Federal Highway Administration
Office of Operations

Incorporating Reliability Performance Measures in Operations and Planning Modeling Tools

February 2022

U.S. Department of Transportation
Federal Highway Administration

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA-HOP-20-042		

4. Title and Subtitle Incorporating Reliability Performance Measures in Operations and Planning Modeling Tools	**5. Report Date** February 2022
	6. Performing Organization Code
7. Author(s) Kittelson. W, Quayle, S.., Nevers, B. (Kittelson & Associates, Inc.); Chiu, Y.C. (Metropia); Zhou, X. (University of Arizona); Nava, E. (Maricopa Association of Governments)	**8. Performing Organization Report No.**
9. Performing Organization Name And Address Kittelson & Associates Inc. 300 M Street SE, Suite 810 Washington, DC 20001	**10. Work Unit No. (TRAIS)**
	11. Contract or Grant No. DTFH61-12-D-00044/5002
12. Sponsoring Agency Name and Address U.S. Department of Transportation Federal Highway Administration (FHWA) Office of Operations 1200 New Jersey Avenue, SE Washington DC 20590	**13. Type of Report and Period Covered** Technical Report Informational Report Sept 2014 to Aug 2016
	14. Sponsoring Agency Code FHWA

15. Supplementary Notes
John Halkias (john.halkias@dot.gov) served as the Government Task Manager

16. Abstract
Scenario Manager and Vehicle Trajectory Processor (NeXTA) are software products developed under the second Strategic Highway Research Program (SHRP2) Project L04 for facilitating the incorporation of reliability performance measures into operations and planning tools. Pilot test sites in both Portland, Oregon and Phoenix, Arizona were used in conjunction with the dynamic traffic assignment (DTA) model DynusT to evaluate the viability of applying these software tools in a real-world environment and for practical everyday purposes. Sources of unreliability that were incorporated into the analysis included incidents and changes in both weather and volume. A whole-year analysis was conducted in which travel time distribution profiles were generated for 4 corridors ranging in length from approximately 6 to approximately 15 miles. The simulation results were then contrasted with actual travel time distribution profiles observed under base-year conditions and found to be comparable. The report includes recommendations for conducting similar analyses and suggested next steps to further enhance the quality and practicality of the analysis procedure.

17. Key Words	18. Distribution Statement
Travel time reliability, planning models, travel demand forecasting, operational improvement strategies	No restrictions.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	68	

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ADOT	Arizona Department of Transportation
ATR	Automatic Traffic Recorder
DMV	Department of Motor Vehicles
DOT	Department of Transportation
DTA	Dynamic Traffic Assignment
FHWA	Federal Highway Administration
HCRS	Highway Condition Reporting System
MAG	Maricopa Association of Governments
MoE	Measure of Effectiveness
MPO	Metropolitan Planning Organization
NeXTA	Network Explorer for Traffic Analysis
NOAA	National Oceanic and Atmospheric Administration
O-D	Origin-to-Destination
ODOT	Oregon Department of Transportation
PORTAL	Portland Archival Listing
SHRP2	Second Strategic Highway Research Program
TDMS	Transportation Data Management System
TDSP	Time-Dependent Shortest Path
TMC	Traffic Message Channel
TOC	Transportation Operatiosn Center
TSMO	Transportation Systems Management and Operations
TTI	Travel Time Index
VMT	Vehicle Miles Traveled

CHAPTER 1. INTRODUCTION

Agencies are increasingly concerned with improving travel time reliability and producing performance measures to track their progress. The Second Strategic Highway Research Program (SHRP2) project "Incorporating Reliability Performance Measures in Planning and Operations Modeling Tools" (referred to as the L04 project, or simply L04) was aimed at addressing this agency need by improving planning and operations models to create suitable tools for the evaluation of projects and policies that are expected to improve reliability. (FHWA n.d.) The L04 project addressed the need for a comprehensive framework and conceptually coherent set of methodologies to:

- Better characterize reliability, and the manner in which the various sources of variability operate individually and in interaction with each other in determining overall reliability performance of a network.
- Assess its impacts on users and the system.
- Determine the effectiveness and value of proposed counter measures.

L04 closed an important gap in the underlying conceptual foundations of travel modeling and traffic simulation, and provided practical means for generating realistic reliability measures using network simulation models in a variety of application contexts. A principal accomplishment of L04 is a unifying framework for reliability analysis using essentially any microscopic or mesoscopic simulation model that produces vehicle travel trajectories.

The framework developed within L04 is built around three main components:

- Scenario Manager, which is a software tool that was developed to generate and manage multiple scenarios composed of various events (specifically weather and incident events) and volume variations that can collectively affect travel time and therefore travel time reliability metrics.
- Reliability-integrated simulation tools that are able to model the sources of unreliability injected into each of the various scenarios generated by the scenario manager software tool.
- Vehicle Trajectory Processor, which is a post processor software tool capable of extracting reliability information, specifically vehicle trajectories, from the simulation output, and then displaying, in a visual and understandable way, a variety of performance metrics that can be derived from this information.

These three components are intended to be used in concert with one another to evaluate the effects of alternative operational improvement strategies on travel time reliability.

Because L04 was primarily a research project, the resultant products were developed to a research grade and were tested only at a proof-of-concept level. That is, Scenario Manager and Vehicle Trajectory Processor, which were bundled into the Network Explorer for Traffic Analysis (NeXTA), were not sufficiently evaluated in a real-world environment to confirm their applicability to everyday use. As well, the simulation tool used in L04 was a proprietary dynamic traffic assignment (DTA) model that is unavailable at an open-source level to the general public.

OBJECTIVES

The objectives of this project were twofold:

- To assist public agencies such as state departments of transportation (DOTs), metropolitan planning organizations (MPOs), and other public sector stakeholders in moving reliability into their business practices through the piloting of the SHRP2 L04 products at two real test sites.
- To provide feedback to the Federal Highway Administration (FHWA) on the applicability and usefulness (benefits and value) of the products piloted and lessons learned, and to suggest potential refinements and approaches, if any, for implementation in other agencies.

ORGANIZATION OF THIS REPORT

The report is organized in the typical sequence of steps required to set up, conduct, and assess the results of an effort designed to evaluate the effects of a planned operational improvement project or strategy on travel time reliability:

- CHAPTER 2. Analysis Component Tools introduces the analysis component tools —Scenario Manager, dynamic traffic simulation model, and Vehicle Trajectory Processor—by describing their fundamental features, capabilities, and limitations.
- CHAPTER 3. Pilot Test Sites presents and characterizes the pilot test sites used in this investigation.
- CHAPTER 4. Data Requirements describes the data elements needed to apply the three framework components (Scenario Manager, simulation model, and Vehicle Trajectory Processor) that were tested and evaluated in this project.
- CHAPTER 5. Analysis Framework presents the analysis framework used in the testing and evaluation process.
- CHAPTER 6. Cluster Analysis Applications and Results describes the cluster analysis tools and techniques used to identify distinct data and scenario groupings.
- CHAPTER 7. Pilot Test Results, Conclusions and Potential Improvements summarizes the results obtained, lessons learned, and suggestions for use of the framework components going forward.

CHAPTER 2. ANALYSIS COMPONENT TOOLS

The first-generation software pilot tested in this project is made up of three component tools that, collectively, offer a new way of applying simulation models to practically generate realistic estimates of travel time reliability performance measures. Figure 1 identifies the three component tools, which include Scenario Manager, a dynamic traffic assignment (DTA) simulation model, and Vehicle Trajectory Processor. Figure 1 also illustrates how these three component tools interact with one another to produce travel time reliability performance measures.

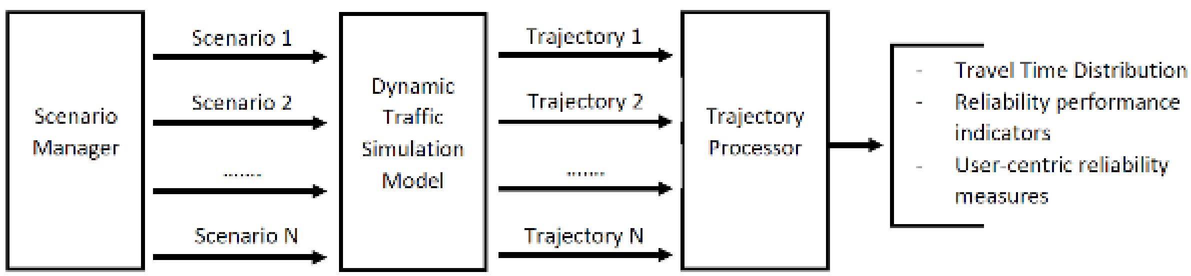


Figure 1. Flow Chart. Conceptualized analysis process.
Source: FHWA.

The remainder of this chapter provides a brief overview of the purpose and functional characteristics of each of these three component tools.

SCENARIO MANAGER

As shown by figure 1, Scenario Manager is essentially a pre-processor that generates simulation input files for a DTA model by capturing the major exogenous sources of travel time variation in the real world. These exogenous sources of variability include travel demand, weather, and incidents.

Scenario Manager provides the ability to construct scenarios that entail any mutually consistent combination of external events. It represents these scenarios through output parameters that can be understood and applied by a variety of microscopic or mesoscopic simulation tools so that the major external sources of travel time unreliability (specifically weather, crashes, and day-to-day variability in travel demand) are taken into explicit account during the simulation process.

Scenario Manager is a platform upon which one or more scenarios of mutually consistent combinations of external events are generated to conduct travel time reliability analyses. This allows experiments to be conducted that replicate certain field conditions, under both actual and hypothetical (proposed) network and control scenarios. For example, Scenario Manager enables execution of exogenous scenario generation that entails simulation over multiple days, hence reflecting daily fluctuations in demand, both systematic and random.

Scenario Manager enables users to generate scenarios randomly, or alternatively, to be very specific and purposeful in designing a particular scenario to be simulated. Thus, there are at least three ways Scenario Manager can be applied in the context of the analysis process illustrated in figure 1. It can:

- Randomly generate a large number of scenarios, from which individual scenarios can be selected for simulation using a Monte Carlo selection process.
- Be constrained into generating one or more specific scenarios reflecting predetermined values for one or more of the input parameters.
- Randomly generate one or more scenarios from within a constrained range of possible values for one or more of the input parameters.

Scenario Manager also allows users to manage the conduct of reliability analyses by providing an environment for storage and retrieval of previously generated scenarios, through a scenario library approach. The scenario management functionality allows retrieval of historically occurring scenarios or of previously constructed scenarios as part of a planning exercise. Given a particular scenario, Scenario Manager's main function then is to prepare corresponding input files for the applicable mesoscopic or microscopic simulation models. Therefore, the Scenario Manager can facilitate direct execution of the simulation software for a series of scenarios by creating the necessary inputs that reflect the scenario assumptions.

A User Guide was produced in SHRP2 Project L04 and is available to assist in the application of Scenario Manager. (Kim, et al. November 2013) The User Guide provides useful information on Scenario Manager's functionality. However, users should be aware that the currently available version of Scenario Manager has some limitations that are not otherwise reflected in the User Guide:

- Scenario Manager was originally designed in a way that will allow it to also account for the effects of long-term work zones on travel time reliability, as shown in figure 2. However, this software feature has not yet been fully implemented, and so long-term work zones were not taken into account in this pilot test project.

- Scenario Manager is also currently unable to accept crash input data in any form other than either a "crashes per hour per lane-mile" basis or a "crashes per million vehicle-miles traveled" basis.

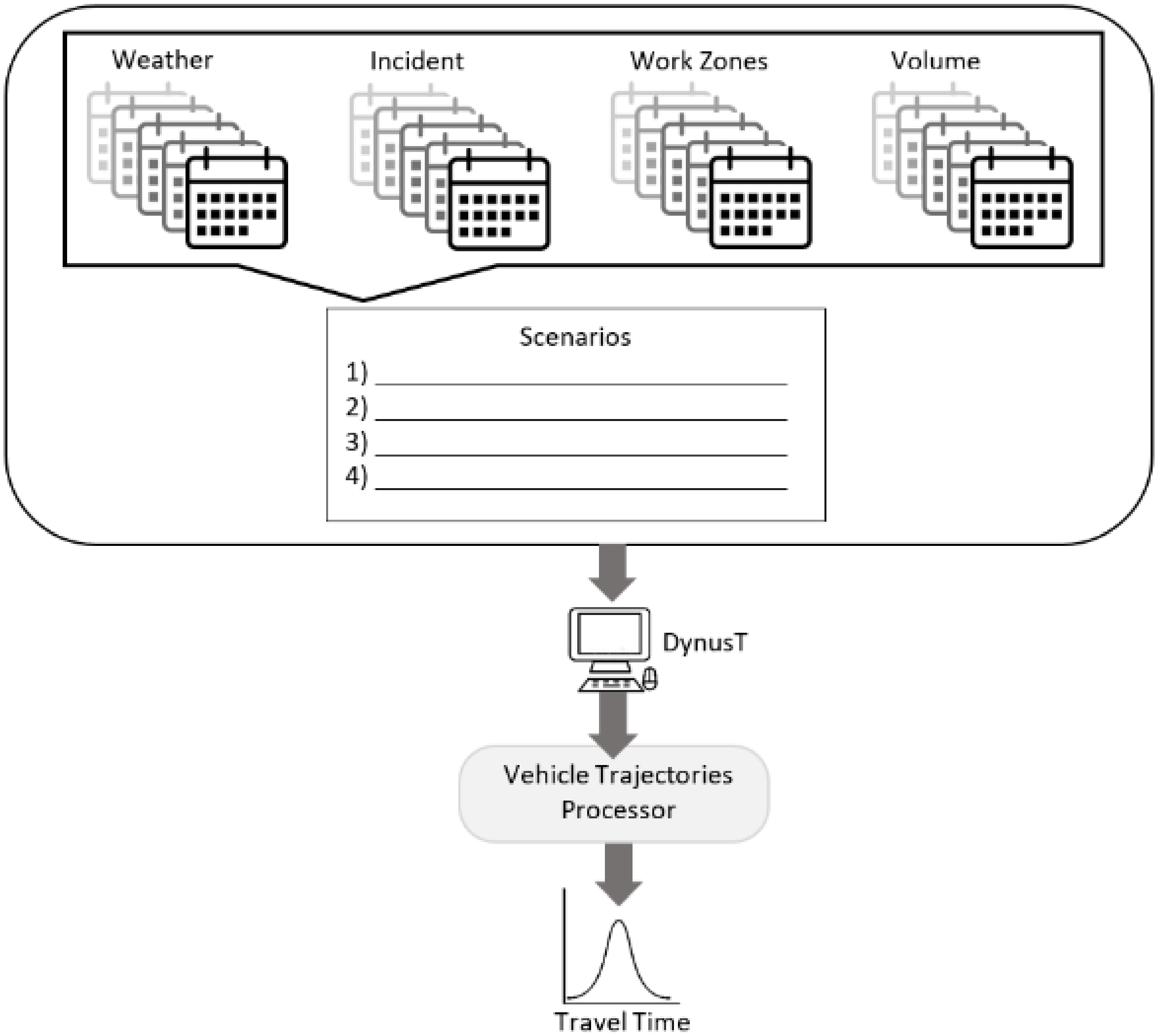


Figure 2. Flow Chart. Implementation concept for Scenario Manager.
Source: FHWA.

DYNUST

General Overview

The dynamic traffic simulation and assignment model DynusT is a model system that is designed and implemented to perform simulation based DTA analysis. Due to its unique algorithmic structure and software implementation, it can perform DTA on regional-level networks with long simulation periods with realistic micro-like traffic flow dynamics and versatile behavior rules. This makes DynusT particularly well-suited for both corridor and regional-level modeling, such as regional transportation planning, corridor studies, integration with activity-based models and mass evacuation modeling.

As shown in figure 3, DynusT consists of iterative interactions between its two main modules—traffic simulation and traffic assignment. Vehicles are created and loaded into the network based on their respective origins and follow a specific route based on their intended destinations. The large-scale simulation of network-wide traffic is accomplished through the mesoscopic simulation approach that omits inter-vehicle, car-following details while maintaining realistic macroscopic traffic properties (i.e., speed, density, and flow). More specifically, the traffic simulation is based on the Anisotropic Mesoscopic Simulation model that simulates the movement of individual vehicles according to the concept that a vehicle's speed adjustment is influenced by the traffic conditions in front of the vehicle. In other words, at each simulation interval, a vehicle's speed is determined by the speed-density curve, and the density is defined as the number of vehicles per mile per lane with a limited distance—defined as the speed-influencing region—downstream of the vehicle (Chiu, Zhou, and Song, 2010).

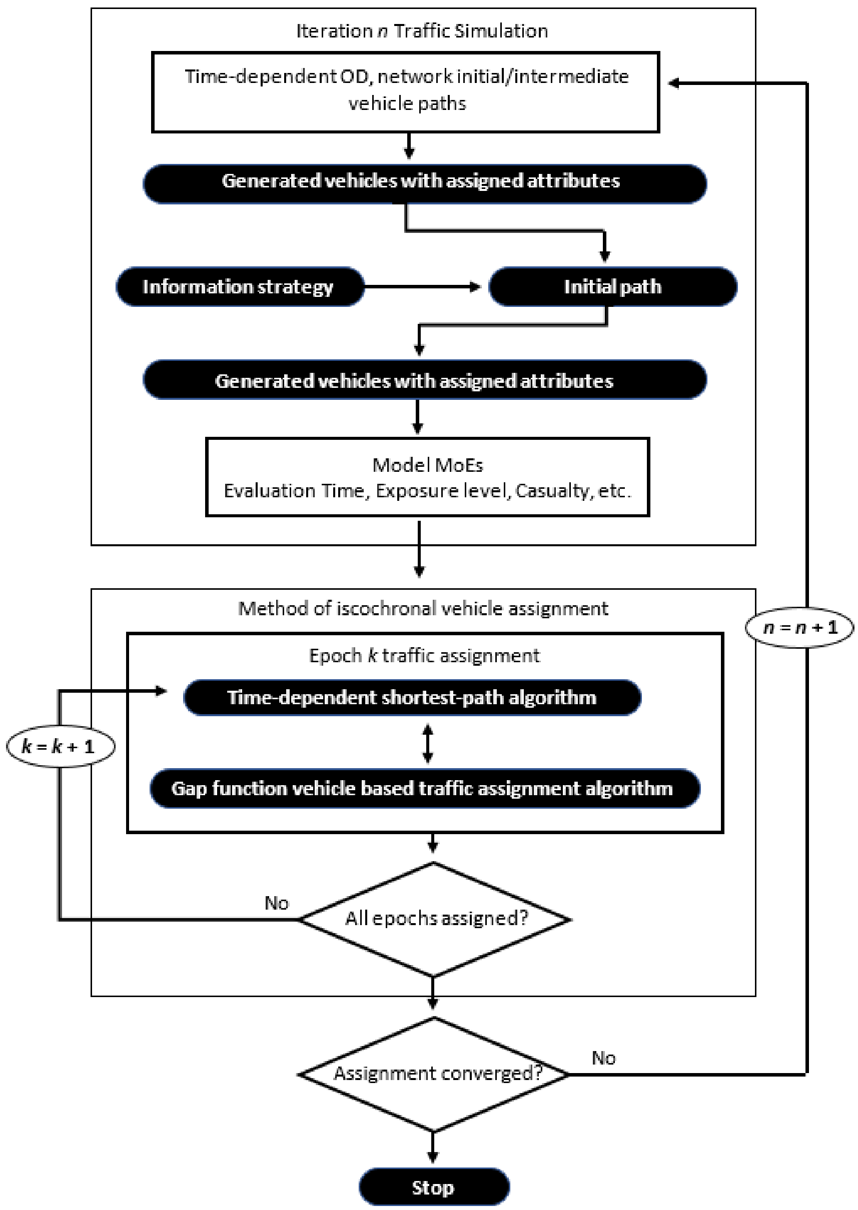


Figure 3. Flow Chart. Traffic simulation, assignment, and link volume estimation framework in DynusT.
Source: Chiu, Y.-C., L. Zhou, and H. Song, 2010.

