure	8	4	12	7	1.000	0.490
6	18	ShoulderClosure	2	4	6	10	1.000	0.830
7	10	ShoulderClosure	8	1	9	11	1.000	0.830
8	4	OneLaneClosure	8	4	12	3	1.000	0.490
9	15	OneLaneClosure	7	1	8	4	1.000	0.490
10	4	OneLaneClosure	1	4	5	8	1.000	0.490
11	15	ShoulderClosure	4	3	7	7	1.000	0.830
12	25	ShoulderClosure	2	3	5	2	1.000	0.830
13	24	OneLaneClosure	11	1	12	8	1.000	0.490
14	29	ShoulderClosure	1	4	5	8	1.000	0.830
15	26	OneLaneClosure	6	2	8	7	1.000	0.490
16	32	TwoLaneClosure	6	3	9	8	1.000	0.170
17	22	ShoulderClosure	9	2	11	9	1.000	0.830
18	33	ShoulderClosure	3	4	7	2	1.000	0.830
19	37	TwoLaneClosure	11	2	13	8	1.000	0.170
20	38	TwoLaneClosure	2	2	4	7	1.000	0.170
21	37	OneLaneClosure	4	4	8	4	1.000	0.490
22	38	OneLaneClosure	4	2	6	5	1.000	0.490
23	53	TwoLaneClosure	2	2	4	4	1.000	0.170
24	56	TwoLaneClosure	7	4	11	7	1.000	0.170
25	57	OneLaneClosure	2	1	3	4	1.000	0.490
26	46	OneLaneClosure	11	4	15	1	1.000	0.490
27	43	TwoLaneClosure	2	2	4	8	1.000	0.170
28	60	ShoulderClosure	4	1	5	6	1.000	0.830

Figure 6. Incident Event List

$\mathrm{Nt} := 180$ (Total number of incidents generated)

Incident Severities Distribution:

$\mathrm{Shoulder} := 0 \quad \mathrm{OneLane} := 1 \quad \mathrm{TwoLane} := 2 \quad \mathrm{ThreeLane} := 3 \quad \mathrm{FourOrMoreLanes} := 4$

Incident severities distribution probabilities:

$$D(\text{IncidentType}) := \begin{cases} 0.75 & \text{if IncidentType} = 0 \\ 0.20 & \text{if IncidentType} = 1 \\ 0.05 & \text{if IncidentType} = 2 \\ 0 & \text{if IncidentType} = 3 \\ 0 & \text{if IncidentType} = 4 \end{cases}$$

(The example facility has three lanes in one direction, so the incident type is not feasible to be more than two lane closure)

$\gamma := 1$ (rounding parameter)

$$\text{IncidentDistributionSum} := \left| \begin{array}{l} \text{for IncidentType} \in 0..4 \\ \quad \text{sum} \leftarrow \text{sum} + \gamma \cdot (\text{round}(\text{Nt} \cdot D(\text{IncidentType}), 0)) \\ \text{sum} \end{array} \right.$$

$\text{IncidentDistributionSum} = 180$

$\text{IncidentType} := 0..4$ $\qquad \gamma \cdot (\text{round}(\text{Nt} \cdot D(\text{IncidentType}), 0)) =$

135
36
9
0
0

Incident duration distribution parameters:

$$\text{Range}(\text{IncidentType}) := \begin{cases} (8.7..58) & \text{if IncidentType} = 0 \\ (16..58.2) & \text{if IncidentType} = 1 \\ (30.5..66.9) & \text{if IncidentType} = 2 \\ (36..93.3) & \text{if IncidentType} = 3 \end{cases}$$

$$\text{Average}(\text{IncidentType}) := \begin{cases} 34 & \text{if IncidentType} = 0 \\ 34.6 & \text{if IncidentType} = 1 \\ 53.6 & \text{if IncidentType} = 2 \\ 69.6 & \text{if IncidentType} = 3 \\ 69.6 & \text{if IncidentType} = 4 \end{cases}$$

$$\text{StdDev}(\text{IncidentType}) := \begin{cases} 15.1 & \text{if IncidentType} = 0 \\ 13.8 & \text{if IncidentType} = 1 \\ 13.9 & \text{if IncidentType} = 2 \\ 21.9 & \text{if IncidentType} = 3 \\ 21.9 & \text{if IncidentType} = 4 \end{cases}$$

