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Jiwon Kim  
*Northwestern University*

Hani S. Mahmassani  
*Northwestern University*

Peter Vovsha  
*Parsons Brinckerhoff*

*See next page for additional authors*

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Scenario-Based Approach to Analysis of Travel Time Reliability with Traffic Simulation Models

Abstract
This study established a conceptual framework for capturing the probabilistic nature of travel times with the use of existing traffic simulation models. The framework features three components: scenario manager, traffic simulation models, and trajectory processor. The scenario manager captures exogenous sources of variation in travel times through external scenarios consistent with real-world roadway disruptions. The traffic simulation models then produce individual vehicle trajectories for input scenarios while further introducing randomness that stems from endogenous sources of variation. Finally, the trajectory processor constructs distributions of travel time either for each scenario or for multiple scenarios to allow users to investigate scenario-specific impact on variability in travel times and overall system reliability. Within this framework, the paper discusses methodologies for performing scenario-based reliability analysis that focuses on (a) approaches to obtaining distributions of travel times from scenario-specific outputs and (b) issues and practices associated with designing and generating input scenarios. The proposed scenario-based approach was applied to a real-world network to show detailed procedures, analysis results, and their implications.

Keywords
Travel Time Reliability, Traffic Simulation Models, Scenario-based Approach, Travel Time Distribution, Scenario Manager, Trajectory Processor

Disciplines
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Authors
Jiwon Kim, Hani S. Mahmassani, Peter Vovsha, Yannis Stogios, and Jing Dong

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Scenario-based Approach to Travel Time Reliability Analysis
Using Traffic Simulation Models

Jiwon Kim
jiwon@u.northwestern.edu

Hani S. Mahmassani*
masmah@northwestern.edu

Transportation Center, Northwestern University,
600 Foster St., Evanston, IL 60208
Phone: (847) 491-2276; Fax: (847) 491-3090

Peter Vovsha
vovsha@pbworld.com
Parsons Brinckerhoff,
1 Penn Plaza, 2nd Floor, New York, NY 10119.

Yannis Stogios
y.stogios@delcan.com
Delcan Corporation
Toronto M3C 1N4, Canada

Jing Dong
jingdong@iastate.edu
Civil and Environmental Engineering Dept.
Iowa State University, Ames, IA, USA

*corresponding author

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ABSTRACT

This paper establishes a conceptual framework for capturing the probabilistic nature of travel times using existing traffic simulation models. The framework features three components: Scenario Manager, Traffic Simulation Models, and Trajectory Processor. The Scenario Manager captures exogenous sources of travel time variation through external scenarios consistent with real-world roadway disruptions. The traffic simulation models then produce individual vehicle trajectories for input scenarios while further introducing randomness stemming from endogenous sources of variations. Finally, the Trajectory Processor constructs travel time distributions either for each scenario or for multiple scenarios to allow users to investigate scenario-specific impact on travel time variability and overall system reliability. Within this framework, this paper discusses methodologies for performing the scenario-based reliability analysis focusing on approaches to obtaining travel time distributions from scenario-specific outputs; and issues and practices in designing and generating input scenarios. The proposed scenario-based approach is applied to a real-world network to show detailed procedures, analysis results and their implications.

KEYWORDS: Travel Time Reliability, Traffic Simulation Models, Scenario-based Approach, Travel Time Distribution, Scenario Manager, Trajectory Processor
1. INTRODUCTION

With growing concern over unreliable travel times in urban networks and the associated costs of unexpected delays and frustration, travel time reliability has become an increasingly important issue in the arena of transportation network planning and traffic operations. Greater emphasis is being placed on the improvement in reliability – consistency or dependability in travel times, along with improvement in average travel time. This calls for incorporating the reliability aspects in planning, operations and economic evaluation models so that outputs of these models can adequately support transportation policy makers and professionals in developing a more reliable transportation system.