After simulation, necessary measures of effectiveness (MoE) that drive the overall assignment process are fed into the traffic assignment module. The traffic assignment module consists of two algorithmic components: a time-dependent shortest-path (TDSP) algorithm and time-dependent traffic assignment. The TDSP algorithm determines the time-dependent shortest path for each departure time, while the traffic assignment component assigns a portion of the vehicles departing at the same time between the same origin-to-destination (O-D) pair to the time-dependent least-travel time path following the “route swapping” type of traffic assignment procedure.

In DynusT, the assignment algorithm maintains a balance between computational efficiency and solution algorithm quality. Also, innovations have been integrated into DynusT with respect to computational efficiency that allow the model to perform a 24-hour assignment, which is critical when estimating daily traffic patterns. Other important computational features include:

- Reuse of vehicle IDs so that computer memory is committed only for those vehicles that exist in the network during simulation. This means that memory usage is not cumulative to the total number of generated vehicles.
- Assignment of vehicles with TDSP that are solved based on an *epoch*, which is the time period over which network statistics are collected for solving for the TDSP. An *epoch* is defined within DynusT to be about 1-2 hours in length. This ensures that the memory usage for the TDSP is limited by the length of the epoch, regardless of the length of the total simulation period.

When the assignment associated with the current iteration is completed, all vehicles are loaded and moved along their paths in the simulation module again to evaluate if the time-dependent user equilibrium condition is satisfied. If so, the algorithmic procedure is terminated; otherwise, the next iteration continues.

VEHICLE TRAJECTORY PROCESSOR

The Vehicle Trajectory Processor is a post-processing software tool developed in the SHRP2 L04 project to extract reliability-related measures from the vehicle trajectory output of simulation models. It produces and helps visualize reliability performance measures (for example, travel time distributions and other performance indicators) from observed or simulated trajectories. Independent measurements of travel time at link, path, and O-D level can be extracted from the vehicle trajectories, which allow the Vehicle Trajectory Processor to construct the travel time distribution profile. Since completion of the SHRP2 L04 project, the Vehicle Trajectory Processor was moved to an open-source software model and rebranded as NeXTA. Important analytic and evaluative features available through NeXTA include the ability to:

- Publish scenario-specific travel time reliability measures and display these measures on the network or on a map.
- Display the aggregate travel time distribution over multiple scenarios by considering the probability of each scenario.
- Compare observed and simulated travel time reliability measures.

From the system operator’s perspective, reliability performance indicators for the entire system allow comparison of different network alternatives, policy, and operational scenarios. Thus, NeXTA can facilitate decision making regarding actions intended to control reliability and evaluation of system performance. Reliability measures (such as 95th Percentile Travel Time, Buffer Time Index, Planning Time Index, frequency that congestion exceeds some expected threshold, etc.) can be derived from the travel time distribution, or alternatively, computed directly from the travel time data.

Figure 4 is an illustrative example of output available from NeXTA and demonstrates some of its capabilities with respect to visualization of calculated performance measures based on vehicle trajectory data inputs.

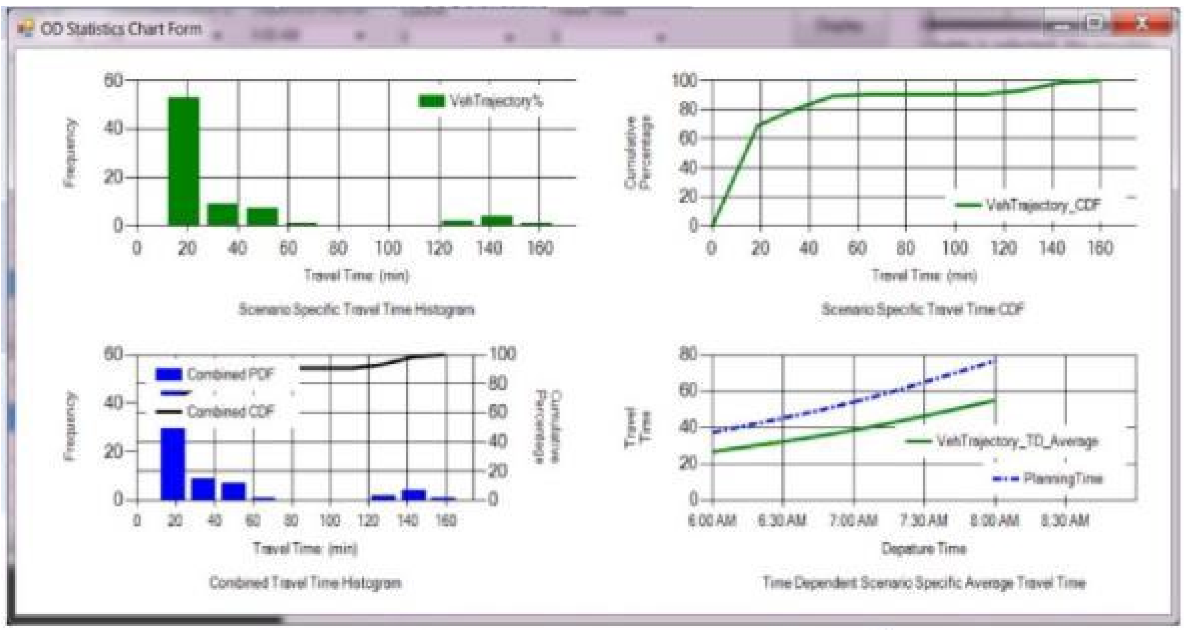


Figure 4. Graph. Example comparison of simulated and observed travel time in NeXTA.
Source: Sample output of simulated and observed travel time in NeXTA.

Several path and subarea data extraction and visualization functions were added to NeXTA during this project so that it could more effectively calculate end-to-end travel times and associated travel time reliability measures. These included the ability to:

- Identify the origin, destination, the total O-D travel time, and the individual segment travel time for each vehicle trip that passes through a specific road segment (shown as the segment from A to B in figure 5) during a specific analysis time period.

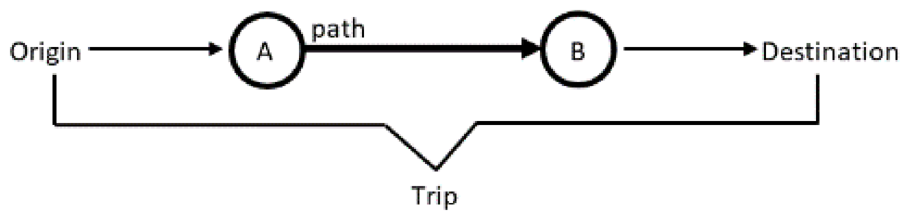


Figure 5. Diagram. Added NeXTA feature: trips passing through a selected path.
Source: FHWA.

- Keep track of the origin, the destination, the trip start time, the trip end time, the overall trip travel time, the overall corridor travel time, and the individual (within-corridor) link travel times for every vehicle trip that passes through a corridor of interest, including:
    - External-to-external trips (i.e., trips with both an origin and a destination outside the subarea).
    - External-to-internal trips (i.e., trips with an origin outside the subarea and a destination inside the subarea).
    - Internal-to-external trips (i.e., trips with an origin inside the subarea and a destination external to the subarea).
    - Internal-to-internal trips (i.e., trips with both an origin and a destiation that are inside the subarea).

CHAPTER 3. PILOT TEST SITES

The Maricopa Association of Governments (MAG) in Phoenix, Arizona and Portland Metro (Metro) in Portland, Oregon are the metropolitan planning organizations (MPOs) for their respective communities. Each has an established and funded transportation system management and operations (TSMO) program as well as upcoming project plans for actively managing congestion, incidents and special events. Both MAG and Metro also have previous and ongoing experience in calibrating and using the dynamic traffic assignment model DynusT in the course of their normal travel demand forecasting activities.

Both of the MPOs were interested and willing to participate in pilot testing the software products that resulted from SHRP2 Project L04. Both were also able to offer viable test sites that, collectively, allowed these software products to be tested in both a corridor and a network-wide environment.

The remainder of this chapter describes each of the two pilot test sites that were selected from within the MAG and Portland Metro MPOs.

AREAWIDE PILOT TEST SITE – PHOENIX, ARIZONA

The Phoenix metropolitan region was selected as the site for pilot testing the usefulness and viability of the SHRP2 Project L04 software products. The focus of this pilot test was on the freeway system highlighted in figure 6, although the integrated arterial and collector system associated with this freeway system was also modeled to assure the realistic generation, distribution, and assignment of traffic throughout the surface street network.

Figure 6. Map. Phoenix area pilot test site.
Source: Google Maps, 2016.

The freeway system shown in figure 6 is composed of 19 corridors and 366 loop detectors. It therefore provides a large area testbed for the purpose of investigating the practical and efficient use of the analysis component tools.

CORRIDOR PILOT TEST SITE – PORTLAND, OREGON

The geographic boundaries of Portland's Southwest Corridor are illustrated in figure 7. It is a well-defined area south of Portland that has, for a number of years, been the focus of past and ongoing efforts to improved multimodal options within a critically important regional transportation corridor. Some of the more recent of these efforts have relied upon the application of a calibrated DynusT simulation model.

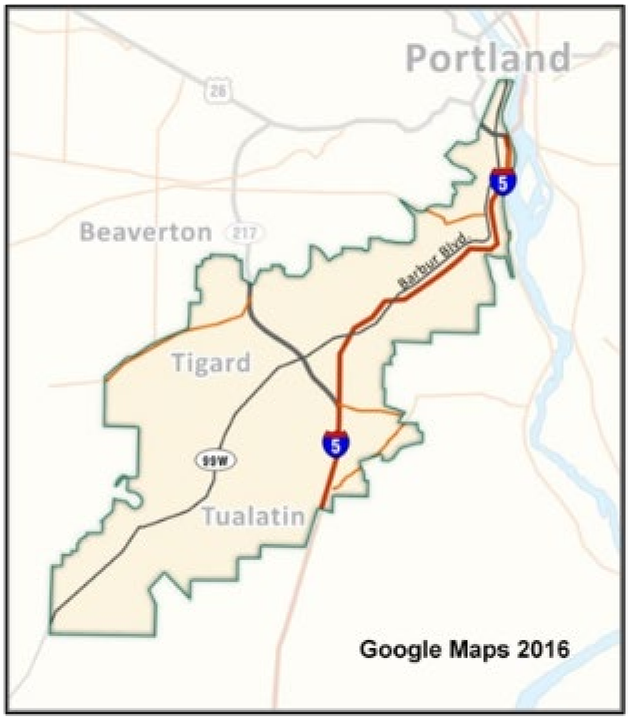


Figure 7. Map. Southwest Corridor Boundaries: Portland.
Source: Google Maps, 2016.

The corridor is approximately seven miles in length and includes a freeway (I-5) as well as a parallel major arterial (Barbur Boulevard).

CHAPTER 4. DATA REQUIREMENTS

INTRODUCTION

For the purposes of this project, the pilot tests were conducted within the context of a whole-year analysis, which was done for several reasons:

- A whole-year analysis provides a relatively robust testbed for the analysis tools and procedures because the major sources of unreliability (weather, incidents, and travel demand variability) are likely to span a significant range of values across a year.
- Many of the operational improvement strategies that metropolitan planning organizations (MPOs) and State departments of transportation (DOTs) might consider for deployment should be expected to be in place for at least a year or more. In such cases, it will be important for decision makers to be able to understand and quantify the expected effects of these strategies across the entire timeframe of their deployment, and not just under design-hour conditions.
- A whole-year analysis also provides a good testbed for judging the amount of effort and resources that agencies can expect will be needed to apply these analysis tools. This is important because the informational and decision-making value gained from the use of these tools must more than offset the costs associated with their application.

The term "whole-year analysis" can of course mean many different things depending on the days of the week and the hours of the day that are of interest. The whole-year analysis conducted as part of this project was defined in terms that are likely to be typical for most urban areas:

- Only non-holiday weekdays were included, resulting in the inclusion of 253 days of a 365-day year.
- Only the afternoon/evening peak period was investigated. The evening peak hour usually occurs sometime between 4:00 PM and 6:00 PM in both the Phoenix and Portland areas. However, the development and dissipation of bottleneck queues can sometimes occur outside of this time window. Therefore, the pilot tests were based on a four-hour weekday time window that began at 3:00 PM and ending at 7:00 PM.
- All data were aggregated into 5-minute time intervals so that, for each weekday, 48 separate 5-minute time intervals were recorded and analyzed. A 5-minute time interval is short enough to capture many of the significant sources of unreliability that can affect travel time, while also being long enough to avoid overwhelming the effects from recognized sources of unreliability with the high flow-rate variabilities that often occur within very short time spans.

Table 1 identifies the input data elements for simulation models that are typically associated with travel time reliability analyses. The remainder of this chapter provides additional detail on the type, source, and quality of the data elements identified in this table with respect to their use in support of the pilot testing effort.

Table 1. Input data elements associated with a reliability analysis.

Data Type	Data Source	Key Attributes
Traffic Demand and Travel Time	Automated Traffic Count Stations, manual counts; Bluetooth readers, probe data, Third Party data aggregators	Disaggregated data by traffic message channel at 1- to 5-minute intervals
Incidents/Crashes	Incident logs; reported crashes	Location, start time, duration, and severity (number of blocked lanes)
Weather	METAR data from airport or other nearby representative station	Weather condition and precipitation intensity at 1-hour intervals and at time of change
Special Events and Work Zones	Incident log; maintenance log; public works calendar	Location, start time, duration, and number of blocked lanes

TRAFFIC DEMAND AND TRAVEL TIME

Traffic volume data are typically available from a variety of traditional sources, many of which are in common use by State DOTs throughout the country. These data are used primarily for calibration purposes since they will be compared with the simulation output.

Volume and demand information is not an input to Scenario Manager, nor is it contained in the output file that is delivered to the simulation model. However, this information is necessary to allow Scenario Manager to provide day-to-day random demand variation as a scenario component. As stated in the Scenario Manager User's Guide, the random demand variation "is modeled by a demand multiplication factor, which is a multiplier that is applied to the average demand level to introduce a certain range of fluctuations in demand." A single demand multiplication factor is applied to the entire simulated network for each simulated time interval and is based on a selected probability distribution type along with defined minimum, maximum, mean, and standard deviation parameters.

Travel time and speed data are not input to Scenario Manager but are used to verify the reasonableness of base case simulation results. Travel time and speed data should be available for each traffic message channel (TMC) and aggregated to 1- to 5-minute time intervals.

Phoenix Test Site

Multiple sources of data were used at the Phoenix test site to obtain the traffic demand and travel time data necessary to this pilot test project. With respect to volume data, the following sources were employed:

- The Arizona Department of Transportation (ADOT) maintains the Transportation Data Management System (TDMS), which houses all traffic count data within the State. The ADOT TDMS contains archived one-time spot counts at interchange ramp locations from various years and automatic traffic recorder (ATR) count data.
- MAG TDMS is a Traffic Count Database System that maintains all traffic count data within the MPO boundaries. The MAG TDMS contains archived one-time spot counts at interchange ramp locations (which may be duplicating the ADOT TDMS count data) and

many surface street locations from various years. The TDMS also contains turn movement count data from the year 2010 for peak periods for the weekday morning (7AM – 9AM) and evening (4PM – 6PM) peak periods in either 5- or 15-minute intervals.

With respect to verification data, the following sources were available and used to produce travel time verification estimates for each non-holiday weekday of the base year between the hours of 3:00 PM and 7:00 PM:

- ADOT's Freeway Management System contains a mainline detection system covering each traffic lane. Mainline detection occurs at a spacing of approximately one mile. Data from these detectors is used to electronically determine travel times and abnormalities in traffic flow.
- MAG also has access to two primary sources of travel time data. HERE data (National Performance Management Research Data Set) has been provided to public agencies for free, with HERE as the vendor. The second source of travel time data is INRIX™ data purchased from previous bottleneck travel time studies from various years, dating back to 2007.

Portland Test Site

Two data sources were used in the Portland area to obtain the necessary volume and verification data. The Portland Archival Listing (PORTAL) is a unique online database developed, maintained, and housed at Portland State University. Oregon DOT (ODOT) has also licensed data from INRIX™, which is a third-party vendor of real-time and historical travel time data.

Weekday p.m. peak hour traffic counts were obtained from the PORTAL ATR station data archive at locations nearest to the boundaries of the Portland Southwest Corridor sub-regional model. These counts were evaluated to determine average 5-minute flow rates over the course of the 4-hour weekday study period between 3:00 PM and 7:00 PM; table 2 and figure 8 provide an example of the available PORTAL Count Station traffic volume data.

Table 2. PORTAL Count Station traffic volumes and speeds (December 4, 2005).

Start Time	Speed (miles per hour)	Volume (vehicles per hour)
12/4/2005 12:00 AM	57.93	164
12/4/2005 1:00 AM	57.54	115
12/4/2005 2:00 AM	57.38	78
12/4/2005 3:00 AM	57.18	52
12/4/2005 4:00 AM	57.88	73
12/4/2005 5:00 AM	60.31	96
12/4/2005 6:00 AM	61.76	185

Source: Data output from PORTAL Count Station.

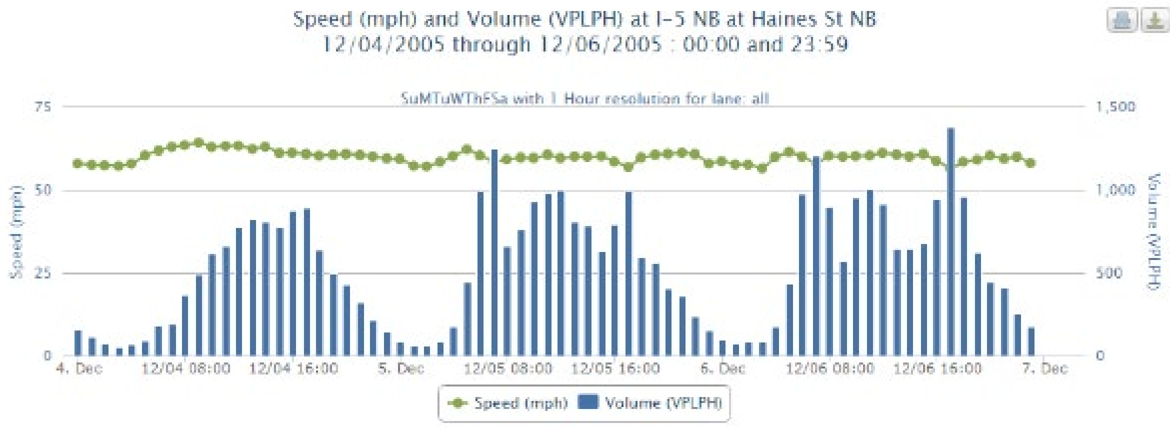


Figure 8. Graph. PORTAL Count Station traffic volumes and speeds (December 4-6, 2005).
Source: Data output from PORTAL Count Station.

For verification purposes, INRIX™ datasets were available to determine corridor-level speeds and travel times. Metro has access to INRIX™ data for multiple years, by month and day of the week (e.g., Mon, Tues, Wed, Thu, Fri). All data is reported at the TMC-level, which provides excellent resolution for freeways. Specifically, INRIX™ has split TMCs so that they break at each decision point (i.e., access and egress points) along limited-access roadways. On arterials, the resolution is coarser, with TMCs often representing multiple miles along an arterial and quite possibly many intersections. While this coarse arterial resolution can make it difficult to pinpoint exact points of congestion along the TMC, prior analysis has found that the INRIX™ derived average travel times through arterial corridors are reasonable.

One of the benefits of the INRIX™ data is that it contains a rich set of statistical attributes, such as averages, standard deviations, and percentile breakdowns (10th, 20th … 80th, 90th, etc.). This allows one to determine ranges of travel times through a corridor (i.e., travel time variability). Figure 9 illustrates the INRIX™ coverage area in the project area along Interstate 5, and figure 10 illustrates example INRIX™ Travel Time calculations along Interstate 5 in the Southwest Corridor project area.