Default adjustment factors (two lanes one direction):

$\text{IncidentCaf} := (0.81 \;\; 0.35 \;\; 0.00 \;\; 0.00 \;\; 0.00)$ $\qquad \text{IncidentSaf} := (1.00 \;\; 1.00 \;\; 1.00 \;\; 1.00 \;\; 1.00)$

$\text{IncidentDaf} := (1.00 \;\; 1.00 \;\; 1.00 \;\; 1.00 \;\; 1.00)$

Generate incident durations by incident severity (example calculation of shoulder closure durations distribution):

$$\text{ShoulderClosureNumber} := \gamma \cdot (\text{round}(\text{Nt} \cdot \text{D(Shoulder)}, 0)) = 135$$

$$\text{ProbabilitySum} := \left| \begin{array}{l} \text{for Duration} \in 15, 30 .. 60 \\ \quad \text{SumPro} \leftarrow \text{SumPro} + \text{dnorm(Duration, Average(Shoulder), StdDev(Shoulder))} \\ \text{SumPro} \end{array} \right.$$

The duration for each incident severity type follows a lognormal distribution, using the average duration and stand deviation as parameters.

$$\text{DurationDistribution} := \left| \begin{array}{l} \text{for Duration} \in 15, 30 .. 60 \\ \quad \text{pro}_{\left(\frac{\text{Duration}}{15} - 1\right)} \leftarrow \dfrac{\text{dnorm(Duration, Average(Shoulder), StdDev(Shoulder))}}{\text{ProbabilitySum}} \\ \text{pro} \end{array} \right.$$

$$\text{DurationDistribution}^{T} = \begin{pmatrix} 0.188 & 0.4 & 0.318 & 0.094 \end{pmatrix}$$

$$\text{DurationDistributionNumber} := \text{round(DurationDistribution} \cdot \text{ShoulderClosureNumber}, 0) = \begin{pmatrix} 25 \\ 54 \\ 43 \\ 13 \end{pmatrix}$$

Do this to all incident types, we will get the incident duration distributions by incident type.

Generate incident start times and locations based on VMT (12 time periods, 11 segments):

$$\text{VMT1(TimePeriod)} := \left| \begin{array}{l} 5081 \text{ if TimePeriod} = 1 \\ 6022 \text{ if TimePeriod} = 2 \\ 6948 \text{ if TimePeriod} = 3 \\ 7196 \text{ if TimePeriod} = 4 \\ 7895 \text{ if TimePeriod} = 5 \\ 8504 \text{ if TimePeriod} = 6 \\ 7353 \text{ if TimePeriod} = 7 \\ 5778 \text{ if TimePeriod} = 8 \\ 5059 \text{ if TimePeriod} = 9 \\ 4308 \text{ if TimePeriod} = 10 \\ 3783 \text{ if TimePeriod} = 11 \\ 3793 \text{ if TimePeriod} = 12 \end{array} \right.$$

$$\text{VMT1Sum} := \left| \begin{array}{l} \text{for TimePeriod} \in 1 .. 12 \\ \quad \text{Sum} \leftarrow \text{Sum} + \text{VMT1(TimePeriod)} \\ \text{Sum} \end{array} \right.$$

$$\text{VMT1Sum} = 7.174 \times 10^{4}$$

Distribution of incident startAPs:

$$\text{ProbabilityStartAP} := \left| \begin{array}{l} \text{for } \ \text{TimePeriod} \in 1..12 \\ \quad \text{Probability1}_{(\text{TimePeriod}-1)} \leftarrow \dfrac{\text{VMT1(TimePeriod)}}{\text{VMT1Sum}} \\ \text{Probability1} \end{array} \right.$$

ProbabilityStartAP =

	0
0	0.0708
1	0.0839
2	0.0968
3	0.1003
4	0.1101
5	0.1185
6	0.1025
7	0.0805
8	0.0705
9	0.0601
10	0.0527
11	0.0529

(Row headers are time periods: 1 to 12)