In the context of travel time reliability, significant progress has been made in measuring reliability, which entails developing and recommending various reliability measures for practical use (1-4), and valuing reliability, which ranges from assessing the value of reliability to incorporating reliability measures into travel demand modeling and network equilibrium frameworks (5-8). Another important, yet less investigated aspect is modeling reliability, which involves identifying and capturing various sources of travel time unreliability in simulation or analytical models to reproduce realistic travel time distributions or reliability measures. While there have been efforts to predict travel time variability in the presence of demand and capacity variations analytically (9) or empirically (3), little attention has been devoted to the use of existing traffic simulation models to produce reliability measures in order to predict and evaluate reliability levels of urban networks. Recognizing the important role of simulation-based DTA models in the field of transportation planning and operations, this study attempts to establish a systematic and practical framework for producing reliability measure as output of simulation tools.

One way to capture the probabilistic nature of travel times using simulation models is to conduct multiple simulation runs with different scenarios (e.g., different combinations of demand, capacity and external events), possibly with different weights or occurrence probabilities, and construct the resulting travel time distribution to characterize the overall system reliability performance. In this approach, primary emphasis is placed on designing and generating input scenarios in order to investigate the realistic travel time variability. This thus forms the basis for the “scenario-based travel time reliability analysis,” which is the main focus of this paper. The paper is structured as follows. A conceptual framework for modeling and evaluating travel time reliability using simulation models is presented. Within this framework, we further discuss scenario-based methodologies for constructing travel time distributions, assessing reliability measures and understanding impacts of scenarios on travel time variability. Next, a real-world application is provided to show detailed procedures and analysis results. Finally, summary and concluding remarks are provided.

2. METHODOLOGY

2.1 Reliability Modeling Framework using Traffic Simulation Models

Before building the methodological framework, it is essential to understand the sources of uncertainty that affect the travel time reliability in the roadway environment. A previous study (10) defined seven major root causes of travel time variability: (i) traffic incidents, (ii) work zones, (iii) weather, (iv) special events, (v) traffic control devices, (vi) fluctuations in demand, and (vii) inadequate base capacity. Many existing simulation tools view and model these factors as exogenous events using user-specified scenarios (11). Distinct from these exogenous factors, there are also endogenous sources of variation that are inherently reproduced, to varying degrees, by given traffic simulation models. Many studies have proposed ways to
capture random variation in various traffic phenomena within particular micro/meso simulation models. Examples include flow breakdown (12), incidents due to drivers’ risk-taking behaviors (13), and heterogeneity in driving behaviors (14).

Based on this identification, this study establishes a conceptual framework for modeling and estimating travel time reliability using simulation models. As shown in FIGURE 1, the framework features three components: Scenario Manager, Traffic Simulation Model, and Trajectory Processor. The primary role of the Scenario Manager is to prepare input scenarios for the traffic simulation models, which is a core part of this framework as it directly affects the final travel time distributions. Once the Scenario Manager generates a set of input scenarios, which represent any mutually consistent combinations of demand- and supply-side random factors, these scenarios are simulated in a selected traffic simulation model in conjunction with average demand obtained at a demand-supply equilibrium point under normal conditions encompassing any systematic variations. While exogenous sources of variation are captured through scenarios by the Scenario Manager, endogenous variation sources are captured in the traffic simulation model, depending on the modeling capability of the selected tool.

In this framework, the traffic simulation models refer to “particle-based” models, namely micro- and meso-scopic simulation models (15, 16) that produce individual vehicle (or particle) trajectories. Regardless of the specific reliability measures of interest, to the extent that they can be derived from the travel time distribution, the availability of particle trajectories in the output of a simulation model enables construction of any level of travel time distributions of interest (e.g., network-wide, OD, path, and link). As such, the key building block for producing measures of reliability in this framework consists of particle trajectories and the associated experienced traversal times through entirety or part of the travel path. Tasks such as converting simulated trajectories into various reliability measures are performed by the Trajectory Processor. The latter obtains the scenario-specific travel time distribution from each simulation run and constructs the overall travel time distribution aggregated over multiple scenarios.