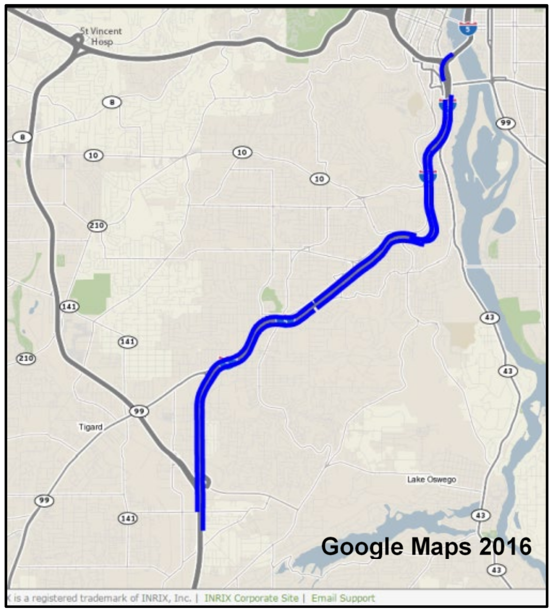


Figure 9. Map. Example INRIX™ data set coverage segments.
Source: Google Maps, 2016, sample INRIX™ data.

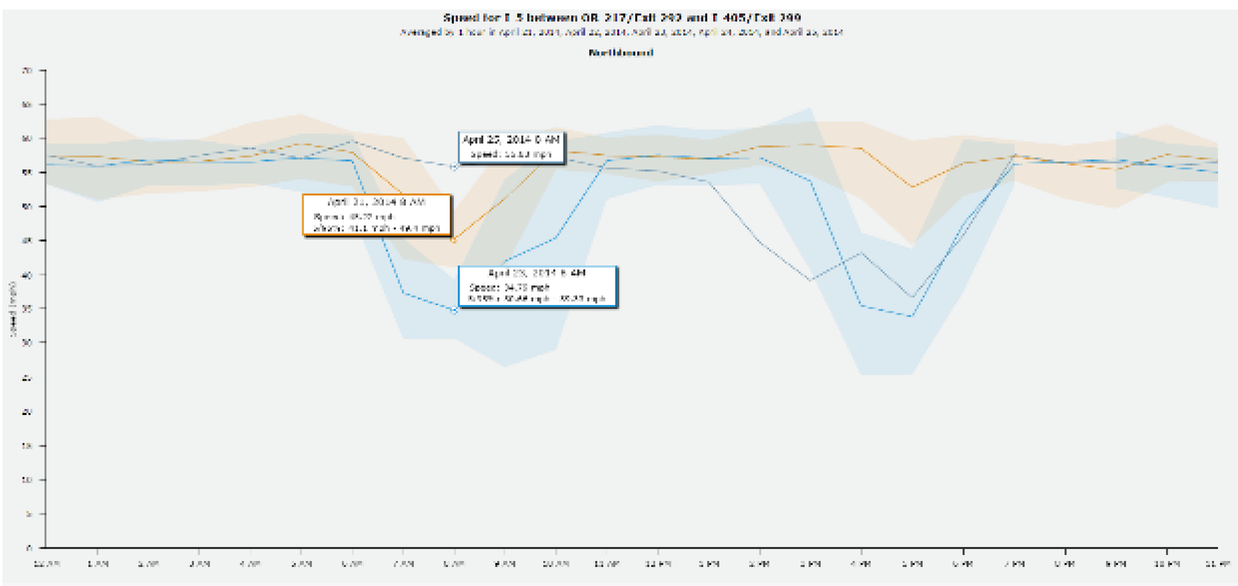


Figure 10. Graph. Example INRIX™ running speed for average, 5th and 95th percentile conditions (April 21, 23, and 25, 2014).
Source: Sample INRIX™ running speed output.

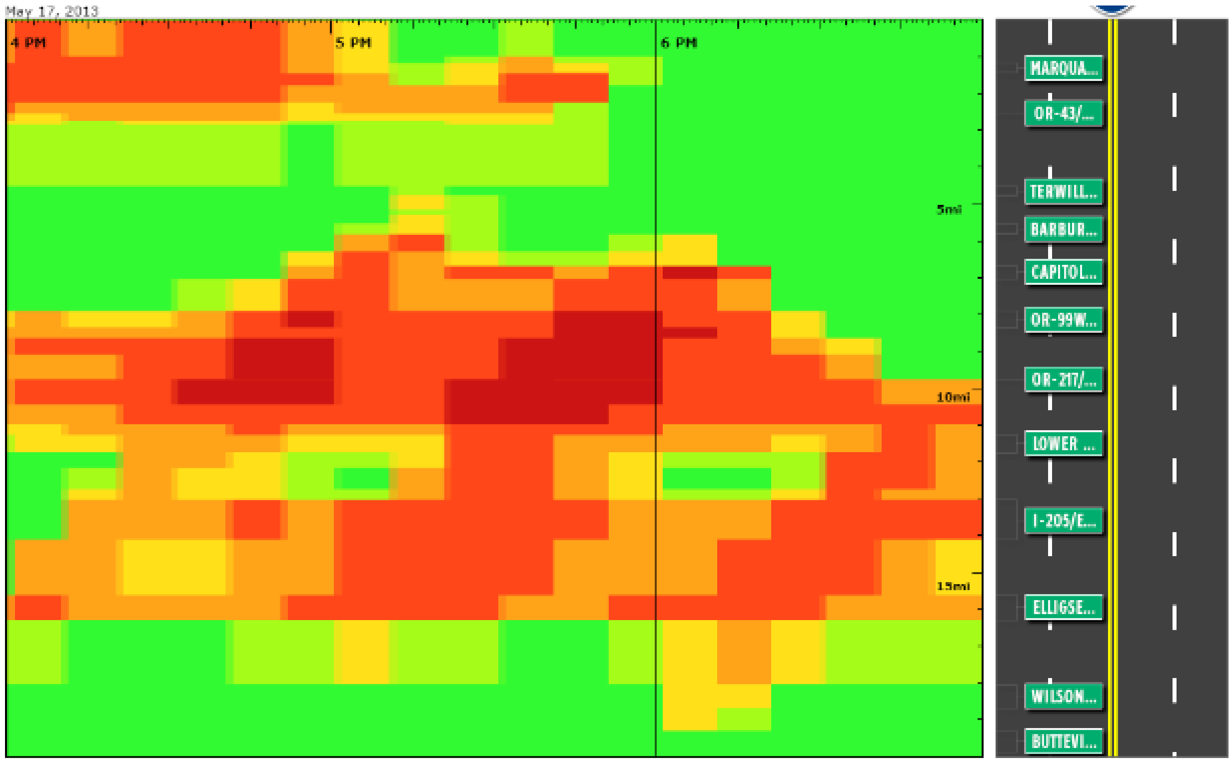


Figure 11. Map. Example congestion heat map for SB I-5 within the study corridor vicinity.
Source: Example INRIX™ congestion heat map, May 17, 2013.

Finally, INRIX™ can produce congestion heat maps such as that shown in figure 11. During this pilot test, these maps proved to be quite useful in identifying the origin, duration, and extent of congestion within a corridor.

INCIDENTS/CRASHES

Incident and reported crash data are available for the Portland and Phoenix pilot test networks. Each data source is briefly described in this section. Table 3 summarizes the Scenario Manager input requirements for crash data and the sources of availability at the pilot test sites.

Table 3. Incident data input requirements for Scenario Manager.

Attribute	Description	Source of Availability at Pilot Test Sites
Start Time and End Time	Date-time information on the onset of the event and either the termination of the event or its duration	Incident logs
Latitude/Longitude	Latitude and longitude coordinate of the event location	Incident logs; crash reports
NoOfLanes	Number of lanes blocked	Incident logs
RoadSide	The road side (left or right) of the incident	Incident logs; crash reports

Reported crash data were sometimes difficult to interpret with respect to number of lanes blocked and so inferences were made based on crash type and severity where necessary. The crash data for the Phoenix and Portland test sites covered all roadways, but incident log data was found to apply only to the DOT patrolled and monitored facilities. The available incident data was typically of high resolution, and included event location, duration, and number of lanes affected.

Phoenix Test Site

The Phoenix test site has access to incident log data through ADOT. More specifically, ADOT operates and maintains the Highway Condition Reporting System (HCRS), which is a Statewide closure and restriction information database. The system is used as an information sharing system and records such things as planned closures, special events, incidents, and advisories. The system information is used to populate a public information website (http://az511.gov/traffic/) and is also connected to its 511-phone system. Historical entry data to the HCRS is archived for future reference. The HCRS contains information regarding event category, event description, start time, end time, and map location. For the purposes of this pilot test, a copy of historical HCRS data was obtained from ADOT as input to the Scenario Manager.

The Phoenix test site also has access to crash inventory data maintained by ADOT's Traffic Records Section. The Accident Location Identification and Surveillance System (ALISS) database archives all reported motor vehicle crashes in Arizona and includes crash data since 1999 on freeway, highway, and local jurisdictional roads with the MAG's metropolitan planning area. MAG has retrieved and used the crash data for road safety analysis purposes via the Regional Transportation Safety Information Management System (RTSIMS) software, which was developed by MAG. MAG staff performed the necessary data queries from the RTSIMS tool to obtain the required input to Scenario Manager. Table 4 presents a sample of the available crash-incident data that were collected for this pilot test.

Table 4. Sample Phoenix incident/crash data set.

Field Name	Sample Field Data
event_id	525390
geo_pos_longit	-112.112222
geo_pos_latit	33.554166
date_start	12/31/2013
time_start	23:44
date_end	1/1/2014
time_end	1:39
hwy_sys_descr	Interstate
hwy_descr	17
hwy_dir_descr	North

Source: Regional Transportation Safety Information Management System.

Table 4. Sample Phoenix incident/crash data set. (continuation)

Field Name	Sample Field Data
hwy_at_mp	207
hwy_to_mp	--
location_descr	On Interstate 17, North-bound at mile post 207.00 (0.10 miles North of NORTHERN AVENUE).
itis_categ_descr	Incidents/Accidents
itis_descr	crash.shoulder blocked
closed_tag	--
block_tag	Shoulder blocked

Source: Regional Transportation Safety Information Management System.

Portland Test Site

The Portland pilot test site has access to two primary incident and crash databases. The first is the ODOT Incident Log data for freeways, also referred to as Transportation Operation Centers (TOCs) data sets. This data set contains information for any incident that required the deployment of a response vehicle. Some of the included data fields are a unique event identifier, location information (viz., facility and milepost), date, event type, and event duration information (viz., start and end times). This data set only covers freeways, so no incident log data is available on the remaining surface street network. Table 5 provides an example of the incident log data collected for I-5 within the Southwest Corridor project area.

Table 5. Sample ODOT TOC Incident Log data set for I-5, Portland.

Field Name	Sample Field Data
Event Id	13T000048
Date	01/01/2013
Event Start	00:14
Event End	04:36
Event Subtype	Crash
GIS Latitude	45.50813
GIS Longitude	-122.77846
Roadway Clearance Duration	21
Closure Involved	Non-Closure
Route No	OR-217
Road Name	BEAVERTON-TIGARD
Event From MP No	--
Event To MP No	--
Lanes Affected Count	1

Source: Oregon Department of Motor Vehicles (DMV).

The second dataset is a crash inventory maintained by the Oregon Department of Motor Vehicles (DMV). This dataset contains information on any crash reported to the DMV that resulted in death, bodily injury, or damage to any individual's property in excess of $1,500. Data fields include a unique event identifier, location information (expressed in latitude and longitude coordinates), date, crash severity, and the status of environmental variables at time of crash (e.g., weather, lighting, and roadway conditions). This data set covers all roadways including freeways and surface street roadways. Figure 12 provides an example of the DMV-Based Crash Data within the Southwest Corridor project area (Interstate 5).

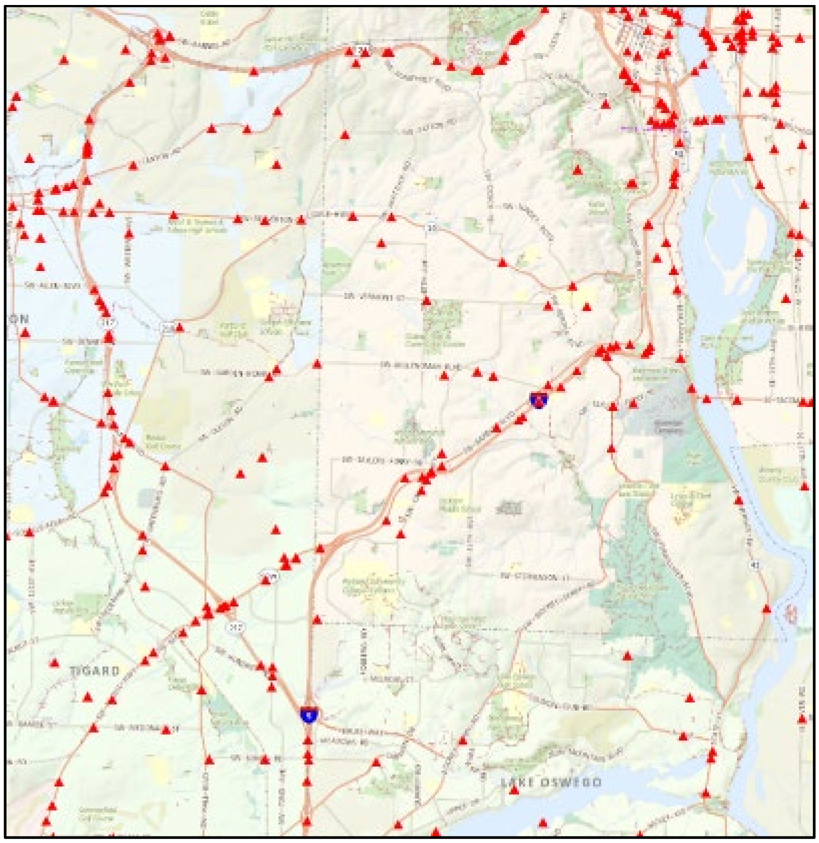


Figure 12. Map. Sample ODOT DMV-based crash data set identifying all crashes in the Southwest Corridor for May 2010.
Source: Oregon Department of Motor Vehicles (DMV).

Comparison of the reported location and duration of incidents contained in the incident logs with separately recorded travel time information revealed numerous inconsistencies. Subsequent discussions with other agencies throughout the United States suggest that this problem is not uncommon. For the purposes of these pilot tests, this problem was largely resolved by relying on crash reports instead of the incident log for all crashes, although this did require some additional time and effort. It is expected that this problem will become less acute as agencies implement or enhance quality control procedures for databases such as incident logs.

WEATHER

Weather data is available for the Portland and Phoenix pilot test networks, in either meteorological aerodrome report (METAR) data format (through archiving sites, like www.weatherunderground.com) or National Oceanic and Atmospheric Administration (NOAA) data format. METAR-formatted data was used in the original SHRP2 Project L04 where Scenario Manager and Vehicle Trajectory Processor were initially developed. METAR-formatted data consists of observed hourly weather conditions from weather stations reported in the World Meteorological Organization standard METAR format. The NOAA-formatted data is from the same sources, but is presented in a slightly different format.

Historical weather data is available for all parts of the country from many sources. NOAA formatted data were used for the pilot tests in this project. These data are available from monitoring stations at every major airport and at many other locations as well. The data were delivered in .csv format, making translation for input into Scenario Manager easier. The NOAA database information is available upon request from NOAA and was delivered within several days of request. Table 6 summarizes the Scenario Manager input requirements with respect to its weather information needs.

Table 6. Weather data input requirements for Scenario Manager.

Attribute	Description	Availability
Latitude / Longitude	Latitude and longitude coordinate of the weather station	Calculated based on the known airport station location
TimeStamp	Year, month, day, hour, and minute time stamp of the given observation	Observations are recorded hourly and also upon each new weather event
Visibility	Visibility in miles	A visibility recording is provided with each observation
PrecType	Type of precipitation (as reported in ASOS METAR data)	Temperature and precipitation amount are available, from which precipitation type and amount can be deduced
PrecIntensityLevel	Precipitation intensity level (as reported in ASOS METAR data)	Precipitation intensity is reported in inches per hour
Rain	Rainfall in inches in the TimeStamp increment (ASOS METAR data format)	Amount of rain is deduced by using temperature to distinguish rain and snow
Snow	Snowfall in inches in the TimeStamp increment (ASOS METAR data format)	Amount of snow is deduced by using temperature to distinguish rain and snow
Temperature	Temperature in degrees Fahrenheit for TimeStamp increment (ASOS METAR data format)	A temperature recording is provided with each observation

Table 6. Weather data input requirements for Scenario Manager. (continuation)

Attribute	Description	Availability
Humidity	Percent humidity (ASOS METAR data format)	A humidity recording is provided with each observation
PrecAmnt Prev1Hr	Precipitation accumulation from previous 1 hour (ASOS METAR data format)	Precipitation accumulation is calculated using previous hourly information

As shown in table 6, all the needed Scenario Manager input data is available either directly or can be calculated from the weather data set.

Phoenix Test Site

The Phoenix test site relied on weather station data in NOAA formatting, and the weather station data site for this Phoenix regional pilot is located at Sky Harbor International Airport (station id: KPHX). Table 7 presents a sample of the NOAA-formatted weather data obtained from NOAA, and table 8 illustrates how the sample data shown in table 7 was reformatted to meet the needs of Scenario Manager.

Table 7. Sample Phoenix NOAA weather data for March 21, 2011.

STATION	STATION_NAME	DATE	HPCP
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 10:00	0
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 11:00	0
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 12:00	0
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 13:00	0
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 14:00	0.02
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 15:00	0.02
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 16:00	0.02
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 17:00	0
COOP:026481	PHOENIX SKY HARBOR INTERNATIONAL AIRPORT AZ US	20110321 18:00	0

Source: NOAA.

Table 8. Sample Phoenix NOAA weather data reformatted for Scenario Manager.

Field Name	Sample Field Data
Station ID	KPHX
StationDesc	PHOENIX SKY HARBOR INTL AIRPORT
Latitude	33.427
Longitude	-112.003
Year	2011
Month	3
Day	21
TimeStamp	03/21/2011 13:11
Visibility	9
Rain	0
Snow	0
Temperature	56
Humidity	78
PrecType	RA BR
PrecIntensityLevel	0
PrecAmntPrev1Hr	0

Source: NOAA.

Portland Test Site

The Portland test site relied on weather station data in NOAA formatting, and the weather station data site is located at Portland International Airport (station id: KPDX). The same data collection and reformatting process used in Phoenix was also applied in Portland to meet the needs of Scenario Manager for the Portland pilot test site.

SPECIAL EVENTS AND WORK ZONES

The current version of Scenario Manager can be used to model the effects work zones and special events that are (a) generally unanticipated by travelers; and (b) in place for a short time period (i.e., less than a day). This is because work zones and special events with these characteristics can be expected to have the same effect as a crash or other unanticipated incident. Therefore, they can be modeled in Scenario Manager as if they were a crash or unexpected incident. Unfortunately, long-term work zones and anticipated special events cannot be modeled in this manner and the currently available version of Scenario Manager does not accept input data that can be used for such purposes. It is clear, however, that these can be significant sources of travel time unreliability. Anticipating that Scenario Manager will at some point be upgraded to be sensitive to long-duration work zones and anticipated special events, this project explored the availability of such data.

In Phoenix, the HCRS dataset described earlier also provides records of work zone and special event data logged by ADOT staff resulting in actions such as lane restrictions, road closures, and road maintenance.

Similarly, the TOC incident logs available within the Portland area include information on anticipated special events (for example, a facility closure for a pre-scheduled foot race) and both short- and long-term work zones.

ANALYSIS OF DATA CONSISTENCY AND APPLICABILITY

Phoenix Test Site

Base-year data obtained for the Phoenix region's freeway system revealed some inconsistencies between specific data sets, but these were resolvable through manual review and modification whenever encountered. The number of inconsistencies found was not so great nor was the correction of these inconsistencies so labor-intensive that it had a significant effect on the overall level of effort required. Therefore, plans for testing the effectiveness of Scenario Manager and Vehicle Trajectory Processor within the Phoenix pilot test site remained unchanged, and the results of executing these plans are described in the remaining chapters of this report.

Portland Test Site

A review of the base year data obtained for the Southwest Corridor pilot test site in Portland revealed that travel time reductions, queuing and congestion frequently occurred during the weekday evening peak hour period because of incidents or bottlenecks located well beyond the geographic limits of the corridor. An example of this can be seen in figure 11, where it is clear that, on the particular day for which the heat map is being displayed, congested conditions migrated across the Corridor's southern boundary (which is approximately at the OR-217 interchange) and into the Corridor from an event or bottleneck located well south of the Corridor's southern boundary.