Rounding parameter: $\alpha := 1.0022$

$$\text{NumberOfStartAP} := \left| \begin{array}{l} \text{for } \ \text{TimePeriod} \in 1..12 \\ \quad \text{Number1}_{(\text{TimePeriod}-1)} \leftarrow \text{round}\left(\alpha \cdot \dfrac{\text{VMT1(TimePeriod)}}{\text{VMT1Sum}} \cdot \text{Nt}, 0\right) \\ \text{Number1} \end{array} \right.$$

NumberOfStartAP =

	0
0	13
1	15
2	17
3	18
4	20
5	21
6	18
7	15
8	13
9	11
10	10
11	10

Distribution of incident locations:

$$
\mathrm{VMT2(Segment)} := \begin{array}{|l}
11248 \ \text{ if } \ \mathrm{Segment} = 1 \\
3470 \ \text{ if } \ \mathrm{Segment} = 2 \\
5275 \ \text{ if } \ \mathrm{Segment} = 3 \\
3468 \ \text{ if } \ \mathrm{Segment} = 4 \\
11424 \ \text{ if } \ \mathrm{Segment} = 5 \\
6285 \ \text{ if } \ \mathrm{Segment} = 6 \\
11856 \ \text{ if } \ \mathrm{Segment} = 7 \\
2788 \ \text{ if } \ \mathrm{Segment} = 8 \\
880 \ \text{ if } \ \mathrm{Segment} = 9 \\
2788 \ \text{ if } \ \mathrm{Segment} = 10 \\
12238 \ \text{ if } \ \mathrm{Segment} = 11
\end{array}
$$

$$
\mathrm{VMT2Sum} := \begin{array}{|l}
\text{for } \ \mathrm{Segment} \in 1..11 \\
\quad \mathrm{Sum} \leftarrow \mathrm{Sum} + \mathrm{VMT2(Segment)} \\
\mathrm{Sum}
\end{array}
\qquad \mathrm{VMT2Sum} = 7.174 \times 10^{4}
$$

$$
\mathrm{ProbabilityLocation} := \begin{array}{|l}
\text{for } \ \mathrm{Segment} \in 1..11 \\
\quad \mathrm{Probability2}_{(\mathrm{Segment}-1)} \leftarrow \dfrac{\mathrm{VMT2(Segment)}}{\mathrm{VMT2Sum}} \\
\mathrm{Probability2}
\end{array}
$$

ProbabilityLocation =

	0
0	0.1568
1	0.0484
2	0.0735
3	0.0483
4	0.1592
5	0.0876
6	0.1653
7	0.0389
8	0.0123
9	0.0389
10	0.1706

Rounding parameter: $\beta := 1$

$$
\mathrm{NumberOfLocation} := \begin{array}{|l}
\text{for } \ \mathrm{Segment} \in 1..11 \\
\quad \mathrm{Number1}_{(\mathrm{Segment}-1)} \leftarrow \mathrm{round}\left(\beta \cdot \dfrac{\mathrm{VMT2(Segment)}}{\mathrm{VMT2Sum}} \cdot \mathrm{Nt}, 0\right) \\
\mathrm{Number1}
\end{array}
$$

$$\text{NumberOfLocation} = \begin{array}{|c|r|} \hline & 0 \\ \hline 0 & 28 \\ \hline 1 & 9 \\ \hline 2 & 13 \\ \hline 3 & 9 \\ \hline 4 & 29 \\ \hline 5 & 16 \\ \hline 6 & 30 \\ \hline 7 & 7 \\ \hline 8 & 2 \\ \hline 9 & 7 \\ \hline 10 & 31 \\ \hline \end{array}$$

Check overlap (temporal and spatial):

Example incident event list:

Inc. #	Scenario #	Severity Type	Staring AP	Duration (min)	Location Segment #
1	8	Shoulder Closure	12	15	4
2	9	Shoulder Closure	10	60	7
3	2	One Lane Closure	7	45	9
4	2	Shoulder Closure	12	30	5
5	15	Shoulder Closure	12	15	1
6	15	One Lane Closure	1	45	1
7	16	Shoulder Closure	11	15	7
8	16	Two Lanes Closure	12	60	8
9	3	Shoulder Closure	10	60	4
10	3	Shoulder Closure	12	15	5
11	10	Shoulder Closure	17	30	2
12	10	One Lane Closure	7	45	1
...	...	...	...	...	...
920	240	Shoulder Closure	9	45	11