While chaining these three modules completes the necessary procedures for performing a scenario-based reliability analysis, there are two feedback loops worth mentioning to further incorporate behavioral aspects of travelers into the reliability modeling framework. The inner loop in FIGURE 1 suggests that information from scenario-specific travel times might be used to make scenario-conditional demand adjustment (e.g., departure time change under severe weather condition). The outer loop indicates that the overall system uncertainty might affect the average demand by shifting the equilibrium point (i.e., reliability-sensitive network equilibrium) based on travel demand forecasting models that predict the impact of reliability measures on travel patterns (e.g. 7, 8).
2.2 Scenario-based Reliability Analysis: Constructing Travel Time Distribution using Multiple Scenarios

In this sub-section, we elaborate on the basic idea of the scenario-based reliability analysis within the aforementioned framework. Conceptually, the traffic simulation models can be viewed as an input-output function, where inputs are scenarios that represent exogenous sources of roadway disruptions and outputs are travel time distributions experienced by travelers under such disruptions. The objective of the scenario-based reliability analysis is to investigate variability in the output travel time distribution by
controlling the input scenario (i.e., input scenarios can be generated completely at random or in a more
directed manner based on a particular experimental design). It is noted that endogenous sources of
random variations are not part of control variables as those are considered as part of the traffic simulation
model logic.

Let \( X \) denote a vector of exogenous sources of random variation (e.g., weather, incident, day-to-
day demand variation) that are selected to characterize input scenario and let \( X_j \) represent the \( j^{th} \) element
of \( X \), which is called “scenario component” throughout this paper. Each scenario component itself is
also a vector of several attributes describing temporal (e.g., start-time and duration), spatial (e.g., event
location) and state (i.e., intensity or condition) aspects of a given demand-
and supply-side factor. Let \( S_i \) denote the \( i^{th} \) input scenario, which is the \( i^{th} \) realization of scenario components \( X \), i.e.,
\[ S_i = X^{(i)} = \{X_1^{(i)}, X_2^{(i)}, \ldots, X_j^{(i)}\} \]. Consider we have \( N \) input scenarios \( S_1, S_2, \ldots, S_N \) drawn from a
joint distribution of \( X \). Then the output travel time distribution for each scenario is obtained by

\[ T_i = H(S_i), \quad i = 1, \ldots, N \]  \hspace{1cm} (1)

where \( T_i \) represents a collection of travel time \( t \) for a given OD/path/link of interest under the \( i^{th} \) scenario
\( S_i \), and \( H(\cdot) \) denotes a black-box representation of a traffic simulation model. Let \( f_i(t) \) denote the
probability density function of scenario-specific travel times under \( S_i \) such that \( \{t \in T_i : t \sim f_i(t)\} \). Then
the main goal of the analysis is to obtain the probability density function of overall travel times \( f(t) \)
based on the scenario-specific travel time distributions \( f_i(t) \). By knowing the probability of each
scenario occurring, \( f(t) \) can be calculated by the weighted sum (i.e., convex combination) of scenario-
specific travel time distribution \( f_i(t) \) as follows:

\[ f(t) = \sum_{i=1}^{N} w_i f_i(t) \]  \hspace{1cm} (2)

where \( w_i \) denotes the weight of the \( i^{th} \) scenario with \( \sum_{i=1}^{N} w_i = 1 \), which is typically obtained from the
scenario probability \( w_i = P(S_i) \). FIGURE 2 presents a schematic diagram to illustrate the procedure of
constructing the overall travel time distribution based on this concept.
2.3 Approaches to Assessing Reliability

Travel time reliability is a relative concept in that it depends on the temporal and spatial boundaries for which travel times are observed. For example, the travel time reliability for weekdays is different from that for weekends on the same road network. Therefore defining time and space domains needs to precede assessing reliability. In general, the time domain is specified by a date range of the overall time period (e.g., 6/1/2012 – 8/31/2012), day of week (e.g., Mon – Fri), and time of day (6AM – 10AM); or it could be a specific season or day of each year (e.g., Thanksgiving Day). The space domain defines at which level travel times are collected and the reliability measures are calculated (e.g., network-level, OD-level, path-level and link-level). Two different approaches are explored to assess the travel time reliability for given time and space domains: (i) Monte Carlo approach and (ii) mix-and-match approach. The former tries to generate all possible scenarios that could occur during the given temporal and spatial boundaries to introduce realistic variations in the resulting travel time distribution; while the latter constructs scenarios by manually choosing various combinations of scenario components. These approaches are discussed in more detail next.
Monte-Carlo Approach: This approach uses Monte-Carlo simulation to prepare input scenarios aimed at propagating uncertainties in selected scenario components \( \mathbf{X} \) into uncertainties in the generated scenarios \( S_j \) (\( i = 1, \ldots, N \)), which can be, in turn, translated into the resulting travel time distribution. As depicted in FIGURE 3, the Scenario Manager performs Monte-Carlo simulation to generate hundreds or thousands of input scenarios by sampling from the joint probability distribution of scenario components. Each scenario is equally likely thereby allowing the Trajectory Processor to simply aggregate travel time distributions from a large number of simulation runs to obtain the most likely (probable) outcome of a set of reliability performance indicators for the given time and space domains.