Further examination of the entire year of data collected for the Portland pilot test site revealed that conditions similar to those shown in figure 11 occurred so frequently on both the north and south Corridor boundaries that it would be impractical to test the effectiveness of Scenario Manager and Vehicle Trajectory Processor in such an environment. This was, in and of itself, a useful thing to learn because it clarified that travel time reliability analyses, even when evaluated at a corridor level, should be performed on a much larger transportation system scale to ensure that the effects of outside bottlenecks and queues are taken into appropriate account. At the same time, the project team determined that the project objectives would be best served by focusing the remaining project efforts on the Phoenix pilot test site, where the analysis was being conducted in the context of simulating the entire regional transportation system. Therefore, the remainder of the project effort and the remainder of this report focus upon the Phoenix pilot test site.

CHAPTER 5. ANALYSIS FRAMEWORK

MODELING TRAVEL TIME RELIABILITY

Travel time reliability is a performance metric that can neither be measured nor estimated for a single instance in time, such as the design hour or the peak 15-minute period, nor can it be measured at a single point, such as a signalized intersection, because it is both a distance- and time-based measure. Instead, it can only be estimated from multiple repetitions of the same trip made at approximately the same time of day from the same origin to the same destination.

This fact suggests that the recurrent random events that contribute to the variability of travel time across multiple trips arise from the integrated effects of several factors:

1. Demand fluctuations that occur on both a daily and a seasonal basis.
2. Weather effects, which are by their nature typically seasonal in nature.
3. Crash frequency, which is not only related to design and operational factors, but also demand and weather conditions.

Taking all of these factors into account over a length of time sufficiently long to adequately evaluate the effects of an operational improvement strategy on travel time reliability results in the need to manage and manipulate substantially more data than has heretofore been the case. The good news is that the result of any such effort is a much more informative and realistic representation of the effects of the proposed improvement strategy—a fact that should help to better inform decision makers and result in the more effective investment of scarce financial resources. Achieving such outcomes requires that modelers and analysts adopt new techniques and tools for managing and analyzing the large quantities of data in ways that were not previously necessary.

The general framework used to organize and direct the pilot test analysis work is presented in flowchart form in figure 13. Observed and recorded data for a calendar year was first subjected to an inter-seasonal cluster analysis, which is a mathematic procedure described more fully in CHAPTER 6. Cluster Analysis Applications and Results, to determine whether distinct seasonal trends were evident and should be recognized in the simulation process. The results of this analysis were then subjected to an additional cluster analysis for data in each identified season to determine the number of scenarios to be produced by Scenario Manager. After using Scenario Manager to generate the appropriate number of scenarios, DynusT was used to simulate each scenario and to produce an output of individual vehicle trajectories from which travel time distribution profiles could be created.

A more detailed discussion of the analysis framework and its underlying basis is provided in the remaining sections of this chapter.

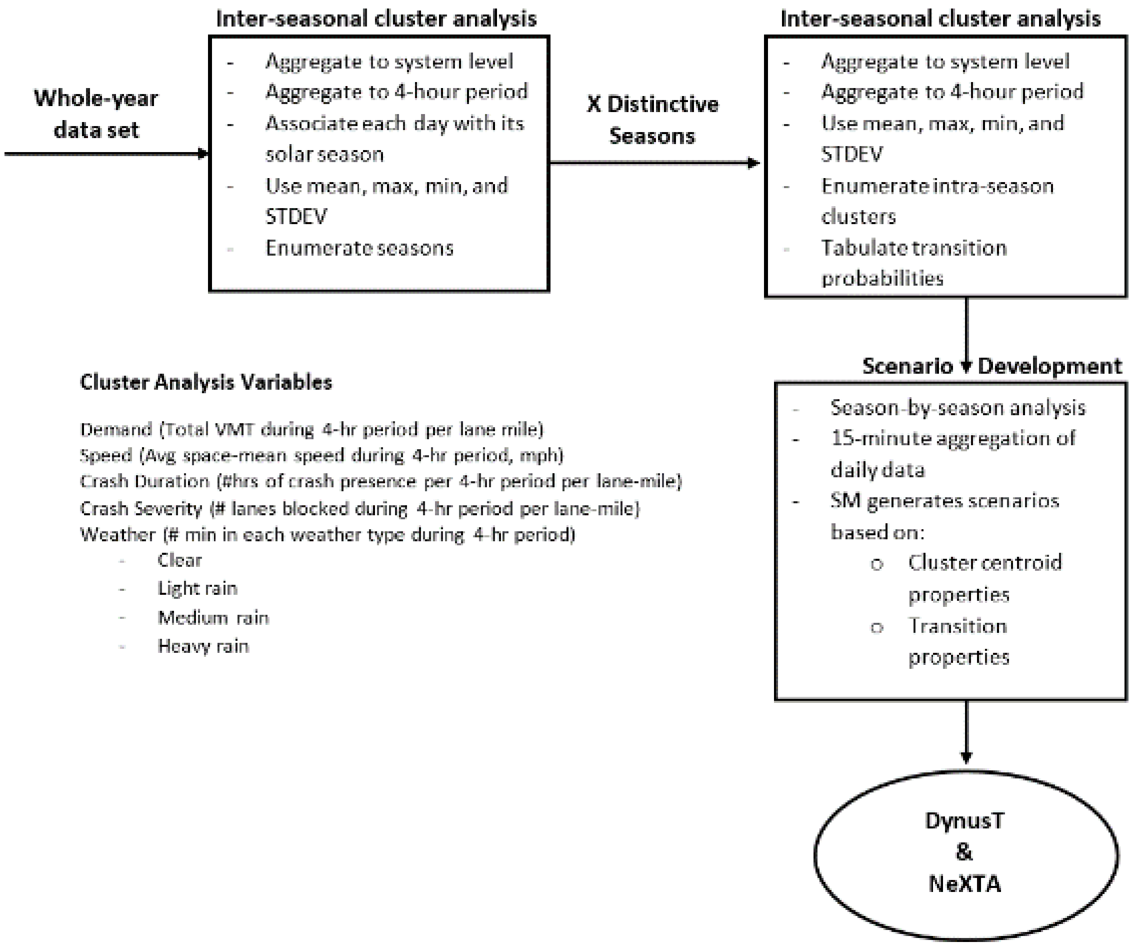


Figure 13. Flow Chart. Pilot test analysis approach.
Source: FHWA.

The Need for Seasonal Analysis

It is intuitive that traffic data, which is time-series in nature, may often exhibit cyclic patterns resulting from demand-supply conditions naturally associated with seasons. For example, weather is often associated with apparent seasonal differences in regional driving patterns, volumes, and speeds. However, weather may not be the only seasonal factor which impacts traffic data for a given area. Whether school is or is not in session, which affects commuting patterns and recreational travel, is another typical example.

Proof that this is a national phenomenon and not limited to just one or a few urban areas can be found in the travel time index (TTI) monthly trends reported for 19 major urban areas in the U.S. (FHWA 2013). Figure 14 shows that TTI values peak in 2007 then sharply drop in 2008 and 2009, most likely due to the national economic downturn that occurred within that timeframe. The TTI values can be seen to gradually climb back up from 2010 to 2012. Despite these differences from one year to the next, the seasonal pattern remains apparent in each year: Congestion rises in May and June; decreases in July and August; gradually increases to another peak in November; trends downward in December; then rises early in the year with a drop in the late winter and early spring.

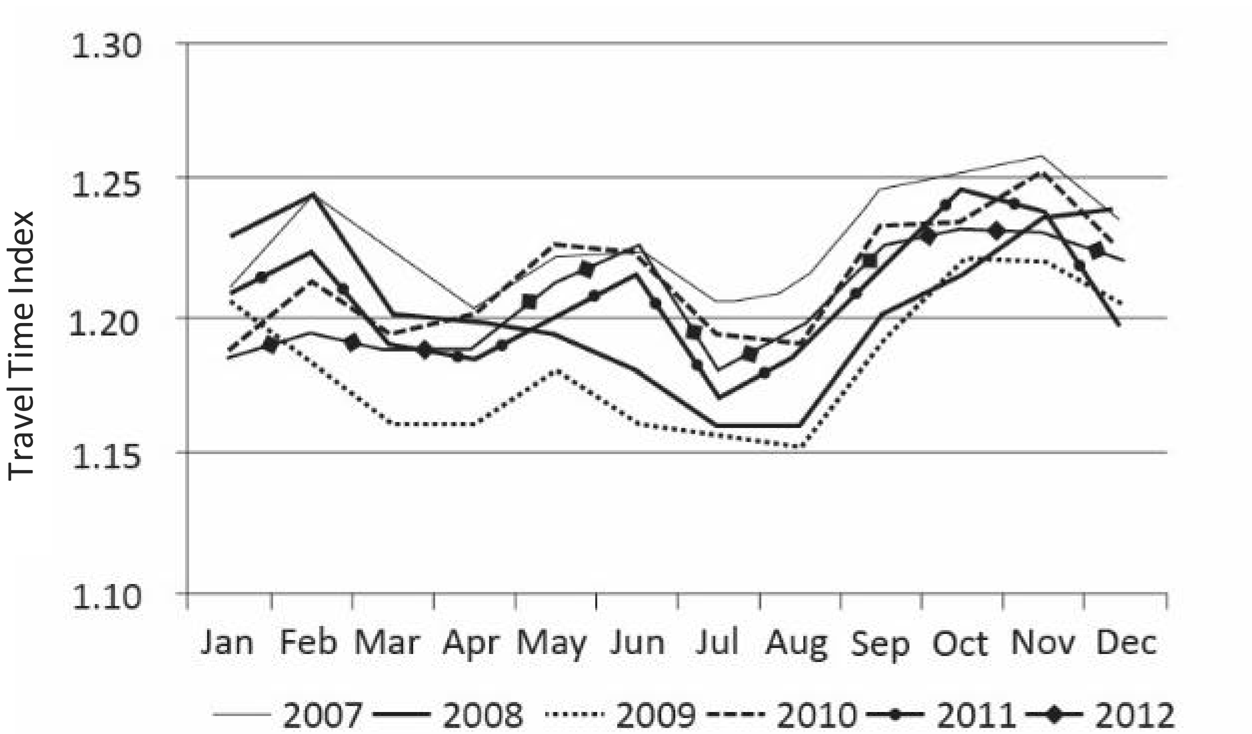


Figure 14. Graph. Monthly Travel Time Index Trends for 19 Urban Areas in the U.S. from 2007 to 2012.
Source: FHWA, 2013.

Furthermore, while the TTI values shown in figure 14 may be at similar levels at different times in each year, the root causes of these TTI values and the congestion that underlies them may be vastly different. For example, the congestion in June may be due to higher demand caused by the end of the school year and holiday-related travel while congestion in October and November might be caused by reduced roadway capacities due to winter weather conditions.

The importance of these observations comes in recognizing that performing cluster analysis on year-long traffic data may fall into a pitfall as illustrated in figure 15 and figure 16. In figure 15, traffic data clearly exhibits two clusters—one with low average and small standard deviation, whereas the other has a higher average and a larger standard deviation. More importantly, these clusters happen in two distinct seasons, one possibly in a good weather season like spring or summer, and the other in winter with more inclement weather situations.

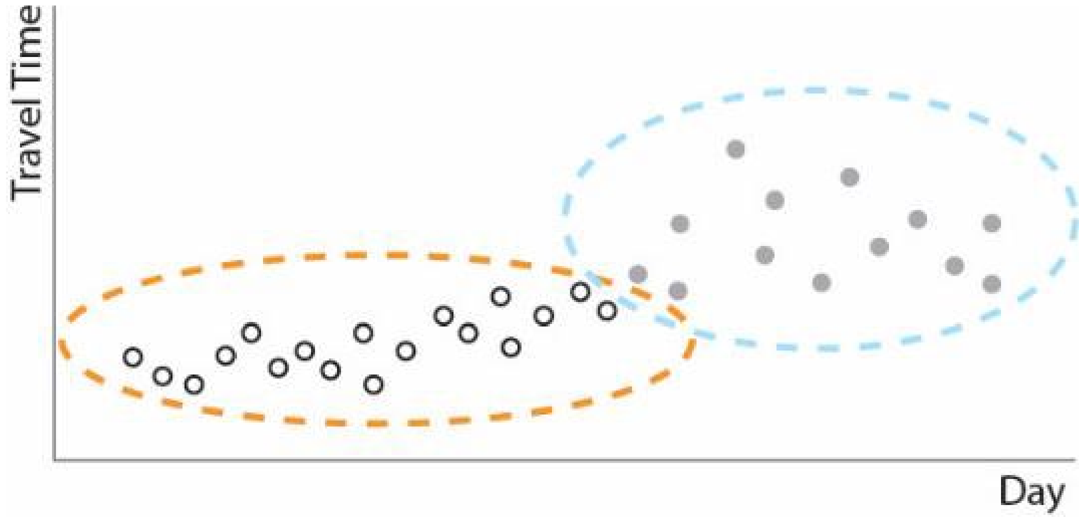


Figure 15. Chart. Traffic data with clear season effects.
Source: FHWA.

If we take figure 15 data points and randomly shuffle them across seasons, then the results would look like the pattern shown in figure 16. Such a pattern could well represent another city where seasonal effect is not prominent within the year but the large variations result from some other reason, such as high incident rates. In the figure 15 case, the transportation agency may benefit from deploying different traffic operational strategies in each of the two seasons, whereas in the figure 16 case a single strategy may be applicable throughout the year. Therefore, and in this particular example, it is clear that combining year-long data into one single cluster analysis would not yield insight to differentiate between the two cases.

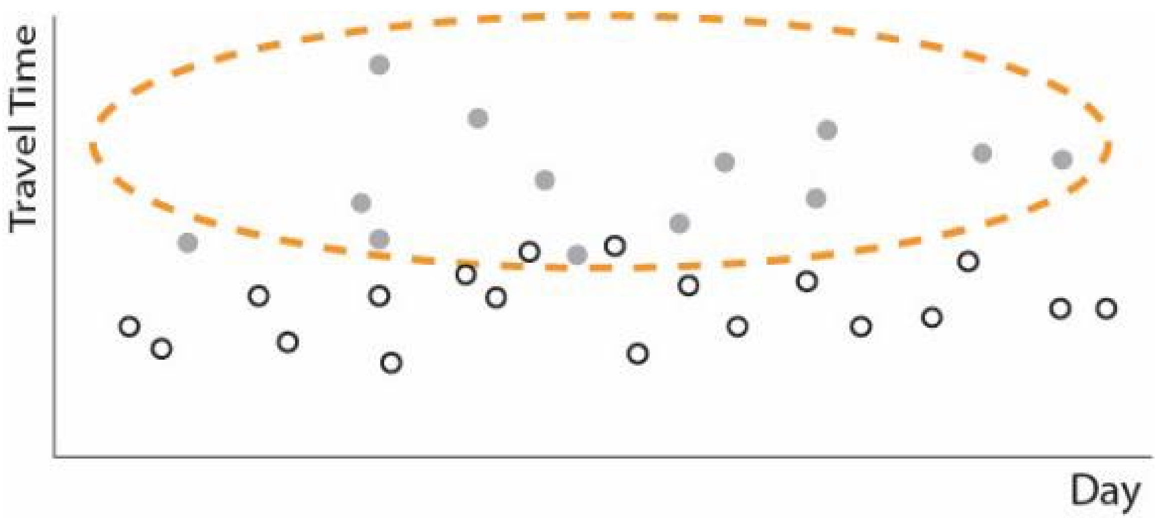


Figure 16. Chart. Traffic data without clear season effects.
Source: FHWA.

Season-Dependent Clustering

In light of these considerations, the project team used a general framework that provided a holistic treatment for various seasonal variability patterns. The methodology is described below.

Stage One – Season Clustering Theory

The season clustering is aimed at determining if the data naturally exhibits distinct variability at different times of the year. Taking figure 17 as an example, if the analysis unit is in weeks, the traffic pattern in Minneapolis exhibits a distinct seasonal pattern.

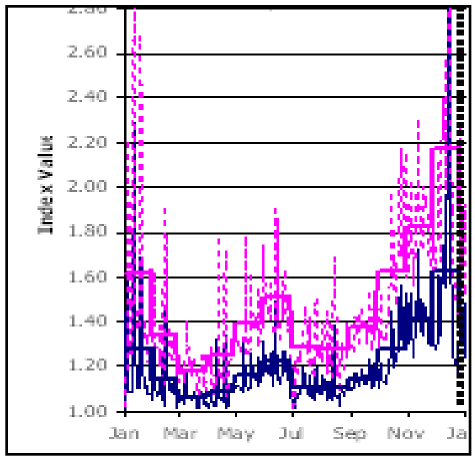


Figure 17. Graph. Minneapolis Monthly TTI Index.
Source: FHWA 2004, Figure D.1.

In this example, the proposed season clustering method would cluster all the weeks into a systematic hierarchy of clusters as illustrated in figure 18. Based on the structure shown in figure 18, if two clusters are selected based on the "Two Cluster" cut, then July, August, September, October, and November are included in one cluster and all other months are included in the remaining cluster. If four clusters are selected, December, January, and February are grouped into one cluster; March, April, May, and June are grouped into a second cluster; July and August are grouped into a third cluster; and September, October, and November are grouped into the fourth cluster.

The unique requirement for this problem is that each cluster would contain contingent weeks. Typical cluster analysis methods cannot guarantee this requirement so that a week from January may be grouped with other weeks from July. Therefore, a modification to the typical cluster analysis methodology is needed to ensure that this contingency condition is met. A related further requirement is that this contingency condition is also applicable to the "end-of-year/start-of-year" weeks due to the cyclic nature of the annual patterns. In other words, November and December should not be excluded from the possibility of being clustered with January or February.

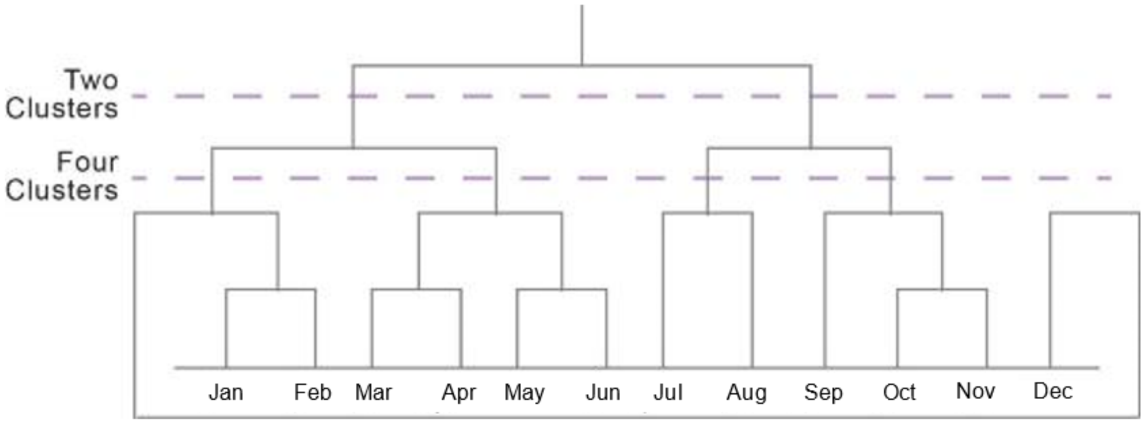


Figure 18. Chart. Season cluster hierarchy.
Source: FHWA.

The technique proposed to meet the above two requirements is to generate an augmented matrix as shown in table 9 by adding the doublet and triplet columns. The Data column contains actual data for multiple years (3 years in this example). The doublet columns reinforce the contingency of each neighboring week pair and the triplet columns further reinforce such contingency relationship for three consecutive weeks. Note that this treatment is also extended to connect week 52 with the weeks 1 and 2 in the following year.

Table 9. Augmented matrix for contingency clustering.

