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SWEDEN/MICHIGAN NATURALISTIC FIELD OPERATIONAL TEST

BENEFITS OF ORIGIN AND DESTINATION INFORMATION IN VII DATA SET

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16. Abstract

Trip origin and destination (O-D) data plays a crucial role in various transportation activities. This information not only includes the starting and end points of a trip, but also information that can be obtained through the ability to track vehicles across a network. Collected information may include the location and speed of a vehicle every second, a record of the links entered during a journey, the time a vehicle has entered each link, the time taken to travel a link, etc. Despite some recognized benefits, there are still concerns, primarily related to privacy, about whether or not probe vehicles should be allowed to collect O-D trip information. Within this context, this report examines various issues associated with the potential collection of O-D data by IntelliDrive probe vehicles. Research findings presented in the report include:

- An overview of current uses of O-D data in activities related to transportation planning and system operations.
- A description of the methods currently used to collect or generate O-D trip data.
- A description of issues associated with current O-D data collection and generation methods, as well as how O-D trip data are applied in transportation applications.
- A discussion on how O-D information collected from IntelliDrive probe vehicles can enhance existing applications and enable the development of new applications.
- A discussion on the potential benefit-cost ratio offered by the inclusion of O-D trip information in IntelliDrive data sets.
- A discussion of privacy issues regarding O-D data collection. This includes a review of current concerns, emerging policies regarding driver privacy in IntelliDrive systems, methods currently promoted to ensure driver privacy, impacts of promoted privacy methods on IntelliDrive applications, and methods available to mitigate privacy concerns.
- A simulation study with the Paramics microscopic traffic simulation model demonstrating the benefits to individual vehicles and network operations of using O-D data reported by IntelliDrive vehicles to provide dynamic route guidance around an incident.

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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)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		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)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		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)

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1. Introduction

Trip origin and destination (O-D) data plays a crucial role in various transportation activities. This information not only includes the identification of the starting and end points of a trip but also information that can be obtained through the ability to track vehicle movements across a network. This additional information may include the location and speed of a vehicle every second, a record of the links entered by a vehicle during its journey, the time a vehicle has entered each link, the time taken to travel across links, etc.

O-D data is a fundamental element in transportation planning methods, where this information is used to estimate travel patterns within a network and assess expected travel demand between various zones. In turn, this expected demand is used to estimate traffic levels on existing roadways, identify locations where the existing infrastructure may not be adequate to accommodate projected demand, assess the level of the resulting congestion, and prioritize infrastructure improvements needs. From an operation standpoint, data characterizing turning movements at intersections, which represent O-D patterns on a small scale, is also fundamental in determining efficient traffic control plans. O-D data further plays a fundamental role in applications seeking to route vehicles across a network, as paths through a network can only be assigned if information is known about the current location of a vehicle and the destination a driver intends to reach.

Various techniques have been proposed over the years to collect or generate O-D data. The most direct method consists in conducting traveler surveys. However, these surveys are often costly and time demanding. For this reason, surveys used to develop regional travel patterns are typically only executed once every few years. Surveys conducted for small scale projects, such as to determine travel movements within a specific corridor, also remain relatively costly and are consequently often confined to collecting O-D data along major thoroughfare during limited time periods. To address these limitations, various alternative methods seeking to indirectly generate O-D data from a range of commonly available surrogate data, such as socioeconomic and traffic flow data, have been proposed. However, while these techniques have allowed obtaining O-D data at relatively lower costs for a range of situations, they do not fully replace the quality of direct O-D trip information. A major concern with these new approaches is the need to infer trip patterns through the use of regression or other mathematical models that may require careful calibration.

The emergence of the IntelliDrive concept (formely known as Vehicle-Infrastructure Integration, or VII), in which wireless technologies are used to enable vehicles to communicate with roadside equipment and other vehicles, is creating a potential for fundamental shift in the collection of O-D data. Within this concept, vehicles could be instructed to retain O-D trip data and communicate this information, either automatically or on demand, to a transportation management center for use in various transportation applications. This concept would in essence converts vehicles in data collection instruments. This offers the potential to directly collect trip data from all IntelliDrive vehicles or at least all the vehicles from which O-D data retrieval has been authorized a driver. This may not only increase the quantity of information collected, but allow the development of more refined and more reliable trip patterns.