Mix-and-Match Approach: Instead of generating scenarios randomly given the underlying stochastic processes, one could explicitly specify scenarios with particular historical significance or policy interest. The mix-and-match approach aims to construct input scenarios in a more directed manner by mix-and-matching possible combinations of specific input factors or by directly using known historical events or specific instances (e.g., holiday, ball game, etc.). FIGURE 4 shows a schematic diagram illustrating this approach with a simple example. Consider two scenario components: “accident” and “heavy rain,” where each component has two discrete states: “occur” and “not occur.” From the Cartesian product of two components’ states, four possible scenario groups are defined as shown in the figure. Suppose that we have a representative scenario for each group with the scenario probability assigned based on the joint probability of accident and heavy rain events. Then a probability-weighted average of travel time distributions under all four scenarios can be used as the expected travel time distribution to approximate the overall reliability measures. A more informative use of this approach is to understand the impact of a particular scenario component on travel time variability by investigating gaps between different combinations of output results.

Combined Approach: Unlike the simple example above, however, it is often necessary to allow randomness in scenarios within each group especially when there is no pre-defined representative scenario. It is also possible to have no probability value for each scenario group known to users. In both cases, the Monte-Carlo approach can be used in conjunction with the mix-and-match approach, i.e., sampling random scenarios from their conditional distributions given each group (for the former); and generating a large number of scenarios for the entire scenario space and categorizing them into the associated groups to obtain the group probabilities (for the latter).
Generate random scenarios by drawing from distributions of input parameters; 
\[ S_i = \{ \text{weather}(X_{1i}), \text{incident}(X_{2i}), \ldots, \text{work-zone}(X_{Ji}) \}, \ i = 1, \ldots, N \]

Realization 1: 
weather+incident \((S_1)\)

Realization 2: 
incident \((S_2)\)

Realization 3: 
No event \((S_3)\)

Realization N: 
Work-zone \((S_N)\)

Traffic Simulation

Output \((t \mid S_1)\) 
Output \((t \mid S_2)\) 
Output \((t \mid S_3)\) 
Output \((t \mid S_N)\)

Travel time distribution aggregated over multiple random scenarios
Overall travel time reliability for given time and space domains

FIGURE 3 Monte Carlo approach.

<table>
<thead>
<tr>
<th>Scenario Manager</th>
<th>No Accident</th>
<th>Accident</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Heavy Rain</td>
<td>(S_1)</td>
<td>(S_3)</td>
</tr>
<tr>
<td>Heavy Rain</td>
<td>(S_2)</td>
<td>(S_4)</td>
</tr>
</tbody>
</table>

Define scenario groups based on different combinations of uncertainty factors and prepare scenarios for each group with the associated probability.

Scenario Manager

Traffic Simulation Model

Traffic Simulation

Output \((t \mid S_1)\) 
Output \((t \mid S_2)\) 
Output \((t \mid S_3)\) 
Output \((t \mid S_4)\)

Impact of heavy rain on travel time variability when there is no accident
Probability-weighted average of travel time distributions under multiple scenarios

FIGURE 4 Mix-and-match approach.
2.4 Generating Scenarios Considering Dependencies

One of the practical issues in generating scenarios is considering dependencies in various random factors. As represented by the dotted arrows in FIGURE 5, certain scenario components are dependent on other components. Incident occurrence is the most prominent example, where event properties (e.g., frequency, duration and severity) tend to be affected by weather and other external events. We investigated weather-conditional incident rates (incidents/hour/lane-mile) by measuring the number of incidents during the total period of time exposed to different weather conditions using historical incident data collected from 2007 to 2010 in Chicago, IL. As shown in FIGURE 6, incident rates tend to increase as the severity of rain or snow events increases. In addition to incidents, dependencies are also observed on the traffic management side: weather-responsive traffic management (WRTM) strategies are deployed based on types and severities of weather events (17); and traffic incident management is triggered by incident events. In the Scenario Manager, such dependencies are taken into account during the generation process. Once the scenario components of interest are defined, it identifies dependency relations between components and derives a generation order such that components that affect others are generated before their dependent ones. Following the generation order, the Scenario Manager generates each component sequentially (e.g., weather → incident → incident management) so that each component is sampled from its distribution conditioned on all the previously sampled components.