When doing the incident event assignment for incident event 6, as we can see that the scenario number is 15, which is the same as the assigned scenario number for weather event 5, and the location for both incident 5 and 6 is segment 1, then we check if there is any temporal overlap for these two events:

For the same scenario and same location:

$$\text{IncidentStartAP5} := 12 \qquad \text{IncidentStartAP6} := 1 \qquad \text{IncidentDuration} := \frac{45}{60} = 0.75 \quad \text{h}$$

$$\text{TimeDifference} := \left|\text{IncidentStartAP5} - \text{IncidentStartAP6}\right| \cdot \frac{15}{60} = 2.75$$

$$\text{CheckOverlap} := \left| \begin{array}{l} \text{out} \leftarrow 0 \quad \text{if TimeDifference} \geq \text{IncidentDuration} \\ \text{out} \leftarrow 1 \quad \text{if TimeDifference} < \text{IncidentDuration} \end{array} \right.$$

$\text{CheckOverlap} = 0$ (0 = No, 1 = Yes)

If there is overlap, reassign the startAP and location segment to the current event; else, move on assigning the next incident event.

Stage 4 Scenario List

Loop through all scenario numbers (1-240), assign the relative demand information (probability and DAF), weather event information (weather type, duration, SAF, CAF and startAP), incident event information (severity type, duration, SAF, CAF, startAP, and location) to each scenario.

For example, one scenario (Monday, January with medium rain and shoulder closure):

Demand information:

$$\text{ScenarioProbability} = 3.846 \times 10^{-3} \qquad \text{Daf} := \frac{\text{DemandMultipliers}_{0,0}}{\text{DemandMultiplierSeed}} = 0.7829$$

Weather event information:

$$\text{MediumRain} := 0 \qquad \text{DurationWea}^{\langle \text{MediumRain} \rangle} = (45) \quad \text{min}$$

$$\text{WeatherCaf}^{\langle \text{MediumRain} \rangle} = (0.93) \qquad \text{WeatherSaf}^{\langle \text{MediumRain} \rangle} = (0.95)$$

$$\text{WeatherStartAP} := \text{round}(\text{runif}(1,1,12),0) = (10)$$

$$\text{WeatherEndAP} := \text{WeatherStartAP} + \text{round}\left(\frac{\text{DurationWea}^{\langle \text{MediumRain} \rangle}}{15}, 0\right) = (13)$$

Incident event information:

$$\text{ShoulderClosureDuration} := \text{Average}(\text{Shoulder}) = 34 \quad \text{min} \qquad \text{IncidentCaf}^{\langle \text{Shoulder} \rangle} = (0.81)$$

$$\text{IncidentStartAP} := \text{round}(\text{runif}(1,1,12),0) = (12)$$

$$\text{IncidentEndAP} := \text{IncidentStartAP} + \text{round}\left(\frac{\text{ShoulderClosureDuration}}{15}, 0\right) = (14)$$

$$\text{IncidentLocation} := \text{round}(\text{runif}(1,1,11),0) = (7)$$

OVERALL RESULTS CALCULATION

Example Calculation (Time period results of the 2 scenarios calculated from HCMCALC_FreewayFacility):

Scenario resutls matrix: (column headers are travel time, TTI, VMT (demand), VMT (volume), VHT, VHD, average speed, density (veh), density (pc) and the last column is the time period probability.