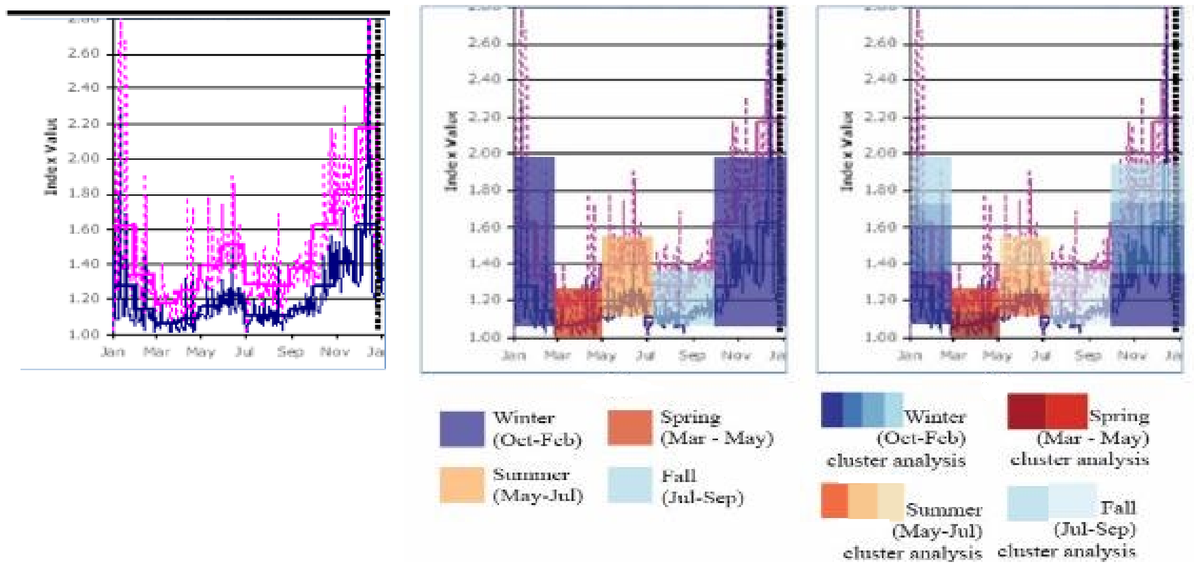
Weeks	Data (Mean)	Data (Variance)	Doublet							Triplet						
1	44	39	100	0	0	0	0	….	….	100	0	0	0	0	….	….
2	37	17	100	100	0	0	0	….	….	100	100	0	0	0	….	….
3	23	24	0	100	100	0	0	….	….	100	100	100	0	0	….	….
4	27	18	0	0	100	100	0	….	….	0	100	100	100	0	….	….
5	56	21	0	0	0	100	100	….	….	0	0	100	100	100	….	….
6	45	29	0	0	0	0	100	….	….	0	0	0	100	100	….	….
-	-	-	0	0	0	0	0	….	….	0	0	0	0	100	….	….
-	-	-						….	….						….	….
-	-	-						….	….						….	….
-	-	-						….	….						….	….
50	24	27						….	….						….	….
51	31	31						100	….						100	….
52	25	29						100	100						100	100
1	22	40	100	0	0	0	0	….	100	100	0	0	0	0	100	100
2	35	37	100	100	0	0	0	….	….	100	100	0	0	0	….	100
3	28	32	0	100	100	0	0	….	….	100	100	100	0	0	….	….
4	30	28	0	0	100	100	0	….	….	0	100	100	100	0	….	….
5	52	21	0	0	0	100	100	….	….	0	0	100	100	100	….	….
6	40	26	0	0	0	0	100	….	….	0	0	0	100	100	….	….
-	-	-	0	0	0	0	0	….	….	0	0	0	0	100	….	….

Table 9. Augmented matrix for contingency clustering. (continuation)

Weeks	Data (Mean)	Data (Variance)	Doublet							Triplet						
-	-	-						….	….						….	….
-	-	-						….	….						….	….
50	21	23						….	….						….	….
51	36	28						100	….						100	….
52	25	37						100	100						100	100
1	44	44	100	0	0	0	0	….	100	100	0	0	0	0	100	100
2	37	20	100	100	0	0	0	….	….	100	100	0	0	0	….	100
3	23	21	0	100	100	0	0	….	….	100	100	100	0	0	….	….
4	27	25	0	0	100	100	0	….	….	0	100	100	100	0	….	….
5	56	28	0	0	0	100	100	….	….	0	0	100	100	100	….	….
6	45	33	0	0	0	0	100	….	….	0	0	0	100	100	….	….
-	-	-	0	0	0	0	0	….	….	0	0	0	0	100	….	….
-	-	-						….	….						….	….
-	-	-						….	….						….	….
-	-	-						….	….						….	….
50	24	30						….	….						….	….
51	31	32						100	….						100	….
52	25	34						100	100						100	100
1	44	44	100	0	0	0	0	….	100	100	0	0	0	0	100	100
2	37	37	100	100	0	0	0	….	….	100	100	0	0	0	….	100

Taking the augmented contingency matrix shown in table 9 into most cluster analysis tools will result in a hierarchy similar to that shown in figure 18. As an example, and in the context of the sample data shown in figure 17, a decision to work with four clusters might result in the data clusters illustrated in figure 19. Note that seasonal clusters do not need to be of equal duration: each cluster may have a different duration and thus a different number of data points. The height of the bar for each cluster in this figure represents the 85th percentile of the data, and so it is clear that each cluster has its own distinct statistical mean and variance.

After the seasonal clustering analysis has been completed, additional cluster analyses can be performed on the data within each season cluster as shown in figure 19. In this example, the October-February season is further classified into four clusters; the March-May season is further disaggregated into two clusters; the May-July season is further classified into three clusters; and the July-September season is further classified into two clusters.



A. Subfigure showing Minneapolis Monthly TTI Index (repeated from Figure 17 for context).

B. Subfigure showing cluster analysis for annual data into season clusters.

C. Subfigure showing cluster analysis from season.

Figure 19. Graphs. Compound figure showing cluster analysis of Minneapolis Monthly TTI Index.

Source: FHWA, 2004. Cluster analysis created for this report.

A numerical example is provided here to help further describe the methodology that was employed in this project. In this example, project team members generated speed data for a 365-day year by emulating the previously reported Los Angeles data shown in figure 14. The data were aggregated by week to produce individual means and standard deviations for each week.

Figure 20 provides a depiction of weekly speed data which shows variation roughly corresponding to the seasons. From weeks 1 to 12, speeds fluctuate between 46 and 56 mph. The speeds gradually increase with relatively smaller variance in week 15 through week 32. After week 35, speeds start to decrease with relatively large variations occurring between week 42 and week 52.

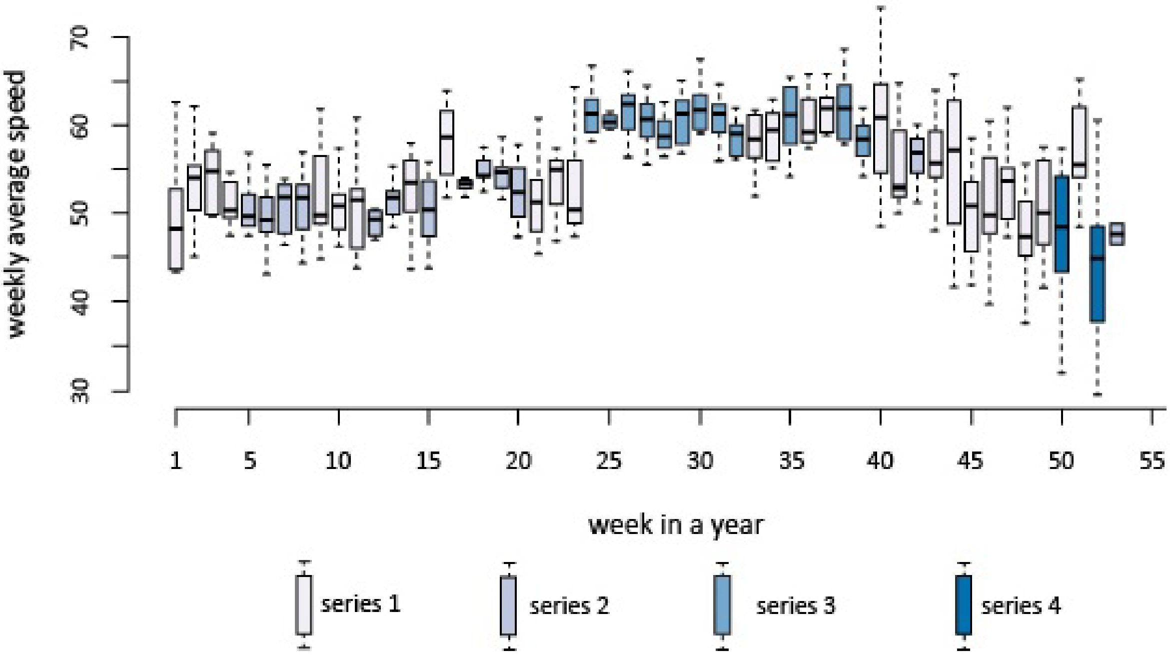


Figure 20. Graph. Clusters with raw data.
Source: FHWA.

The results of a cluster analysis exhibit several hierarchies, including four major clusters. However, one cluster includes only two weeks, while another includes data from across the entire year. It is possible that these clusters may incorporate similar weeks from a pure data standpoint, but from an operational perspective, the clusters do not seem to suggest a season-based strategy response.

Using the augmented matrix for contingency clustering method described above, four clusters are again identified within the data. However, the "height" values used by the clustering method are larger, indicating that the four clusters are more distinct from one another.

The association of the individual weeks of the year with the season-based cluster hierarchies from the augmented matrix method is illustrated visually in figure 21. Cluster 1, including weeks 1 to 13, clearly includes the early spring weeks with moderate congestion and considerable variations. Cluster 2, including weeks 14-31, represents the gradually improved speeds with relatively smaller variations. Cluster 3, including weeks 32-44, exhibits high speed but larger variations. Finally, Cluster 4 exhibits both lower speed and large variations.

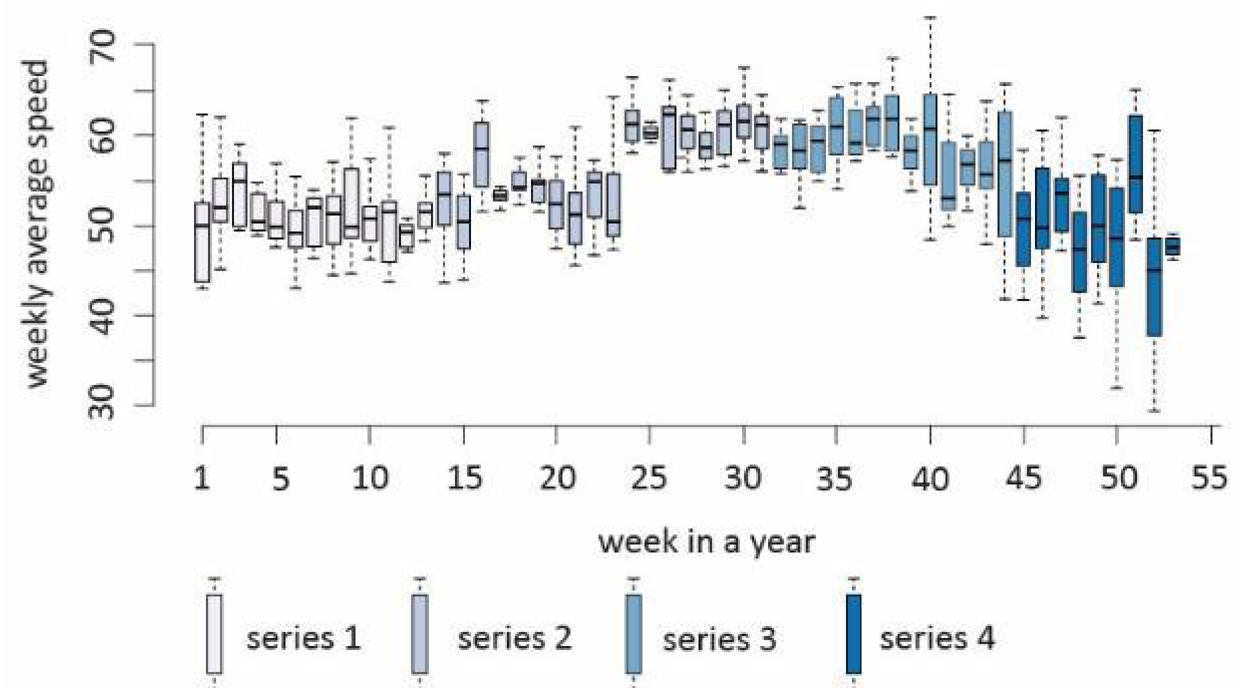


Figure 21. Graph. Final season cluster results.
Source: FHWA.

Based on the season clustering theory and example applications described in the preceding paragraphs, the project team elected to include a season cluster analysis as one of the first steps in analyzing the pilot test site data. More specifically, the project team found that the seasonal clustering method described in the preceding paragraphs can successfully cluster year-long data into meaningful seasonal clusters, when they exist, and in compliance with the seasonable contingency rules described previously.

CHAPTER 6. CLUSTER ANALYSIS APPLICATIONS AND RESULTS

INTRODUCTION TO CLUSTER ANALYSIS

The 1-year analysis process that this project pilot tested relied upon a large amount of observed baseline data and individual simulations, because the project team needed to systematically and accurately represent the wide range of traffic and environmental conditions that occurred over the course of the year for which actual conditions were observed and simulated. A well-tested mathematical procedure known as a hierarchical cluster analysis was used to minimize the number of simulation runs needed to develop a good representation of the actual whole year travel time distribution profile. The term "cluster analysis" encompasses several different algorithms that have been developed for grouping large numbers of objects with similar characteristics into much smaller discrete sets or taxonomies that can then be analyzed more efficiently.

The cluster analysis algorithm employed in this pilot test is embedded in an open-source statistical software package called *R*. The R software package was applied according to the following two-step procedure:

1. *Select an appropriate measure for quantifying the distance between clusters.* This project employed the commonly-used Euclidean distance as the means for calculating the composite distance between observed data points and for calculating the distance between the centroids of the respective clusters. Figure 22 presents the equation used for these purposes. All variables used in this project were normalized to values between zero and one, so the result of applying figure 23 is a relative distance measurement that has no dimensional units.

$$D_{ij} = \sqrt{\sum_{k=1}^{n} \left(x_{ki} - x_{kj} \right)^2}$$

WHERE D_{ij} = distance between cases i and j

x_{ki} = value of variable X_k for case j

Figure 22. Equation. Calculation of composite distances between observed data points.

2. *Determine the appropriate number of clusters using the K-mean cluster analysis technique*. The K-mean cluster analysis technique is a well-documented method for partitioning a set of observed data points into clusters, wherein each observed data point is assigned to the particular cluster within a pre-established group of clusters that possesses the nearest mean. The user establishes the number of clusters to be created at the outset of the analysis, with two clusters being the minimum. With this input, the K-mean cluster analysis technique then assigns each data point to one of the pre-established clusters in such a way as to maximize the Euclidean distance between each of the clusters. The mean for each cluster then becomes reflective of the total of all data points

assigned to that cluster, and the cluster mean will thereafter serve as the prototype for all the observed data points assigned to that particular cluster. Determining an appropriate number of clusters is an iterative process that usually begins with the minimum two clusters and then incrementally increases the number of clusters by one with each iteration until the point of diminishing returns is identified.

APPLICATION OF CLUSTER ANALYSIS IN THE PHOENIX PILOT TEST

The observed data set for base year conditions on the Phoenix area freeway system consisted of observations across 253 separate weekdays (weekday holidays were excluded). The dataset covers 19 two-way corridors within the Phoenix area for a total of 38 one-way corridors. The temporal coverage of the data is from 3:00PM to 7:00PM in the year 2014.

In this pilot test, two separate cluster analyses were conducted. The first focused upon identifying significant seasonal differences in the observed data. The second focused on identifying significantly different data clusters within each of the previously-identified seasons.

The seasonal analysis was conducted by including date information as one of the variables in the cluster analysis process. It was expected and found that including a "date" variable at this analysis stage resulted in a high likelihood of data observed during the same week or month being assigned to the same seasonal cluster.

The results of the iterative cluster analysis procedure conducted at the seasonal analysis stage are presented in figure 23. Based on these results, it was concluded that three is the appropriate number of seasons to use for the 2014 observed data in the Phoenix pilot test site.

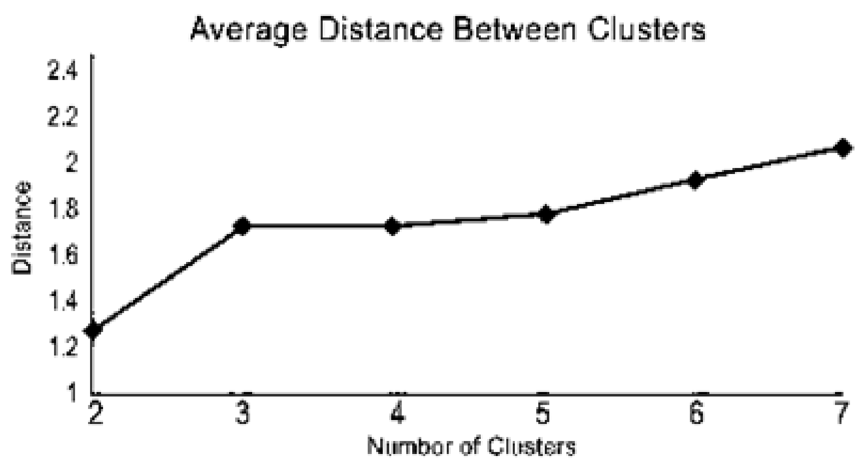


Figure 23. Graph. Seasonal cluster analysis results for Phoenix pilot test site.
Source: Phoenix pilot test site data.

For each of the three seasonal data clusters that resulted from the previous analysis, an additional cluster analysis was conducted to evaluate the need for separate data clusters within each season. The only difference between the seasonal cluster analysis conducted earlier and these cluster analyses is the exclusion of the "date" variable for each within-season cluster analysis.

The result of the iterative process of cluster investigations within seasons 1, 2, and 3 is shown in figure 24, figure 25, and figure 26, respectively. The analysis results presented in these figures indicate that no significant benefit will be gained from analyzing more than two clusters in any of the three seasons. This finding also highlights a key characteristic of the cluster analysis methodology that can have an important effect on the analyst's ultimate workload: to calculate the maximum distance between clusters, one must begin the analysis with at least two clusters. Thus, the remaining unanswered question is whether even two clusters are necessary.

To answer this question, the project team determined the centroid of the single cluster for each season and then applied the cluster analysis methodology manually to calculate the Euclidean distance between the single-cluster centroid for each season and the centroids of the two initial clusters developed for each season. The results of this analysis are presented in table 10 for Season 1 and show that, in this case, two clusters were found to be better than one.

For this project, two within-season clusters were found to be the most appropriate number of clusters for each of the three seasons.

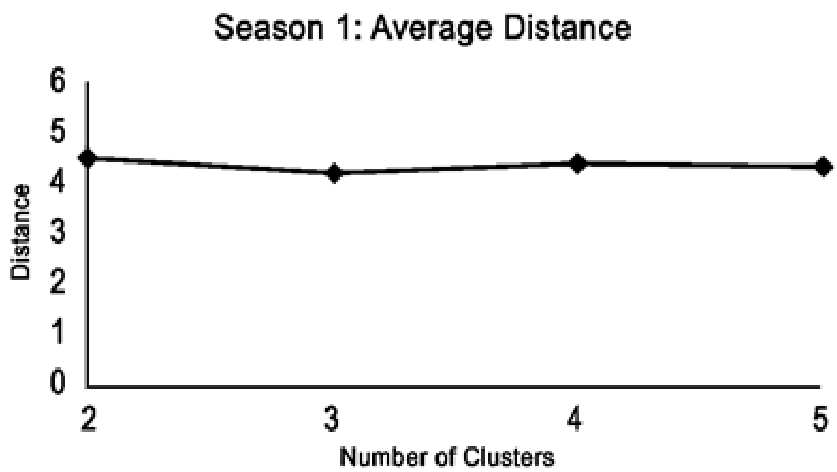


Figure 24. Graph. Within-season cluster analysis for Season 1.
Source: Phoenix pilot test site data.