FIGURE 5 Various scenario components and dependency relations.
FIGURE 6 Weather-conditional incident rates (Chicago incident data from 2007-2010).
3. APPLICATION

In this section, the presented framework is applied to a real-world network to show detailed procedures and analysis results using a mesoscopic traffic simulation tool, DYNASMART-P (16, 18).

3.1 Time-Space Domains and Data Collection

Suppose that we want to evaluate the reliability of travel times in a Long Island network during weekday (Monday – Friday) morning peak (6AM – 10AM) in winter season (November, 2010 to February, 2011). More specifically, we select the O-D pair between Washington Avenue and Cross Island Parkway, a major route of which is a 27.5 mile stretch of Long Island Expressway (I-495), and investigate westbound travel times as shown in FIGURE 7. Two uncertainty factors are considered as scenario components: weather and incident. To obtain necessary information for generating weather and incident scenarios, data were collected for the specified time and space domains. Weather data were obtained from the nearest ASOS station at Farmingdale, Republic Airport (KFRG), where %hours of each weather condition is as follows.

• Clear : 92.05 %
• Rain : 4.91 % (Light: 84.86%; Moderate: 12.97%; Heavy: 2.18%)
• Snow : 3.05 % (Light: 84.85%; Moderate: 8.76%; Heavy: 6.39%)

Incident data were collected from the INFORM system (19) and provided by New York State DOT. The incident data contain information on event locations (red triangles in FIGURE 7) and severities in terms of the number of lanes closed, which are distributed as follows.

• No lane closed : 35.34%
• 1 lane closed : 50.32%
• 2 lanes closed : 11.17%
• ≥ 3 lanes closed : 3.17%

The overall incident rate (i.e., the total number of incidents/total observation hours/total lane-miles) is measured as 0.002 incidents/hr/lane-mile.

Figure 7 Study network and selected O-D pair (Long Island, NY).
3.2 Input Parameters and Sampling Methods

Each scenario component is characterized by four major event properties: frequency, duration, intensity and location, where each property is specified either parametrically or nonparametrically. TABLE 1 presents input parameters and sampling methods for each property of weather and incident components. For weather, it is recognized that modeling weather events in a fully parametric manner requires identifying underlying stochastic processes and calibrating the associated parameters, which is beyond the scope of this paper. As such, we use a nonparametric sampling approach, where the historical data are directly used for generating weather scenarios. The Scenario Manager is populated with 5-minute ASOS weather observations for the selected time period and randomly samples a 4-hour daily weather scenario from the time series of actually measured values. This approach is especially useful as it preserves the dependency structure between properties (e.g., precipitation intensity, visibility, duration, etc.). Based on the categorization used in ASOS data, seven mutually exclusive and exhaustive states are defined: clear, light rain, moderate rain, heavy rain, light snow, moderate snow and heavy snow; and any point in time during the scenario horizon is assigned one of these states as illustrated in FIGURE 8(a).

In contrast, many random properties of incident events can be modeled using known parametric probability distributions. For frequency, incidents are assumed to occur following a Poisson process with the mean incident rate. As pointed out previously, however, the rate is highly dependent on the prevailing weather condition and therefore we estimated the weather-conditional mean incident rates for seven weather conditions based on the historical data as presented in TABLE 1. To reproduce incident instances following this state-contingent incident rate, we apply a discrete-event simulation (DES) approach that identifies discrete points in time where the weather state changes based on a given (sampled) weather time series; and determines the incident occurrence pattern at such variable time intervals by applying the associated mean incident rates. To validate this approach, we tested 1,000 scenarios with and without considering dependencies between weather and incident and compared simulated incident rates with the actual observed ones as shown in FIGURE 9. The results show that the scenarios from the weather-dependent incident sampling reproduce the real-world incident frequency successfully while the scenarios generated in the weather-independent manner significantly underestimate the likelihood of incident occurrence under severe weather conditions. For incident duration, the Gamma distribution is selected based on model-fitting results and two input parameters are estimated as follows: shape = 1.210 and scale = 31.553. Incident intensity is expressed as the percentage capacity loss (the fraction of link capacity lost due to the instance) and the empirical mass function (PMF) is constructed based on the observed pattern for the number of lanes closed as presented in TABLE 1.
### TABLE 1 Input Parameters and Sampling Methods