$$\text{Results} := \begin{pmatrix}
6.73 & 1.04 & 4660.98 & 4660.98 & 69.05 & 2.47 & 67.5 & 12.15 & 12.46 & 0.00109375 \\
6.74 & 1.04 & 5126.89 & 5126.89 & 76.03 & 2.79 & 67.43 & 13.38 & 13.72 & 0.00109375 \\
6.74 & 1.04 & 5639.2 & 5639.2 & 83.72 & 3.16 & 67.36 & 14.74 & 15.1 & 0.00109375 \\
6.75 & 1.04 & 6199.81 & 6199.81 & 92.18 & 3.61 & 67.26 & 16.22 & 16.63 & 0.00109375 \\
6.77 & 1.04 & 6826.14 & 6826.14 & 101.7 & 4.18 & 67.12 & 17.9 & 18.35 & 0.00109375 \\
6.79 & 1.05 & 7504.73 & 7504.73 & 112.17 & 4.96 & 66.91 & 19.74 & 20.23 & 0.00109375 \\
6.84 & 1.05 & 8249.05 & 8249.05 & 124.21 & 6.36 & 66.41 & 21.86 & 22.41 & 0.00109375 \\
6.93 & 1.07 & 9088.07 & 9088.07 & 138.69 & 8.86 & 65.53 & 24.41 & 25.02 & 0.00109375 \\
6.83 & 1.05 & 8175.19 & 8175.19 & 122.98 & 6.19 & 66.48 & 21.64 & 22.18 & 0.00109375 \\
6.78 & 1.04 & 7363.64 & 7363.64 & 109.96 & 4.76 & 66.97 & 19.35 & 19.84 & 0.00109375 \\
6.76 & 1.04 & 6623.11 & 6623.11 & 98.6 & 3.99 & 67.17 & 17.35 & 17.79 & 0.00109375 \\
6.75 & 1.04 & 5965.91 & 5965.91 & 88.64 & 3.42 & 67.3 & 15.6 & 15.99 & 0.00109375 \\
6.74 & 1.04 & 5364.96 & 5364.96 & 79.6 & 2.96 & 67.4 & 14.01 & 14.36 & 0.00109375 \\
6.73 & 1.04 & 4827.65 & 4827.65 & 71.55 & 2.58 & 67.48 & 12.59 & 12.91 & 0.00109375 \\
6.73 & 1.04 & 4343.75 & 4343.75 & 64.31 & 2.25 & 67.55 & 11.32 & 11.6 & 0.00109375 \\
6.72 & 1.03 & 3910.98 & 3910.98 & 57.85 & 1.98 & 67.6 & 10.18 & 10.44 & 0.00109375 \\
6.73 & 1.04 & 5018.94 & 5018.94 & 74.39 & 2.69 & 67.47 & 13.09 & 13.42 & 0.0021875 \\
6.74 & 1.04 & 5520.83 & 5520.83 & 81.91 & 3.05 & 67.4 & 14.42 & 14.78 & 0.0021875 \\
6.75 & 1.04 & 6072.92 & 6072.92 & 90.23 & 3.47 & 67.31 & 15.88 & 16.28 & 0.0021875 \\
6.76 & 1.04 & 6675.19 & 6675.19 & 99.35 & 4 & 67.19 & 17.49 & 17.92 & 0.0021875 \\
6.78 & 1.04 & 7350.76 & 7350.76 & 109.71 & 4.7 & 67 & 19.31 & 19.79 & 0.0021875 \\
6.82 & 1.05 & 8080.49 & 8080.49 & 121.36 & 5.92 & 66.58 & 21.36 & 21.89 & 0.0021875 \\
6.9 & 1.06 & 8883.52 & 8883.52 & 135 & 8.1 & 65.8 & 23.76 & 24.35 & 0.0021875 \\
7.03 & 1.08 & 9786.93 & 9786.93 & 151.57 & 11.76 & 64.57 & 26.68 & 27.34 & 0.0021875 \\
6.89 & 1.06 & 8803.98 & 8803.98 & 133.61 & 7.84 & 65.89 & 23.52 & 24.1 & 0.0021875 \\
6.81 & 1.05 & 7929.92 & 7929.92 & 118.89 & 5.61 & 66.7 & 20.93 & 21.45 & 0.0021875 \\
6.77 & 1.04 & 7132.58 & 7132.58 & 106.34 & 4.45 & 67.07 & 18.72 & 19.18 & 0.0021875 \\
6.76 & 1.04 & 6424.24 & 6424.24 & 95.55 & 3.77 & 67.24 & 16.82 & 17.24 & 0.0021875 \\
6.74 & 1.04 & 5775.95 & 5775.95 & 85.75 & 3.23 & 67.36 & 15.09 & 15.47 & 0.0021875 \\
6.74 & 1.04 & 5198.86 & 5198.86 & 77.08 & 2.81 & 67.44 & 13.57 & 13.91 & 0.0021875 \\
6.73 & 1.04 & 4677.08 & 4677.08 & 69.27 & 2.45 & 67.52 & 12.19 & 12.5 & 0.0021875 \\
6.72 & 1.04 & 4210.23 & 4210.23 & 62.3 & 2.15 & 67.58 & 10.96 & 11.24 & 0.0021875
\end{pmatrix}$$

Consideration of the length of this document, this example calculate the time period results of 2 scenarios, each scenario has 16 time periods, so a total of 32 time period results are calculated to obtain the overall results. Screen shot of the overall results from the software based on the same 2 scenarios is also attached for comparison.