Within the above context, this report examines various issues associated with the use of O-D data in transportation applications. It summarizes research activities that were executed as part of a project jointly sponsored by the Michigan Department of Transportation and Swedish Ministry of Transportation and which sought to investigate the potential benefits that can be obtained from allowing IntelliDrive probe vehicles to report trip O-D information. At the time of the study, there were still some discussions as to whether IntelliDrive vehicles should be allowed to report such information, primarily due to concerns regarding the privacy of drivers.

The research findings presented in this report include:

- An overview of current uses of O-D data in activities related to transportation planning and system operations (Section 2).
- A description of the methods currently used to collect or generate O-D trip data (Section 3).
- A description of issues associated with current O-D data collection and generation methods, as well as how O-D trip data are applied in transportation applications (Section 4).
- A discussion on how O-D information collected from IntelliDrive probe vehicles can enhance existing applications and enable the development of new applications (Section 5).
- A discussion on the potential benefit-cost ratio offered by the inclusion of O-D trip information in IntelliDrive data sets (Section 6).
- A discussion of privacy issues regarding O-D data collection. This includes a review of current concerns, emerging policies regarding driver privacy in IntelliDrive systems, methods currently promoted to ensure driver privacy, impacts of promoted privacy methods on IntelliDrive applications, and methods available to mitigate privacy concerns (Section 7).
- A case study demonstrating the benefits of using O-D data reported by IntelliDrive vehicles to enhance network operations following the occurrence of a major incident. This case study looks at the ability to use O-D data to enable dynamic vehicle routing. This application has been selected based on the high level of interest that is currently directed towards advanced traveler information systems, and more specifically the emerging ability to provide context-sensitive routing directions to drivers (Section 8).

2. Current Uses of Origin-Destination Data in Transportation Applications

O-D data has long been associated with transportation system planning activities as network planning is built upon a knowledge of existing or anticipated traffic patterns. However, various transportation system operations applications also significantly benefit from O-D data. As an example, the turning movement patterns used to determine signal timings at intersections can in fact be viewed as localized O-D trip patterns. This section aims to provide a general overview of current O-D data uses in transportation practice. The first part outlines the importance and traditional uses of O-D data in transportation system planning activities, while the second part focuses on transportation system operation activities that also rely on O-D data. The results of this review are to be used as a basis of evaluation for the potential benefits that could be achieved by using emerging technologies to enable the automated collection of O-D data from vehicles traveling within a network.

2.1. Uses in Transportation System Planning

Use of O-D data in the transportation field has traditionally been associated with urban road network planning activities. For instance, the vast majority of regional travel surveys that have been conducted in the past were executed to support planning activities executed by Metropolitan Planning Organizations (MPOs). The primary purpose of transportation system planning activities is to generate information that can be used by decision makers to determine the best course of action to attain specific goals with respect to the development and continued operation of a transportation network. For instance, planning activities are often executed to determine the amount of traffic projected to travel to and from a given zone following the completion of specific construction projects or general urban growth assumptions. This information is then used to assess congestion levels on existing roads at various points in the future and determine where and when improvements may be needed.

At the center of transportation planning activities is the need to develop an accurate modeling of traffic patterns within a network, i.e., an understanding of where individuals are traveling from and to, at what time, and for which purpose. This knowledge has traditionally be expressed in the form of an O-D matrix, in which travel patterns are summarized as flow rates between pairs of origin and destination nodes. Depending on the need, the matrices could express trips made by vehicles, buses or individuals. From the information contained in O-D matrices, loads on roads and transit routes are then estimated using various route selection algorithms attempting to replicate the process by which traveler build their travel plans by considering distance to travel, travel time, out-of-pocket cost, or other factors.