<table>
<thead>
<tr>
<th>Scenario Component</th>
<th>Properties Required for Sampling Event Instances</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Frequency</strong></td>
<td>Discrete states: {CL, LR, MR, HR, LS, MS, HS}¹</td>
</tr>
<tr>
<td><strong>Duration</strong></td>
<td>Network-wide</td>
</tr>
<tr>
<td><strong>Intensity</strong></td>
<td>Apply to the entire network.</td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td></td>
</tr>
</tbody>
</table>

#### Weather

**Input Parameter**
- Always²

**Sampling Method**
- Nonparametric
  - Use the actual measured values; randomly draw from historical time series of weather data.

#### Incident

**Input Parameter**
- Mean incident rate \( \lambda \) (incidents/hr/lane-mile)
- Two parameters in fitted model
- \% capacity loss (number of lanes closed)

**Sampling Method**
- Parametric - Poisson distribution:
  - \( \lambda_{CL} = 0.0019 \)
  - \( \lambda_{LR} = 0.0024 \)
  - \( \lambda_{MR} = 0.0047 \)
  - \( \lambda_{HR} = 0.0071 \)
  - \( \lambda_{LS} = 0.0043 \)
  - \( \lambda_{MS} = 0.0095 \)
  - \( \lambda_{HS} = 0.0189 \)

- Gamma distribution:
  - \( \text{Shape} = 1.210 \)
  - \( \text{Scale} = 31.553 \)

- Empirical PMF:
  - \( P(0.15) = 0.35 \)
  - \( P(0.3) = 0.5 \)
  - \( P(0.6) = 0.11 \)
  - \( P(0.9) = 0.04 \)

- (homogenous) Poisson point process in space

---

¹ CL: Clear; LR: Light Rain; MR: Moderate Rain; HR: Heavy Rain; LS: Light Snow; MS: Moderate Snow; HS: Heavy Snow

² In this experiment, weather events are viewed as always present with one of the seven states: CL, LR, MR, HR, LS, MS and HS.

³ \( \lambda_x \): mean incident rate under weather condition \( x \)

⁴ \( P(x) \): probability that the fraction of link capacity lost due to the instance becomes \( x \) (remaining capacity becomes 1-x).
FIGURE 8 Example of one instance of scenario consisting of weather and incident events: temporal profiles represented by “rectangular pulse” with duration (width) and intensity (height).

FIGURE 9 Weather-conditional incident rates: observed vs. simulated (Long Island incident data)
3.3 Scenario Specification and Generation

In this application, we used the combined approach, where a discrete set of scenario groups were defined as in the mix-and-match approach but random scenarios for each group and the group probability were obtained from Monte-Carlo sampling. Six scenario groups were defined based on the Cartesian product of three weather states – Clear, Rain and Snow – and two incident states – Incident and No incident. Total 10,000 scenarios were generated and classified into one of those six scenario groups to calculate scenario group probabilities. Each scenario represents a single-day (6AM – 10AM) scenario with the combination of weather and incident events (e.g., FIGURE 8). The probability of each group occurring is presented in TABLE 2. Scenarios with clear weather and incidents accounted for 61% of the total trials as the most likely scenario and scenarios with snow and no incident accounted for 0.4 % as the least likely scenario.

In sampling random scenarios for each group, the initial sample size was calculated to ensure the mean travel time is estimated with no worse than a 10% error with at least 90% confidence (20, Ch.9). The calculation result requires approximately 20 scenarios. However, considering the interest in variability measures such as the standard deviation or other reliability metrics in addition to the mean, which tend to require a larger sample size, we used 40 scenarios for this experiment. As such, forty scenarios were randomly selected for each group and simulated using DYNASMART-P to obtain scenario-specific (or “scenario group”-specific) travel time distribution. For the “clear/no incident” group, however, only one scenario was simulated as it did not involve any randomness.