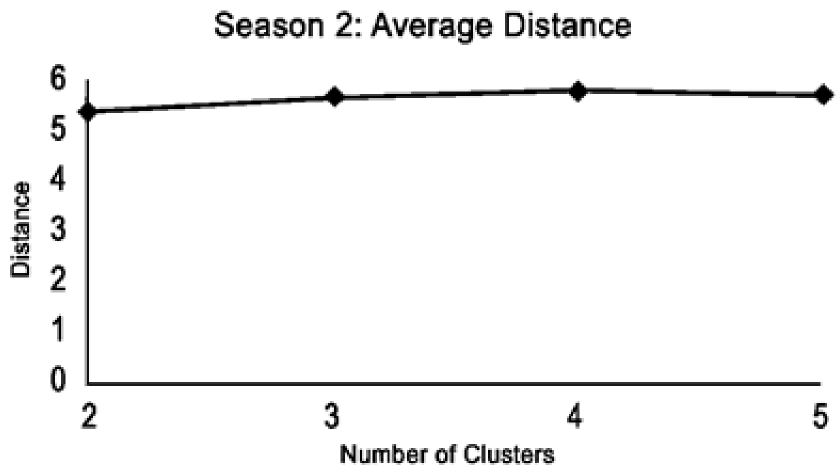


Figure 25. Graph. Within-season cluster analysis for Season 2.
Source: Phoenix pilot test site data.

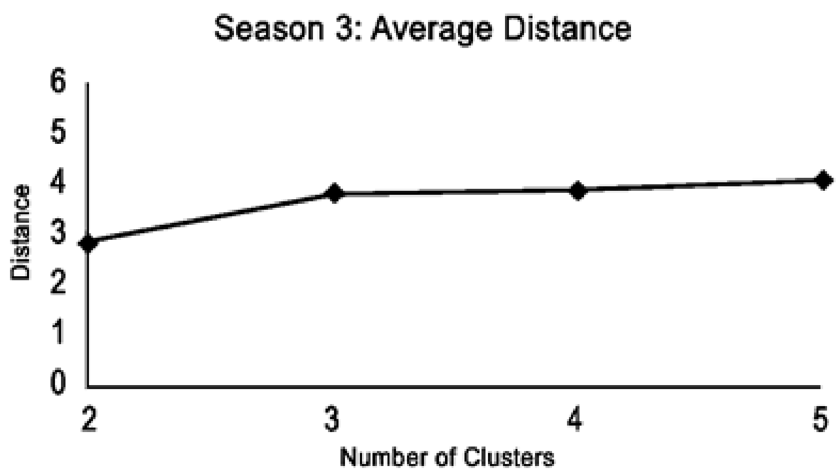


Figure 26. Graph. Within-season cluster analysis for Season 3.
Source: Phoenix pilot test site data.

Table 10. Comparison of single cluster versus 2-cluster analysis results.

Scenario	Scaled Distance
Comparison of single-cluster centroid with centroid of Cluster 1	3,184
Comparison of single-cluster centroid with centroid of Cluster 2	1.045
Comparison of Cluster 1 centroid with Cluster 2 centroid	4.434

Source: Phoenix pilot test site data.

CHAPTER 7. PILOT TEST RESULTS, CONCLUSIONS AND POTENTIAL IMPROVEMENTS

INVESTIGATED CORRIDORS

Four separate corridors were evaluated in the Phoenix pilot test site, ranging in length from 6 to 15 miles:

- *Corridor 1: SB I-17 from Van Buren Street to the I-10 freeway interchange*. The location of this 6.3-mile section within the Phoenix area is shown in figure 27, and an aerial view of a section of the corridor is shown in figure 28. This freeway section consists of three basic lanes and is often congested during the evening peak period.

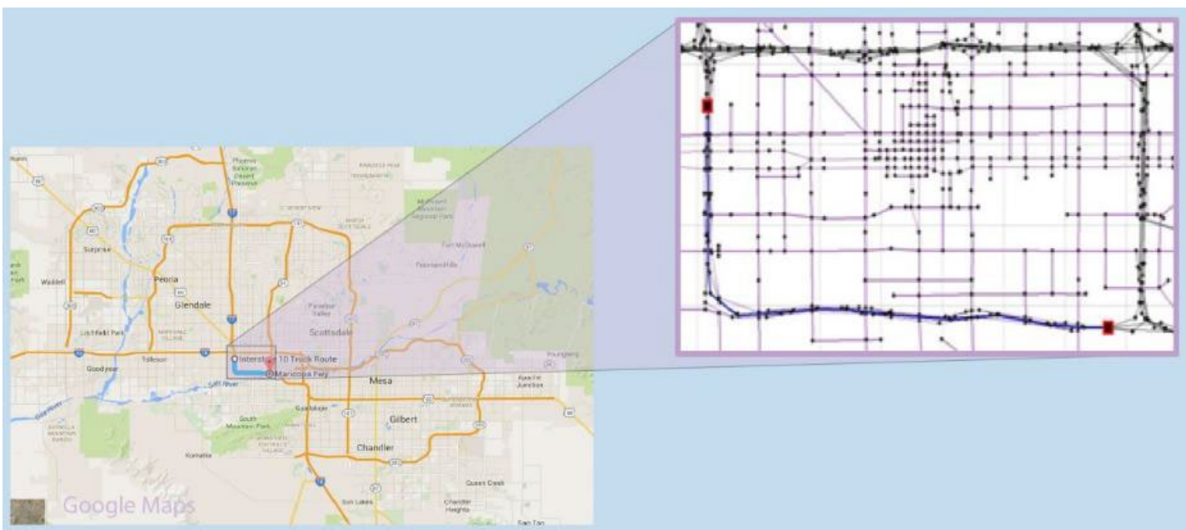


Figure 27. Map. Corridor 1: SB I-17 (Van Buren to I-10).
Source: Phoenix pilot test site data.

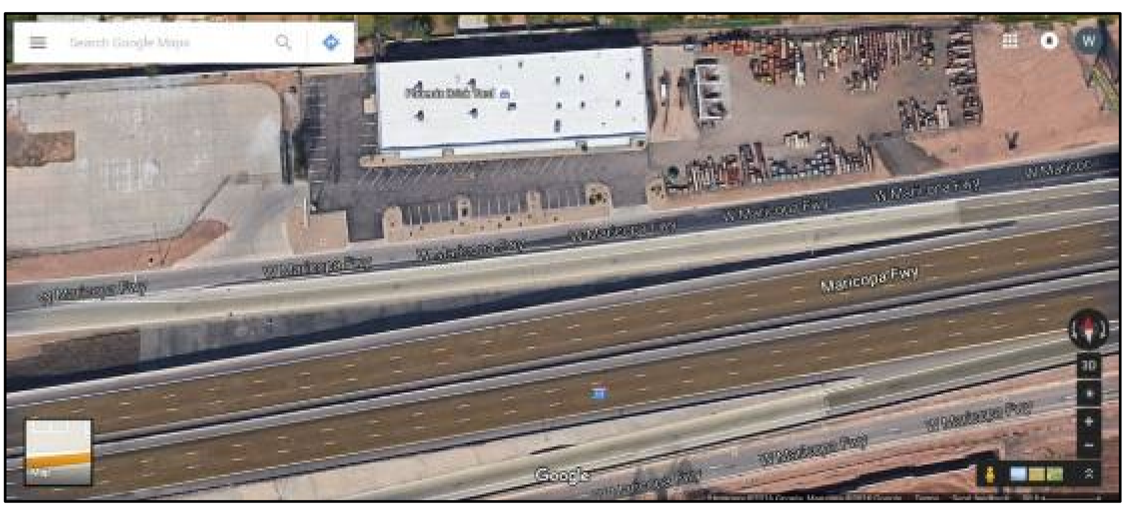


Figure 28. Photo. Aerial view of Corridor 1.
Source: Google Earth.

- *Corridor 2: EB I-10 from Roosevelt Street to Southern Avenue*. The location of this 6.5-mile section within the Phoenix area is shown in figure 29, and an aerial view of a section of the corridor is shown in figure 30. This freeway section consists of four basic lanes and is sometimes congested during the evening peak period.

Figure 29. Map. Corridor 2: EB I-10 (Roosevelt to Southern).
Source: Phoenix pilot test site data.

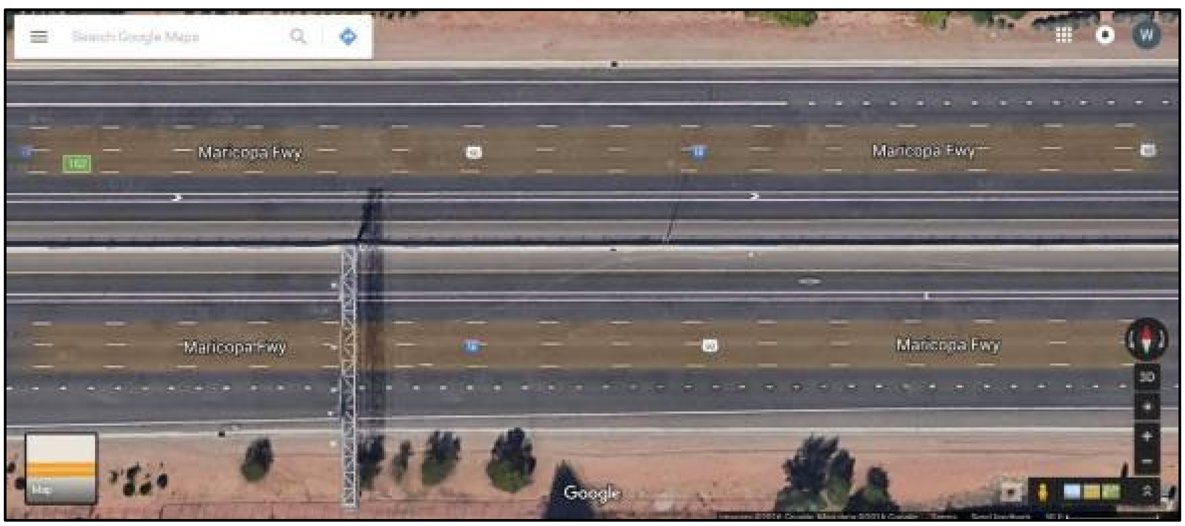


Figure 30. Photo. Aerial view of Corridor 2.
Source: Google Earth.

- *Corridor 3: EB I-10 from 107th Avenue to 11th Street*. The location of this 15.08-mile section within the Phoenix area is shown in Figure 31 and an aerial view of a section of the corridor is shown in figure 32. This freeway section consists of four basic lanes and is sometimes congested during the evening peak period.

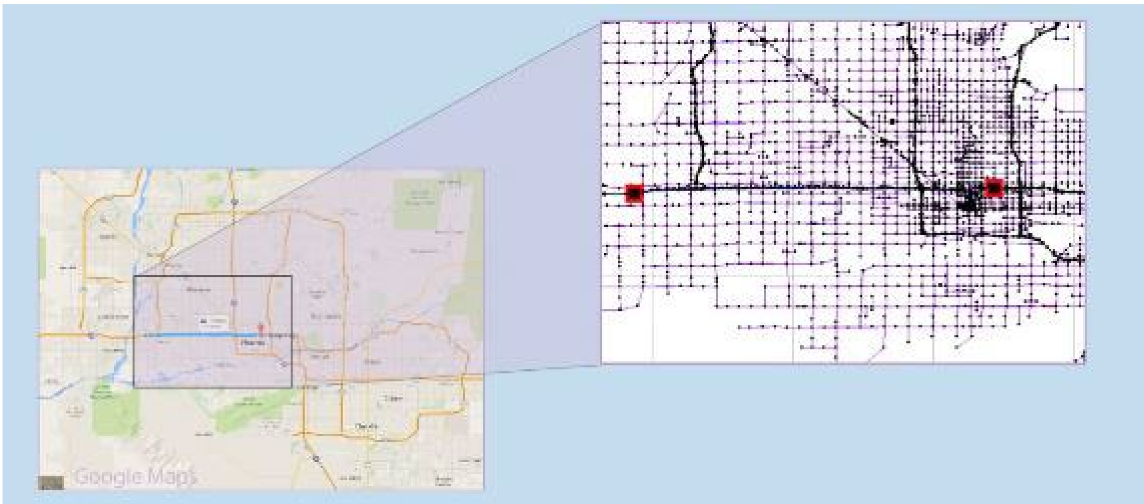


Figure 31. Map. Corridor 3: EB I-10 (107th to 11th).
Source: Phoenix pilot test site data.

Figure 32. Photo. Aerial view of Corridor 3.
Source: Google Earth.

- *Corridor 4: WB US 60 from Higley Road to Dobson Road*. The location of this 10.3-mile section within the Phoenix area is shown in figure 33, and an aerial view of a section of the corridor is shown in figure 34. This freeway section consists of three basic lanes and is quite often uncongested during the evening peak period.

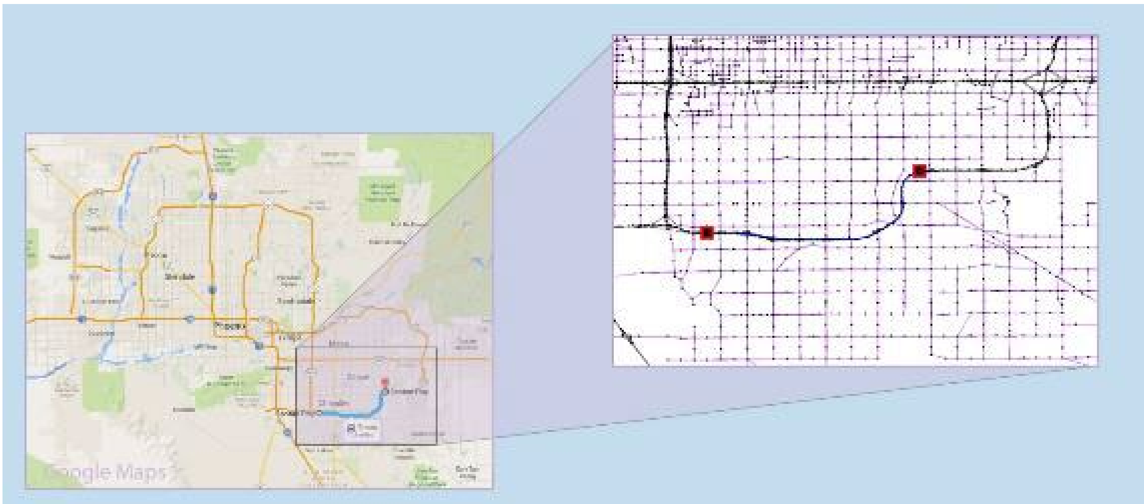


Figure 33. Map. Corridor 4: WB US 60: Higley to Dobson.
Source: Phoenix pilot test site data.

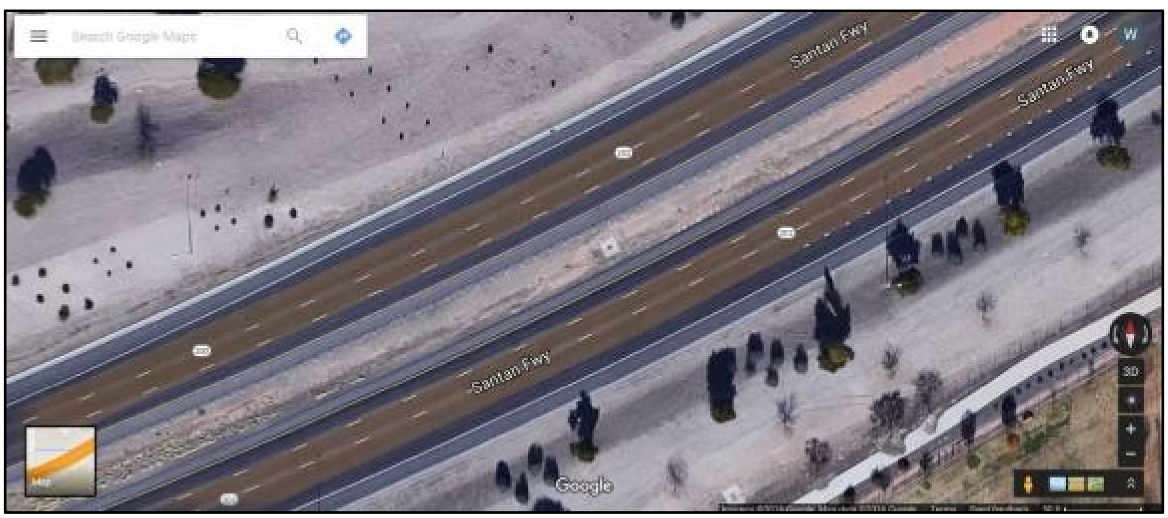


Figure 34. Photo. Aerial view of Corridor 4.
Source: Google Earth.

SIMULATION PROCEDURE AND IMPLEMENTATION OF DTA RUNS

The 120 scenarios generated by Scenario Manager for the Phoenix pilot test collectively represent the range of PM peak period conditions experienced by the Maricopa Association of Governments (MAG) and Phoenix region during 2014. More specifically, a set of 20 scenarios was created for each of two clusters within each of three seasons. Individual scenarios differed from one another according to the particular combination of three non-recurring event factors (demand, weather, and incident variations) that were incorporated into each. These factors were then translated into demand and network changes that were then applied to the base model for each dynamic traffic assignment (DTA) simulation run. The details of such translation are discussed below.

Scenario Inputs

Demand

The demand factor used in the simulation runs is in the form of a multiplier applied to the base demand. The demand factors used in the Phoenix area pilot test, and reflective of the actual observed demand variation, ranged between 0.69 and 1.22. This variation in demand across the year illustrates some seasonal patterns in demand. The demand factors are small (less than 5 percent above or below base demand) in weeks 1 through 20, notably positive (indicating an increase in demand of roughly 10 to 20 percent) for weeks 21 through 40, and somewhat negative for the remainder of the year (up to 10 percent under base demand) except for weeks 60 through 80 where more significant reductions in demand appear (up to 30 percent under demand for certain weeks).

With respect to the application of DynusT and to maintain temporal and O-D consistency among all scenario runs, a master vehicle roster was created at the outset, representing the base demand multiplied by a factor of 1.25. Then for each simulated scenario, a random selection process was used to select the number of vehicles from the master roster that exactly matched the targeted scenario total. The details of master roster are discussed in the later section.

Weather

The weather factor implemented in DynusT is composed of five variables that collectively define the important characteristics of each weather event (see also figure 35):

1. Visibility (miles)
2. Rain precipitation (inches)
3. Snow precipitation (inches)
4. Start time (nearest 5-minute period)
5. End time (nearest 5-minute period)

Where multiple weather events occurred during a single simulation time interval, the most severe weather event was assumed to be in place for the entire time interval to simplify and expedite the simulation runs. It is recognized that the assumption also introduced some inaccuracy into the analysis process, but it is believed that any such inaccuracies will have an insignificant to minor overall effect on the final results.

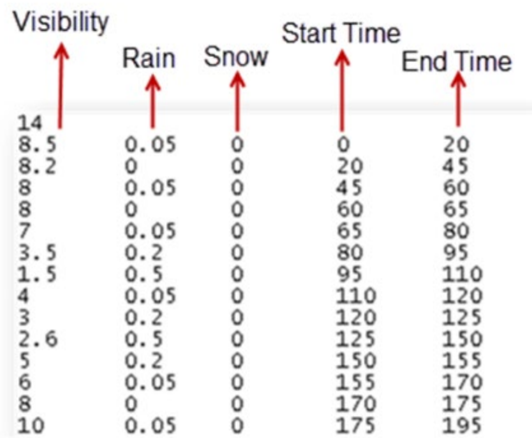


Figure 35. Screenshot. Example weather data input record format for DynusT.
Source: Weather data input for DynusT.

The effects of each weather event on capacity and speed were simulated in DynusT through use of the capacity and free-flow speed adjustment factors presented in table 11, which were developed in SHRP2 Project L08 and are incorporated as default values into the most recent edition of the *Highway Capacity Manual.* (Transportation Research Board 2014, Transportation Research Board 2015)

Table 11. Capacity and speed reduction effects of weather events.