Number of sceanrio results: $Ns := 16 \cdot 2 = 32$ $\quad$ $FreeFlowTravelTime := 6.49\ min$

Sum of scenario probabilities:

$$Sp := \left| \begin{array}{l} \text{for } n \in 0..Ns-1 \\ \quad sum \leftarrow sum + Results_{n,9} \\ sum \end{array} \right. \qquad Sp = 0.053$$

Calculate Overall Results (loop through all scenario results for each time period):

$$OverallMin := \left| \begin{array}{l} \text{for } MOE \in 0..8 \\ \quad \left| \begin{array}{l} min \leftarrow e^{100} \\ \text{for } Num \in 0..Ns-1 \\ \quad min \leftarrow Results_{Num,MOE} \ \text{ if } Results_{Num,MOE} < min \\ Min_{MOE} \leftarrow min \end{array} \right. \\ Min \end{array} \right.$$

$$OverallMin^T = \begin{pmatrix} 6.72 & 1.03 & 3.911 \times 10^3 & 3.911 \times 10^3 & 57.85 & 1.98 & 64.57 & 10.18 & 10.44 \end{pmatrix}$$

$$OverallMax := \left| \begin{array}{l} \text{for } MOE \in 0..8 \\ \quad Max_{MOE} \leftarrow max\left(Results^{\langle MOE \rangle}\right) \\ Max \end{array} \right.$$

$$OverallMax^T = \begin{pmatrix} 7.03 & 1.08 & 9.787 \times 10^3 & 9.787 \times 10^3 & 151.57 & 11.76 & 67.6 & 26.68 & 27.34 \end{pmatrix}$$

$$OverallMean := \left| \begin{array}{l} \text{for } MOE \in 0..8 \\ \quad \left| \begin{array}{l} sum \leftarrow 0 \\ \text{for } n \in 0..Ns-1 \\ \quad sum \leftarrow sum + Results_{n,MOE} \cdot Results_{n,9} \\ Average_{MOE} \leftarrow \dfrac{sum}{Sp} \end{array} \right. \\ Average \end{array} \right.$$

$$OverallMean^T = \begin{pmatrix} 6.785 & 1.045 & 6.562 \times 10^3 & 6.562 \times 10^3 & 98.247 & 4.511 & 66.952 & 17.292 & 17.724 \end{pmatrix}$$

Order the time period results for each MOE from small to large:

$$\text{ResultSorted} := \left| \begin{array}{l} \text{for } \ \text{MOE} \in 0..8 \\ \quad \text{result}_{\text{MOE}} \leftarrow \text{sort}\left(\text{Results}^{\langle \text{MOE} \rangle}\right) \\ \text{result} \end{array} \right.$$

The probability is tied with each time period, the Probability1 is the list of probabilities for the sorted time period results for all MOEs except the average speed, Probability2 is the list of probabilities for the sorted time period results for average speed:

$$\text{Probability1} := \begin{pmatrix} 0.0011 \\ 0.0022 \\ 0.0011 \\ 0.0011 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0011 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0011 \\ 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0022 \end{pmatrix} \qquad \text{Probability2} := \text{reverse}(\text{Probability1}) = \begin{pmatrix} 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0022 \\ 0.0011 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0011 \\ 0.0011 \\ 0.0022 \\ 0.0022 \\ 0.0011 \\ 0.0011 \\ 0.0011 \\ 0.0022 \\ 0.0011 \end{pmatrix}$$

```
FiftyPercent :=  | for  MOE ∈ 0,1,2,3,4,5,7,8
                 |   | sum ← 0
                 |   | for  n ∈ 0..31
                 |   |   | sum ← sum + Probability1_n / Sp
                 |   |   | index ← n + 1  if  sum < 0.5
                 |   | FiftyPercent_MOE ← (ResultSorted_MOE)_index
                 | for  MOE ∈ 6
                 |   | sum ← 0
                 |   | for  n ∈ 0..31
                 |   |   | sum ← sum + Probability2_n / Sp
                 |   |   | index ← n + 1  if  sum < 0.5
                 |   | FiftyPercent_MOE ← (ResultSorted_MOE)_index
                 | FiftyPercent
```