3.4 Analysis Results

After completing traffic simulation for the selected scenarios, travel time distributions were obtained as presented in FIGURE 10, where the y-axis represents the PMF and the x-axis represents the OD travel time in minutes. FIGURE 10(a) shows the combined (probability-weighted) travel time distribution obtained using the method in Eq.(2) and FIGURE 10(b-g) show the scenario-specific travel time distributions. From the scenario-specific PMFs, It can be seen that travel times become more dispersed as the weather state changes from Clear to Snow and the incident state changes from No-incident to Incident. Significantly high dispersions are observed in travel time distributions under snow conditions, but their impact on the combined distribution appears to be small due to the low probabilities.

Various statistics and reliability performance measures were extracted from each travel time distribution and presented in FIGURE 11 and TABLE 2. For the individual scenario group, the mean and median travel times tend to grow from left to right, while the standard deviation is higher on the sides than in the middle. It appears reasonable to have such a high standard deviation in the Snow/Incidents case as the travel time distribution is highly dispersed as shown in FIGURE 10(g). But the relatively high standard deviation for the Clear/No-Incident case seems to require a different explanation. One of the reasons might be that the standard deviation is very sensitive to the tails of a distribution and slight changes in the tails could lead to substantially different standard deviations (21). Although the travel time distributions for Clear/No-Incident and Clear/Incidents have little visible difference and the maximum travel time for Clear/No-Incidents is found to be smaller than that for Clear/Incidents, the relative impact of the tail of Clear/No-Incident on the standard deviation appears to be greater than that of Clear/Incidents. This could be partly because of its much smaller sample size. This tendency is also revealed in the Misery Index measure, where Clear/No-Incident shows a higher value than other groups do (except for Snow/Incidents) indicating that the average of the highest five percent of travel times is higher in this group.
For the 95\textsuperscript{th} percentile travel time, all the scenario groups have similar values and only Snow/Incidents shows a noticeable difference. This is also true for the Planning Time Index, which is the 95\textsuperscript{th} percentile travel time divided by the free flow travel time. This suggests that the 95\textsuperscript{th} percentile may be too extreme to reflect different characteristics under different scenarios. A previous study (3) also pointed out this issue and recommended the use of the 80\textsuperscript{th} percentile instead. As shown in FIGURE 11(c), the 80\textsuperscript{th} percentile travel time appears to better capture the effects of different weather and incident conditions.

Another important observation concerns the Buffer Index, which measures the relative distance between the central (mean) and extreme (95\textsuperscript{th} percentile) values, and represents the extra “buffer time”, i.e., the percentage of the mean travel time that travelers should add to the mean in order to ensure on-time arrival 95 percent of the time. From the scenario-specific travel time distributions, Buffer Index values for Clear/No-Incident and Clear/Incident are estimated to be higher than that of Snow/Incidents. It is, however, noted that the actual buffer time calculated as the difference between the mean and 95\textsuperscript{th} percentile travel times is higher under Snow/Incidents. In general, caution is required when comparing reliability measures across groups as some measures are normalized by scenario-dependent reference values (e.g., mean and median) and such relative distances should be interpreted differently from measures of absolute distance to a global reference point (e.g., free-flow travel time).
### TABLE 2 Traffic Simulation Results and Estimated Reliability Measures

<table>
<thead>
<tr>
<th>Scenario Group</th>
<th>CL_nINC</th>
<th>CL_INC</th>
<th>RA_nINC</th>
<th>RA_INC</th>
<th>SN_nINC</th>
<th>SN_INC</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clear/ No Incident</td>
<td>1.000</td>
<td>2.000</td>
<td>0.500</td>
<td>0.500</td>
<td>0.250</td>
<td>0.250</td>
<td>1.000</td>
</tr>
<tr>
<td>Rain/ No Incident</td>
<td>1.000</td>
<td>2.000</td>
<td>0.500</td>
<td>0.500</td>
<td>0.250</td>
<td>0.250</td>
<td>1.000</td>
</tr>
<tr>
<td>Snow/ No incident</td>
<td>1.000</td>
<td>2.000</td>
<td>0.500</td>
<td>0.500</td>
<td>0.250</td>
<td>0.250</td>
<td>1.000</td>
</tr>
<tr>
<td>Snow/ Incidents</td>
<td>1.000</td>
<td>2.000</td>
<td>0.500</td>
<td>0.500</td>
<td>0.250</td>
<td>0.250</td>
<td>1.000</td>
</tr>
</tbody>
</table>