Weather Type		Capacity Adjustment Factors (CAF)					Free-Flow Speed Adjustment Factors (SAS)				
Free-Flow Speed (mph)		55 mph	60 mph	65 mph	70 mph	75 mph	55 mph	60 mph	65 mph	70 mph	75 mph
Clear	Dry Pavement	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Wet Pavement	0.99	0.98	0.98	0.97	0.97	0.97	0.96	0.96	0.95	0.94
Rain	<=0.10 in/h	0.99	0.98	0.98	0.97	0.97	0.97	0.96	0.96	0.95	0.94
	<=0.25 in/h	0.94	0.93	0.92	0.91	0.90	0.96	0.95	0.94	0.93	0.93
	>0.25 in/h	0.89	0.88	0.86	0.84	0.82	0.94	0.93	0.93	0.92	0.91
Snow	<=0.05 in/h	0.97	0.96	0.96	0.95	0.94	0.94	0.92	0.89	0.87	0.84
	<=0.10 in/h	0.95	0.94	0.92	0.90	0.88	0.92	0.90	0.88	0.86	0.83
	<=0.50 in/h	0.93	0.91	0.90	0.88	0.87	0.90	0.88	0.86	0.84	0.82
	>0.50 in/h	0.80	0.78	0.76	0.74	0.72	0.88	0.86	0.85	0.83	0.81

Table 11. Capacity and speed reduction effects of weather events. (continuation)

Weather Type		Capacity Adjustment Factors (CAF)					Free-Flow Speed Adjustment Factors (SAS)				
Free-Flow Speed (mph)		55 mph	60 mph	65 mph	70 mph	75 mph	55 mph	60 mph	65 mph	70 mph	75 mph
Temp	<50 deg. F	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98
	< 34 deg. F	0.99	0.99	0.99	0.98	0.98	0.99	0.98	0.98	0.98	0.97
	< -4 deg. F	0.93	0.92	0.92	0.91	0.91	0.95	0.95	0.95	0.93	0.92
Wind	<10 mph	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	<=20 mph	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.97	0.96
	>20 mph	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.97	0.97	0.96
Visibility	<1 mi	0.90	0.90	0.90	0.90	0.90	0.96	0.95	0.94	0.94	0.93
	<=0.50 mi	0.88	0.88	0.88	0.88	0.88	0.95	0.94	0.93	0.92	0.91
	<=0.25 mi	0.90	0.90	0.90	0.90	0.90	0.95	0.94	0.93	0.92	0.91

Source: Developed in SHRP2 Project L08 and incorporated as default values in the most recent edition of the *Highway Capacity Manual.*

Figure 36 and figure 37 show the distribution of visibility and rain events, respectively, across the 120 simulated scenarios. It is likely that the reported weather events were not uniform in how they affected the entire region, but for the purposes of this pilot test, they were assumed to be uniform and that any resulting capacity and speed adjustments are applicable to the entire network.

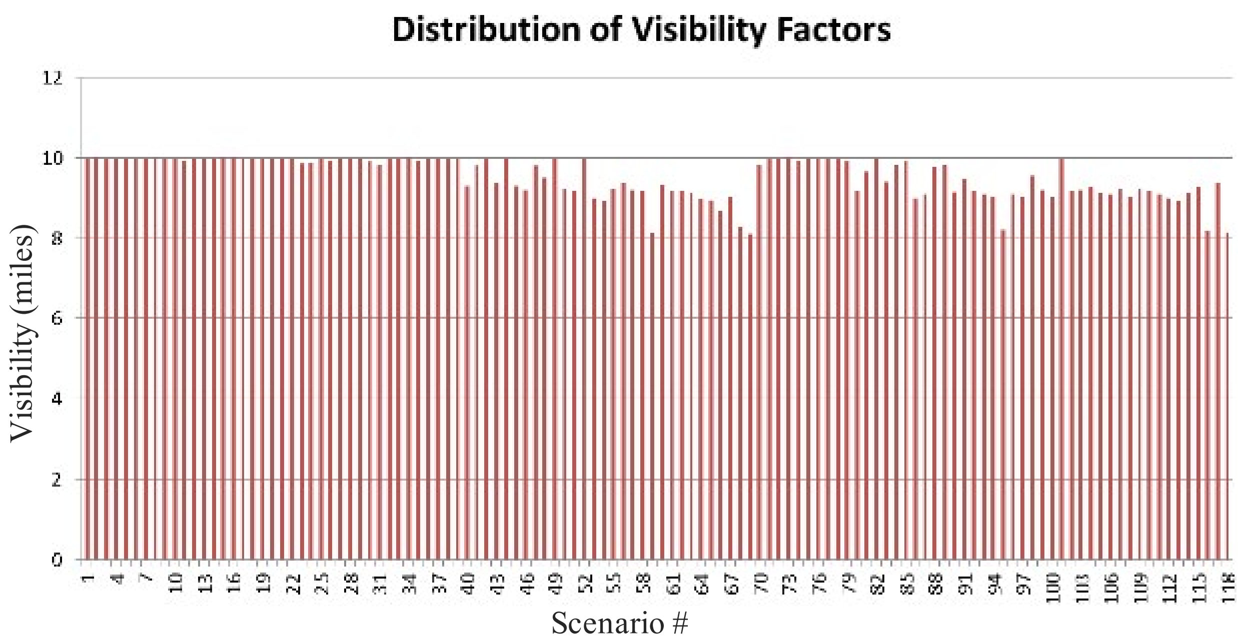


Figure 36. Graph. Distribution of visibility factors across simulated scenarios.
Source: DynusT simulation output.

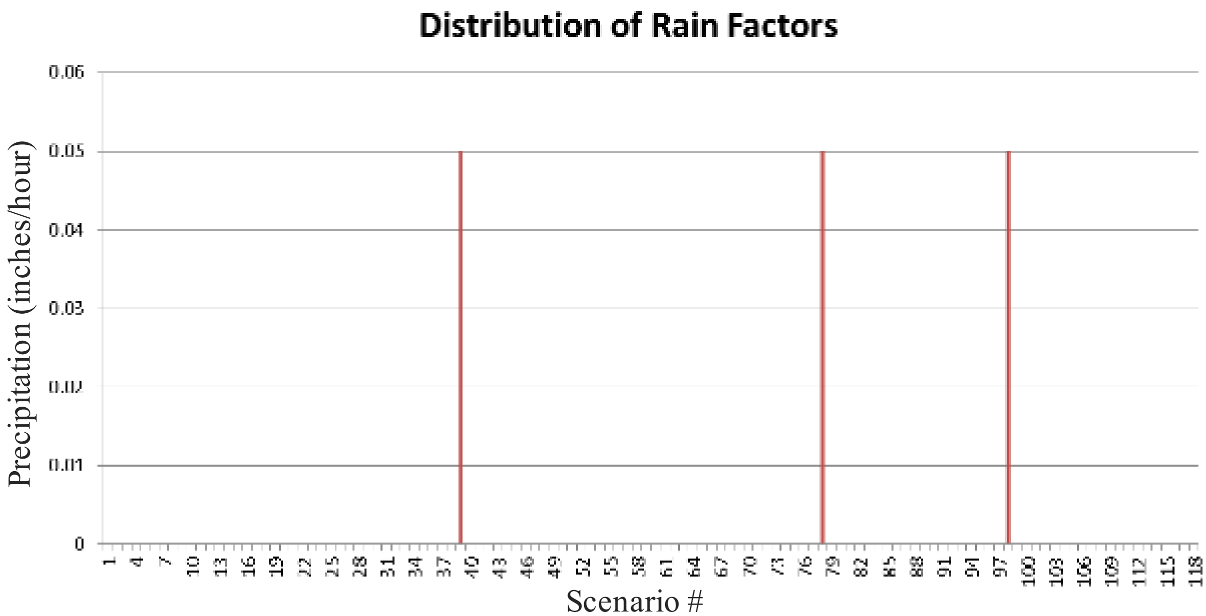


Figure 37. Graph. Distribution of rain precipitation levels across simulated scenarios.
Source: DynusT simulation output.

Incidents

Scenario Manager generates an "incident.dat" file. This file includes the link ID number for the location where the incident occurred, the incident duration (in minutes), and an incident severity factor. The incident severity factor is expressed in terms of the fraction of lane capacity that is estimated to have been lost due to the incident.

Figure 38 identifies the location of all incidents incorporated into the 120 scenarios simulated by DynusT. In this figure, the incidents are identified in the form of a link bandwidth plot. That is to say, the size of the bandwidth represents the total duration of all incidents that occurred on a particular link over the course of all 120 simulation scenarios. Therefore, a tall bar can indicate a high frequency of short-duration incidents or a relatively long duration of fewer incidents.

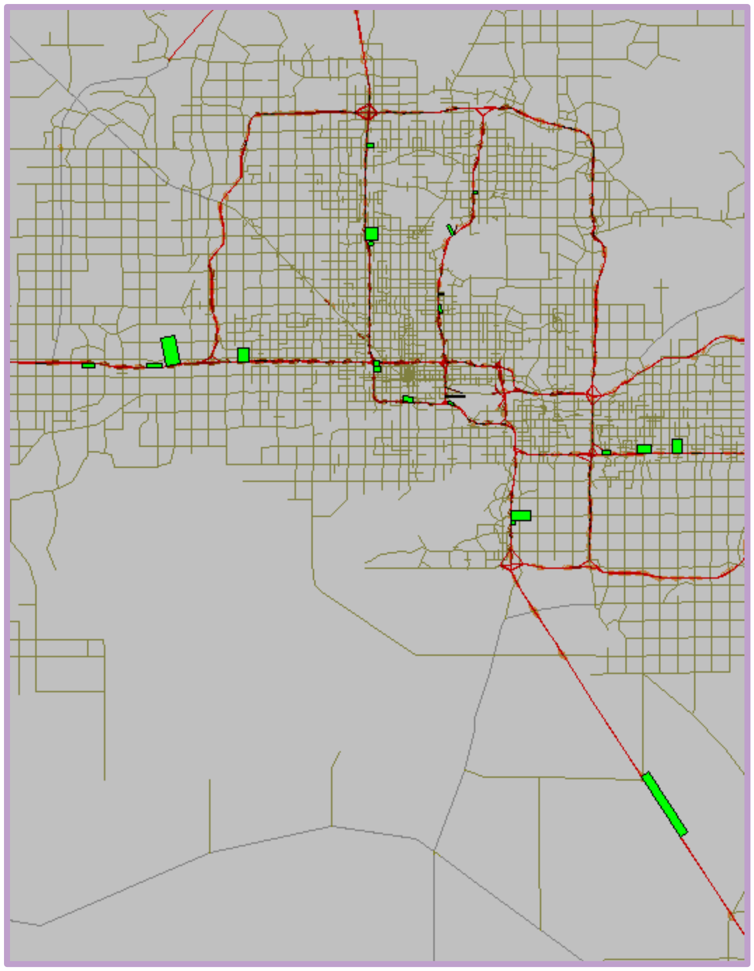


Figure 38. Map. Distribution of simulated incident locations on the Phoenix pilot test site freeway system.
Source: Simulation of Phoenix pilot test site data.

Master Vehicle Roster

As noted earlier, a master vehicle roster was created at the outset of the simulation effort to maintain temporal and O-D consistency throughout the DTA runs. The master vehicle roster was designed to include enough vehicles to accommodate every demand level present in the 120 simulated scenarios. The process by which the master roster was created is described as follows:

- The weekday PM peak period O-D demand tables from the calibrated base year DTA model for single-occupancy vehicles, high-occupancy vehicles, and trucks were increased by a factor of 1.25, resulting in a total of 5.6 million trips.
- DynusT was run to the point of user equilibrium with the updated demand tables.
- Individual vehicle trajectories generated during the simulation were saved into a HDF5 database, which could subsequently be easily queried to generate the demand levels needed to exactly match the individual scenario demand levels.

Batch Run Process

To efficiently execute the large number of DTA runs required in this project, a Python script was written within the DynuStudio platform to allow for batch runs to be conducted. The script can be easily modified and re-run for different numbers of scenarios. The essential functional steps performed by the script include the following:

1. The demand factor associated with each scenario is read to determine the total number of vehicles to be simulated.
2. A subset of vehicles is randomly drawn from the master vehicle roster database that equals the targeted total number of vehicles to be simulated. From this new dataset, a pair of "vehicle.dat" and "path.dat" files are created and then used as the demand for the next DTA run.
3. Weather characteristics associated with the scenario are read to determine adjustments for the base capacity and speeds. A new network.dat file is created to reflect these adjustments.
4. Incident characteristics associated with the scenario are read and used to produce a new "incident.dat" file that will be used in the next DTA run.
5. DynusT was launched under the one-shot assignment method and with 540 minutes of simulated time using the given vehicle/path data. More importantly, all vehicles were assigned with the driving behavior assumption using the historical information to eliminate any possible route changes. Each run took about one hour to finish, with variations in actual simulation time being the result of variations in the number of vehicles simulated in each scenario.
6. The vehicle trajectory data resulting from each simulation was saved into a renamed file that could be used subsequently by the Vehicle Trajectory Processor (NeXTA) for comparative analyses.
7. Steps (1) through (6) were repeated for each scenario that was simulated.

METHODOLOGY FOR CONSTRUCTING A WHOLE-YEAR TRAVEL TIME PROFILE

20 simulated "days" for each of the six distinct clusters resulted in 120 simulations of the Phoenix network.

The travel time distribution patterns that resulted from each of the six sets of 20 simulations were combined by weighting each set in proportion to the number of days represented by each of the six clusters.

Determination of an Appropriate Vehicle Trajectory Sampling Rate

It became clear early on that the computer resources typically available to most MPOs would be unable to load the entire set of vehicle trajectories produced in a whole-year analysis simultaneously. This is because, for the Phoenix pilot test site, approximately 4 million vehicle trajectories were produced in each simulated scenario, and 20 scenarios were necessary to complete the analysis for a single data cluster. The project team had sufficient computer resources at its disposal to accomplish this feat but recognized that many other organizations would probably be unable to do so without undertaking an expensive and disruptive upgrade of available computer resources. Therefore, the project team undertook to identify an acceptable alternative approach.

One alternative that has also been successfully used in other studies is to select and load only a sample of the generated trajectories. Under this alternative, the selected trajectories are distributed uniformly across the full duration of the simulation and are chosen in a repeatable, ordered manner (for example, by selecting every third or fourth or fifth vehicle trajectory that is produced, depending on the sampling rate that is ultimately chosen).

Since the project team had the ability to load the entire set of vehicle trajectories produced in each data cluster analysis, it was possible to test the loss of accuracy associated with different sampling rates to select one that would minimize the total work effort without unduly compromising the accuracy of the final results. More specifically, the project team tested the effects of multiple sampling rates (5 percent, 10 percent, and 20 percent) on the resulting travel time distribution profile across each of the four corridors being investigated within the Phoenix pilot test site. The results indicated that a 20 percent sampling rate can be used to reasonably reflect the travel time distribution of all vehicle trajectories produced in a single data cluster analysis, and so a 20 percent sampling rate was used for the purposes of the analysis and conclusions that follow.

RESULTS AND CONCLUSIONS

Whole Year Analysis Results

As stated previously, DynusT simulated 4 hours of weekday time (3PM – 7PM) across 20 scenarios that Scenario Manager had generated for each of two data clusters contained in each of three separately-defined seasons. The research team assigned a different number of days to each season. It was necessary to weight the results of each simulated scenario so that each represented its appropriate proportion of the year. The travel time results for each corridor were combined in this fashion to create whole-year travel time distribution profiles that could be fairly compared to the corresponding base year (2014) travel time profiles generated from observed and recorded field data. The results of this comparative effort are presented in figure 39 through figure 42 for corridors 1 through 4, respectively.

The simulated versus observed travel times presented in these figures for each of the four corridors provide a strong basis for concluding that the software tools and the analysis methodology combine to produce a very good approximation of the operational conditions being simulated. Some differences can be seen between the simulated and observed travel time results for every corridor, but the research team concluded that a good match was achieved with one observation and caveat: the best fit between observed and simulated results occurred on the corridor with the lowest level of observed congestion (corridor 4).

The variation between observed and simulated results shown for corridor 3 in figure 41 is judged to be due primarily to the mis-calibration of one or more key car-following parameters rather than a failure of Scenario Manager, Vehicle Trajectory Processor, or the analysis methodology.

In this regard, it should be noted that the links included within this corridor were not explicitly modeled or adjusted during an earlier model calibration exercise. Also, it seems apparent from the results shown in figure 41 that DynusT is estimating a lower capacity for at least one of the links within this corridor than is actually the case.

The research team judged that the displacement between the observed and simulated results shown for corridor 2 in figure 41 was because this corridor is immediately downstream from corridor 3, and so the mismatch between simulated and actual capacity in corridor 3 has the effect of underestimating simulated travel times in corridor 2.

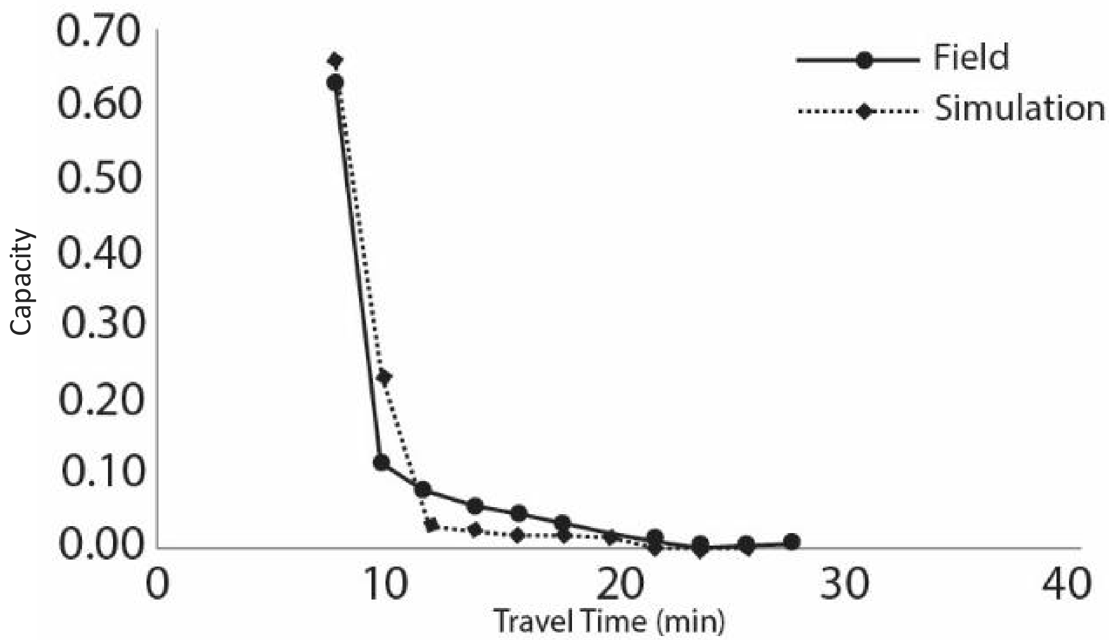


Figure 39. Graph. Corridor 1 whole year analysis travel time results.
Source: Corridor 1 field versus simulated data.