$\text{FiftyPercent}^T = (6.76 \quad 1.04 \quad 6424.24 \quad 6424.24 \quad 95.55 \quad 3.77 \quad 67.19 \quad 16.82 \quad 17.24)$

```
EightyPercent :=  | for  MOE ∈ 0,1,2,3,4,5,7,8
                  |   | sum ← 0
                  |   | for  n ∈ 0..31
                  |   |   | sum ← sum + Probability1_n / Sp
                  |   |   | index ← n + 1  if  sum < 0.8
                  |   | EightyPercent_MOE ← (ResultSorted_MOE)_index
                  | for  MOE ∈ 6
                  |   | sum ← 0
                  |   | for  n ∈ 0..31
                  |   |   | sum ← sum + Probability2_n / Sp
                  |   |   | index ← n + 1  if  sum < 0.8
                  |   | EightyPercent_MOE ← (ResultSorted_MOE)_index
                  | EightyPercent
```

$\text{EightyPercent}^T = \left(6.82 \quad 1.05 \quad 8.08 \times 10^3 \quad 8.08 \times 10^3 \quad 121.36 \quad 5.92 \quad 67.47 \quad 21.36 \quad 21.89\right)$

$$\text{NinetyFivePercent} := \left|\begin{array}{l} \text{for } MOE \in 0,1,2,3,4,5,7,8 \\ \quad \left|\begin{array}{l} sum \leftarrow 0 \\ \text{for } n \in 0..31 \\ \quad \left|\begin{array}{l} sum \leftarrow sum + \dfrac{\text{Probability1}_n}{Sp} \\ index \leftarrow n+1 \ \text{ if } \ sum < 0.95 \end{array}\right. \\ \text{EightyPercent}_{MOE} \leftarrow \left(\text{ResultSorted}_{MOE}\right)_{index} \end{array}\right. \\ \text{for } MOE \in 6 \\ \quad \left|\begin{array}{l} sum \leftarrow 0 \\ \text{for } n \in 0..31 \\ \quad \left|\begin{array}{l} sum \leftarrow sum + \dfrac{\text{Probability2}_n}{Sp} \\ index \leftarrow n+1 \ \text{ if } \ sum < 0.95 \end{array}\right. \\ \text{EightyPercent}_{MOE} \leftarrow \left(\text{ResultSorted}_{MOE}\right)_{index} \end{array}\right. \\ \text{EightyPercent} \end{array}\right.$$

$$\text{NinetyFivePercent}^{T} = \left(6.93 \quad 1.07 \quad 9.088\times10^{3} \quad 9.088\times10^{3} \quad 138.69 \quad 8.86 \quad 67.58 \quad 24.41 \quad 25.02\right)$$

$$\text{Std} := \left|\begin{array}{l} \text{for } MOE \in 0..8 \\ \quad \text{Std}_{MOE} \leftarrow \text{Stdev}\left(\text{Results}^{\langle MOE\rangle}\right) \\ \text{Std} \end{array}\right.$$

$$\text{Std}^{T} = (0.07 \quad 0.01 \quad 1584.861 \quad 1584.861 \quad 24.751 \quad 2.239 \quad 0.694 \quad 4.357 \quad 4.463)$$

$$\text{Misery} := \left|\begin{array}{l} \text{for } MOE \in 0 \\ \quad \left|\begin{array}{l} \text{Array} \leftarrow \text{reverse}\left(\text{ResultSorted}_{MOE}\right) \\ \text{for } i \in 0..1 \\ \quad \left|\begin{array}{l} sum \leftarrow sum + \text{Array}_i \\ n \leftarrow n+1 \end{array}\right. \\ \text{Misery}_{MOE} \leftarrow \dfrac{\dfrac{sum}{n}}{\text{FreeFlowTravelTime}} \end{array}\right. \\ \text{Misery} \end{array}\right.$$