#### Descriptive Statistics

| Number of Scenarios | 40 | 40 | 40 | 40 | 40 | 201 |
| Number of Observations | 56,140 | 57,640 | 57,690 | 56,310 | 57,640 | 56,676 |
| Mean Travel Time (min) | 27.65 | 27.52 | 28.69 | 28.74 | 29.24 | 31.64 |
| Median Travel Time (min) | 25 | 26 | 27 | 27 | 28 | 29 |

#### Reliability Measures

| Standard Deviation (min) | 7.41 | 6.48 | 6.26 | 6.13 | 6.15 | 8.29 | 6.86 |
| Coefficient of Variation | 0.27 | 0.24 | 0.22 | 0.21 | 0.21 | 0.26 | 0.25 |
| 80th Percentile (min) | 27 | 27 | 28 | 29 | 29 | 33 | 28 |
| 95th Percentile (min) | 41 | 41 | 41 | 41 | 42 | 46 | 42 |
| Buffer Index (%) | 48.27 | 48.98 | 42.9 | 42.67 | 43.64 | 45.37 | 50.7 |
| Percent On Time (%) | 91.4 | 91.22 | 90.72 | 90.39 | 91.3 | 85.65 | 90.61 |
| Planning Time Index | 1.64 | 1.64 | 1.64 | 1.64 | 1.68 | 1.84 | 1.68 |
| Misery Index | 2.27 | 2.09 | 2.09 | 2.05 | 2.09 | 2.35 | 2.15 |

1. The difference between the 95th percentile travel time and the average travel time, normalized by the average travel time
2. The difference between the 95th percentile travel time and the average travel time
3. The percent of trips with travel times < (1.25 * median travel time)
4. The 95th percentile travel time divided by free-flow travel time
5. The average of the highest five percent of travel times divided by the free-flow travel time

Note: above definitions are found in the recent study (3).
FIGURE 10 Overall and scenario-specific travel time distributions (right-truncated).
FIGURE 11 Travel time reliability measures for different scenario groups.
4. CONCLUSION

While simulation-based traffic prediction models have been widely used for operational and planning purposes for decades, there has not been a systematic development of approaches to modeling travel time reliability within the framework of traffic simulation models. This paper establishes a conceptual framework for capturing the probabilistic nature of travel times using existing traffic simulation models. The framework features three components: Scenario Manager, Traffic Simulation Models, and Trajectory Processor. The Scenario Manager captures exogenous sources of travel time variation through external scenarios consistent with real-world roadway disruptions. The traffic simulation models then produce individual vehicle trajectories for input scenarios while further introducing randomness stemming from endogenous sources of variations. Finally, the Trajectory Processor construct travel time distributions either for each scenario or for multiple scenarios based on simulated trajectories to allow users to investigate scenario-specific impact on the travel time variability as well as the overall system performance. Within this framework, this paper discusses methodologies for performing the scenario-based reliability analysis focusing on approaches to obtaining overall travel time distribution from scenario-specific outputs; and issues and practices in designing and generating input scenarios. The proposed scenario-based approach is applied to a real-world network to show detailed procedures, analysis results and their implications.

This paper demonstrates the use of traffic simulation models in generating travel time distributions that reflect various demand- and supply-side uncertainty factors. Although we excluded endogenous variations from scenario components at this point, the scenario-based approach is not limited to modeling external events only. Rather it expands our view of what can be specified as scenarios. Any phenomena that are characterized by certain event properties (e.g., frequency, duration and intensity) can be generated and provided as inputs to traffic simulation models. For instance, flow breakdown can also be specified as an external event by identifying triggering mechanisms and dependencies with other external factors such as weather as discovered by (22). As such, many extensions and developments are possible on this framework.

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