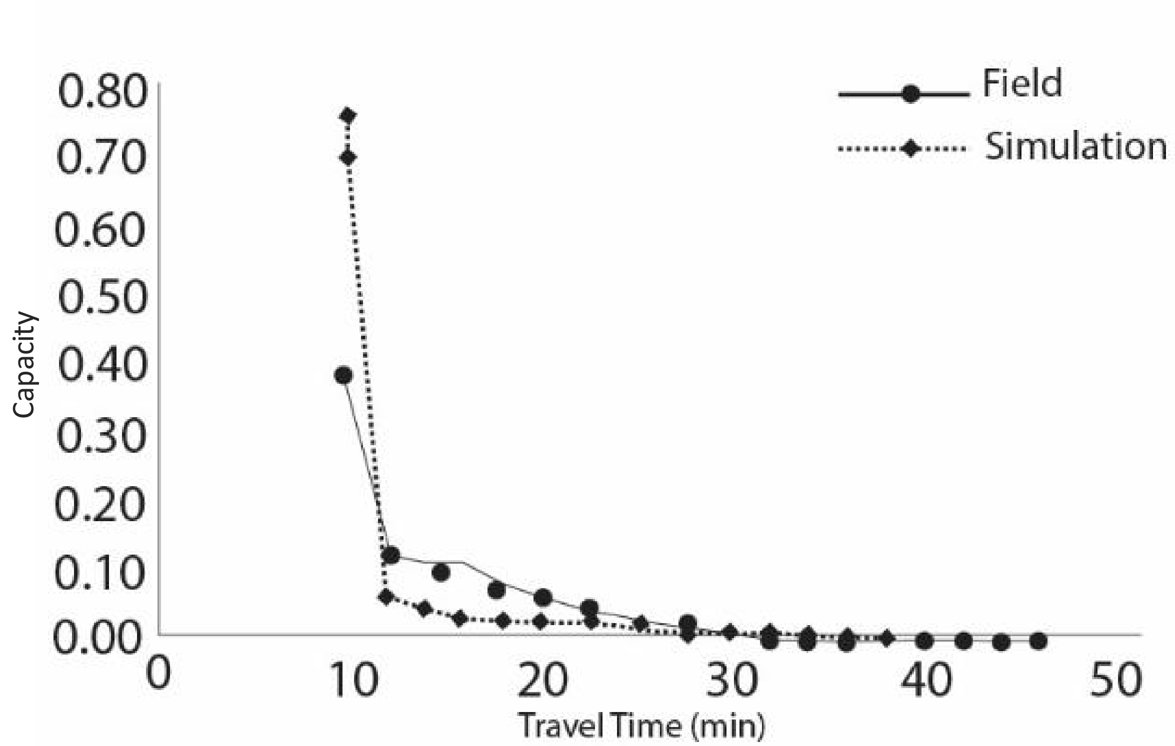


Figure 40. Graph. Corridor 2 whole year travel time analysis results.
Source: Corridor 2 field versus simulated data.

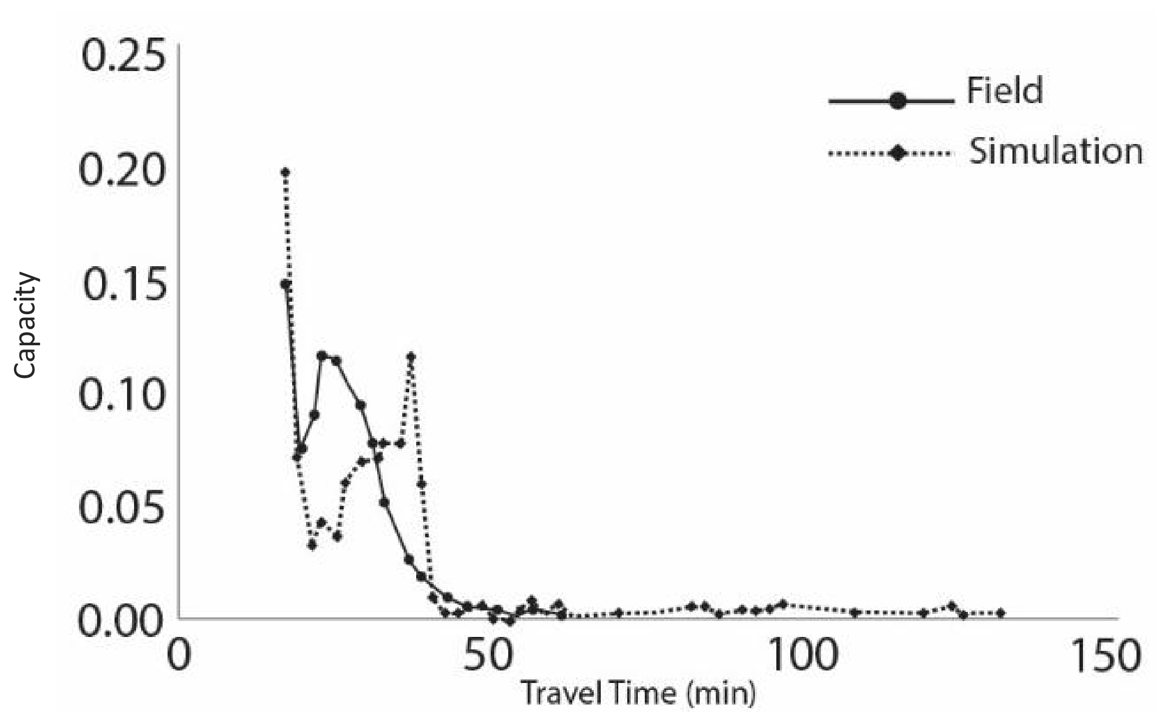


Figure 41. Graph. Corridor 3 whole year travel time analysis results.
Source: Corridor 3 field versus simulated data.

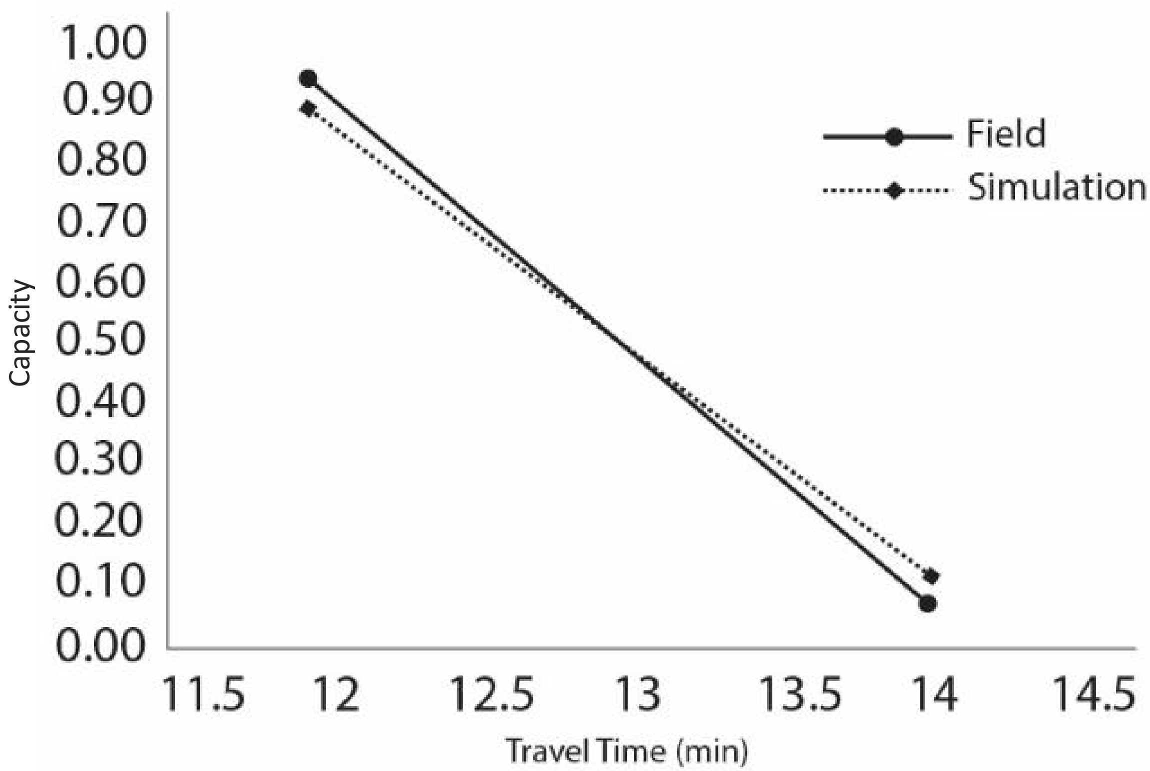


Figure 42. Graph. Corridor 4 whole-year analysis travel time results.
Source: Corridor 4 field versus simulated data.

Findings and Conclusions

Scenario Manager and Vehicle Trajectory Processor (and its enhanced successor, NeXTA) can have the effect of dramatically improving an agency's ability to estimate the likely net effects of one or more operational improvement strategies when used in conjunction with an open-source DTA simulation model, such as DynusT. This improvement is achieved because the tools allow an evaluation of the strategy's effects as they accumulate over a long period of time and in conjunction with varying combinations of weather; demand; and crash location, duration, and intensity conditions.

The analysis procedure described in this report and pilot tested in this project produces a travel time distribution profile that is more informative than the single design-hour travel time estimate traditionally provided by traditional analytic tools.

Some of the project's findings and conclusions relate to specific elements of the analysis methodology, including data collection, model calibration and validation, TSMO strategies, and analysis metrics. A detailed enumeration of these findings and conclusions is provided in the remaining paragraphs.

Data Collection

The quality (that is, the reliability, consistency, and continuity) of the input data used in any analysis always has a direct effect on the confidence that can be placed in the final analysis findings and conclusions. For both the Portland and Phoenix pilot test sites, the quality of the initial data sets was insufficient, and so project team members needed to perform manual checks and cleanings to achieve a sufficient level of quality. This was particularly true with respect to assuring consistency among the various required data sets. For example, initial attempts to correlate travel time data obtained from detectors and probe vehicles with incident data available from separate incident logs found discrepancies. Figure 43 shows an example where southbound travel times on I-5 within the Portland pilot test site are overlaid with incident data reported in the region's incident logs for the same time period. Both incidents shown in this figure were reported to have blocked two of the three available lanes, for a total of 39 minutes in the case of the first incident and for a total of 79 minutes in the case of the second incident.

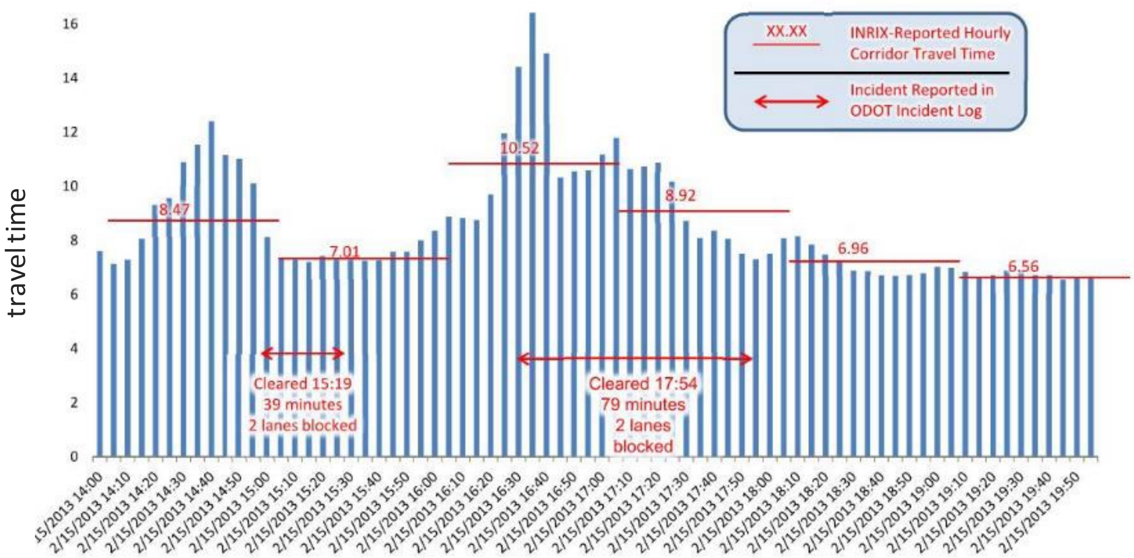


Figure 43. Graph. Comparison of reported corridor travel times with incident occurrence and duration: Southwest Corridor Test Site (I-5 SB).
Source: Portland pilot test site data.

Average travel time did decline during the first incident although not by a lot when considering that two of the three available lanes were reported to have been blocked. In the case of the second incident, travel times did not seem to be affected very much at all, even though the incident was reported to have lasted nearly 80 minutes.

Similar issues were found in the initial data sets for the Phoenix pilot test site and other agencies around the country have reported encountering similar issues of data inconsistencies. It is expected that consistency among data sets will continue to improve over time, particularly as agencies gain more experience and as awareness of the issue increases.

Calibration and Validation

An important finding from this project is that travel time reliability within a corridor must be determined through a regional or large area analysis and not through a subarea study with boundaries drawn narrowly around the subject corridor. This is because, in virtually all urban areas today, corridor traffic volumes and travel time characteristics are frequently affected by congestion and incidents in other parts of the region that can be far-removed from the corridor itself. These effects come not only from queue backups, but also from vehicle path diversions affecting volume and speed in the subject corridor.

In the case of Portland's Southwest Corridor pilot test site, observed congestion and reduced travel times within the corridor were frequently found to be due to incidents and bottlenecks located well outside of the corridor boundaries. An example of this can be seen in figure 44, where it is clear that the initial source of the congestion and queueing experienced inside the Corridor was located south of the Corridor's southern boundary, which is approximately at the OR-217 interchange.

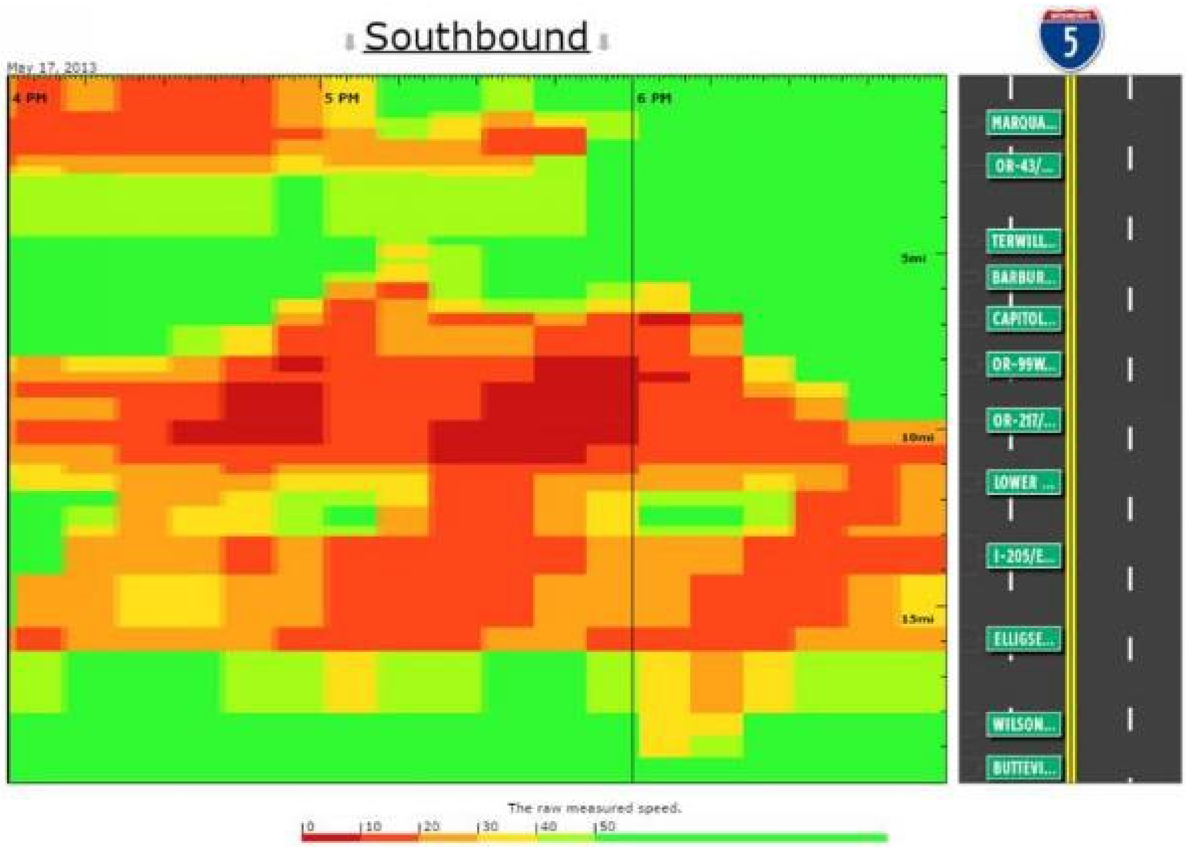


Figure 44. Map. Travel time heat map for SB I-5: 4:00 PM – 7:00 PM sample weekday.
Source: Sample INRIX™ heat map output.

Analysis Metrics and TSMO Strategies

For any analysis of the type conducted in this project, some sources of unreliability will dominate others in terms of their overall impact on travel time. In the cases of both the Phoenix and Portland pilot test sites, vehicle miles travelled (VMT) seemed to play the most important role in affecting travel time, with incidents having the next most significant effect, and weather having a very minor effect. The overall importance of these variables can be expected to change by season of the year and by geographic location. Thus, for example, weather will likely be a much more significant source of unreliability during the winter months in northern cities (where winters are generally more severe) than was observed to be the case in Portland and Phoenix.

POTENTIAL IMPROVEMENTS

This project has demonstrated that Scenario Manager and NeXTA are effective new tools that can be used in concert with DTA models such as DynusT to provide analysts and decisions makers with a more comprehensive assessment of the likely effects of alternative transportation operational improvement strategies. The actions described in this section could potentially extend and enhance the benefits agencies receive by applying these methodologies:

1. In its current first-generation form, Scenario Manager is unable to accept input data related to either short-term or long-term work zones. The addition of this capability would increase the accuracy, realism, and defensibility of all analysis results.
2. In its current first-generation form, Scenario Manager is also unable to distribute generated incidents across the target region in any manner other than on a per-lane-miles basis. Adding the ability to distribute generated incidents on a per-VMT basis could potentially improve the accuracy of the analysis in some situations.
3. A simulation model that explicitly recognizes the day-to-day learning experienced by drivers who travel from the same origin to the same destination at about the same time every day could potentially improve the model's ability to estimate how such trips should be distributed among the available alternative routes. As drivers become more familiar with how the major sources of travel time unreliability affect each of the available routes, their propensity to select a particular travel path will be likely to change. Project team members have developed a conceptualized model for estimating these effects but have not yet implemented or tested the model.
4. Agencies and stakeholders determine together the supported data sets, workflow, and system architecture. It is important to make this tool flexible to meet a variety of needs from different stakeholders. A discussion with stakeholders could help determine what types of data should be supported and importable for this tool. Further discussion regarding user interface, documentation, tutorials and expected outputs could also help to improve the tool.
5. Agencies use an expanded set of statistical libraries and data analysis software packages to use Big Data sources to address key input requirements of Scenario Manager and to fuel the cluster analyses conducted at the front end of the methodology. Such specialized tools for large-scale data management and manipulation are available but have been rarely needed in typical day-to-day transportation analysis activities. Information about how to use and evaluate a variety of open-source statistical tools and software libraries could help individual agencies select the most suitable tools for their use in conjunction with Scenario Manager and Vehicle Trajectory Processor.

REFERENCES

Chiu, Y.-C., L. Zhou, and H. Song. *Development and calibration of the Anisotropic Mesoscopic Simulation model for uninterrupted flow facilities.* Transportation Research Part B: Methodological, 2010. 44(1): p. 152-174.

FHWA (n.d.) Reliability in Simulation and Planning Models (L04) Resources. https://ops.fhwa.dot.gov/shrp2/products.htm#simulation-tools

FHWA 2004. *Traffic Congestion and Reliability: Linking Solutions to Problems.* https://ops.fhwa.dot.gov/congestion_report_04/appendix_d.htm

FHWA 2013. *Urban Congestion Report: A Snapshot of Congestion Trends in the U.S. for October 2012 through December 2012.* https://ops.fhwa.dot.gov/perf_measurement/ucr/reports/fy2013_q1.pdf

FHWA. 2013. https://ops.fhwa.dot.gov/perf_measurement/ucr/reports/fy2013_q1.pdf.

—. 2004. https://ops.fhwa.dot.gov/congestion_report_04/appendix_d.htm.

Kim, J., H.S. Mahmassani, G. Marcu, and A. Brijmohan. November 2013. *Scenario Manager User's Guide.* Washington, DC: Transportation Research Board.

Transportation Research Board 2014. *SHRP 2 L08.* https://apps.trb.org/cmsfeed/TRBNetProjectDisplay.asp?ProjectID=2197

Transportation Research Board 2015. Highway Capacity Manual, 5th Edition. https://www.trb.org/Main/Blurbs/164718.aspx

U.S. Department of Transportation
Federal Highway Administration
Office of Operations
1200 New Jersey Avenue, SE
Washington, DC 20590

Office of Operations Website
https://ops.fhwa.dot.gov

February 2022
FHWA-HOP-20-042