$$\text{Misery} = (0.801)$$

$$
\text{SemiStd} := \left|
\begin{array}{l}
\text{for } \ \text{MOE} \in 0 \\
\quad \left|
\begin{array}{l}
\text{sum} \leftarrow 0 \\
\text{for } \ i \in 0..31 \\
\quad \text{sum} \leftarrow \text{sum} + \text{Results}_{i,\text{MOE}} \cdot \text{Results}_{i,\text{MOE}} \cdot \dfrac{\text{Results}_{i,9}}{\text{Sp}} \\
\text{semiStd}_{\text{MOE}} \leftarrow \sqrt[2]{\text{sum} - \text{FreeFlowTravelTime}^2}
\end{array}
\right. \\
\text{semiStd}
\end{array}
\right.
$$

Overall Results form Mathcad:

$\text{OverallMin}^T = (6.72 \quad 1.03 \quad 3910.98 \quad 3910.98 \quad 57.85 \quad 1.98 \quad 64.57 \quad 10.18 \quad 10.44)$

$\text{OverallMax}^T = (7.03 \quad 1.08 \quad 9786.93 \quad 9786.93 \quad 151.57 \quad 11.76 \quad 67.6 \quad 26.68 \quad 27.34)$

$\text{OverallMean}^T = (6.78 \quad 1.05 \quad 6561.56 \quad 6561.56 \quad 98.25 \quad 4.51 \quad 66.95 \quad 17.29 \quad 17.72)$

$\text{FiftyPercent}^T = \left(6.76 \quad 1.04 \quad 6.424 \times 10^3 \quad 6.424 \times 10^3 \quad 95.55 \quad 3.77 \quad 67.19 \quad 16.82 \quad 17.24\right)$

$\text{EightyPercent}^T = \left(6.82 \quad 1.05 \quad 8.08 \times 10^3 \quad 8.08 \times 10^3 \quad 121.36 \quad 5.92 \quad 67.47 \quad 21.36 \quad 21.89\right)$

$\text{NinetyFivePercent}^T = \left(6.93 \quad 1.07 \quad 9.088 \times 10^3 \quad 9.088 \times 10^3 \quad 138.69 \quad 8.86 \quad 67.58 \quad 24.41 \quad 25.02\right)$

$\text{Std}^T = \left(0.07 \quad 0.01 \quad 1.585 \times 10^3 \quad 1.585 \times 10^3 \quad 24.751 \quad 2.239 \quad 0.694 \quad 4.357 \quad 4.463\right)$

$\text{Misery} = (0.8)$

$\text{SemiStd} = (1.98)$

Description	Travel Time (min)	Travel Time Index	VMT (demand)	VMT (volume)	VHT	VHD	Speed Avg. (mi/h)	Density (veh/mi/ln)	Density (pc/mi/ln)
Before Scenarios (Min)	6.72	1.03	3910.98	3910.98	57.85	1.98	64.57	10.18	10.44
Before Scenarios (Max)	7.03	1.08	9786.93	9786.93	151.57	11.76	67.60	26.68	27.34
Before Scenarios (Mean)	6.78	1.04	6561.56	6561.56	98.25	4.51	66.95	17.29	17.72
Before Scenarios (50%)	6.76	1.04	6424.24	6424.24	95.55	3.77	67.24	16.82	17.24
Before Scenarios (80%)	6.82	1.05	8080.49	8080.49	121.36	5.92	67.47	21.36	21.89
Before Scenarios (95%)	6.93	1.07	9088.07	9088.07	138.69	8.86	67.58	24.41	25.02
Before Scenarios (Std. Dev)	0.07	0.01	1576.58	1576.58	24.70	2.31	0.72	4.35	4.46
Before Scenarios (Misery Index)	1.08								
Before Scenarios (SemiStd.Dev)	1.98								

Figure 1. Overall results from the software

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BIOGRAPHICAL SKETCH

Wei Sun was born in 1991 in the Shandong province, China. An only child in the family, he grew up in Weifang city. He graduated from Weifang Number One High School and got admitted to South China University of Technology in 2010. Wei earned his B.E. in civil engineering, specializing in transportation in 2014 and then came to the University of Florida to study in the graduate program for transportation engineering. After obtaining his master's degree, Wei will continue to pursue his graduate studies in the doctoral program at the University of Florida.