Most of the travel demand forecasting methods in use by transportation professionals today were developed to provide a capability to assess travel patterns in situations for which such patterns are not directly observable. The traditional approach to estimate travel demand patterns typically focuses on the sequential execution of four primary activities, as illustrated in Figure 1 and detailed below:

- **Trip generation:** Prediction of the number of trips originating from and destined to each zone in a network based on the socioeconomic characteristics of each zone (population, number of jobs located in zone, retail space available, number of schools, etc.).
- **Trip distribution:** Prediction of number of trips originating from a given zone and destined to another zone (O-D flows).
- **Mode choice:** Prediction of the number of trips between each O-D travel pair made by car, bus, or other transportation mode.

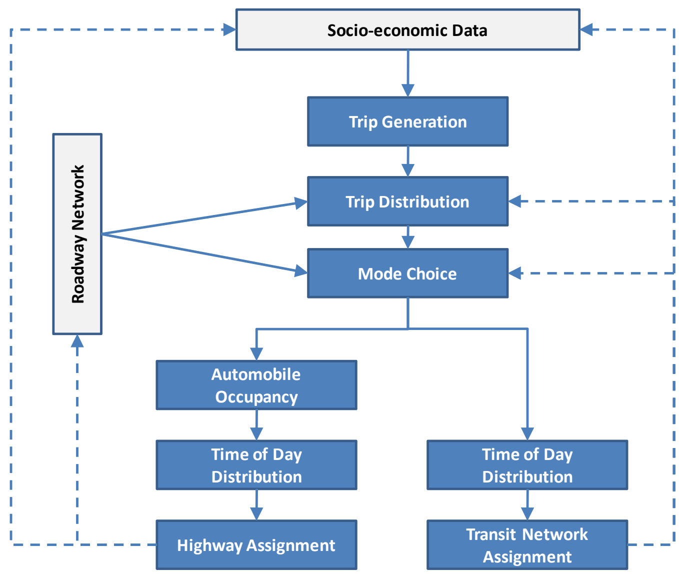


Figure 1 – Traditional Travel Demand Forecasting Process [NCHRP Report 365, 1998]

- **Network assignment:** Determination of routes within the transportation network used by travelers along each O-D travel pair.

Over the past 50 years, various methods have been developed to execute each of the four major steps described above. Since the emphasis of early transportation planning activities was predominantly on building major urban facilities, early demand forecasting methods primarily focused on system-level applications, where the concern was to provide roads with enough capacity to handle the expected traffic [Easa, 1991, 1993]. Over time, the emphasis gradually shifted from capital-intensive improvements to transportation system management. This led to a greater focus on understanding travel behavior in small urban areas, and a need for more detailed network representations, improved traffic assignment techniques, and improved methods for calibrating demand prediction models. In recent years, the development of computer technology has further allowed the implementation of forecasting methods featuring information feedback loops, iterative travel demand estimations, and increasingly complex estimation or assignment methods.

Despite significant improvements in how information is graphically displayed, many of the currently available transportation planning software applications are still built around implementations of the four-step demand forecasting method describe above. Examples of current commercial models built around the four-step planning methodology include EMME/2 [INRO, 2008], the Florida Standard Urban Transportation Model (FSUTMS) [Zhao *et al.,* 2001; FDOT, 2006], Quick Response System II (QRS II) [Beimborn and Horowitz, 2000],Transportation Planning Plus (TP+) [Citilabs, 2008], TRansport Improvement Planning System (TRIPS) [Citilabs, 2008], TransCAD [Caliper Corporation, 2008], TranPlan [Citilabs, 2008], and VISUM [PTV America, 2008]. While individual models offer variations in the techniques used to forecast travel demands between pairs of zones and load the estimated demand onto a road network, they essentially all follow the same sequential approach. As an example, Figure 2 illustrates the structure of the four-step planning process that was recently developed in the TransCAD software for the Southeast Michigan Council of Government (Volpe, 2004). Within this model, the four traditional transportation planning steps – trip generation, trip distribution, mode choice and trip assignment – can all be recognized. The model also shows the extent to which feedack loops are now being used to develop iterative travel demand estimation procedures.

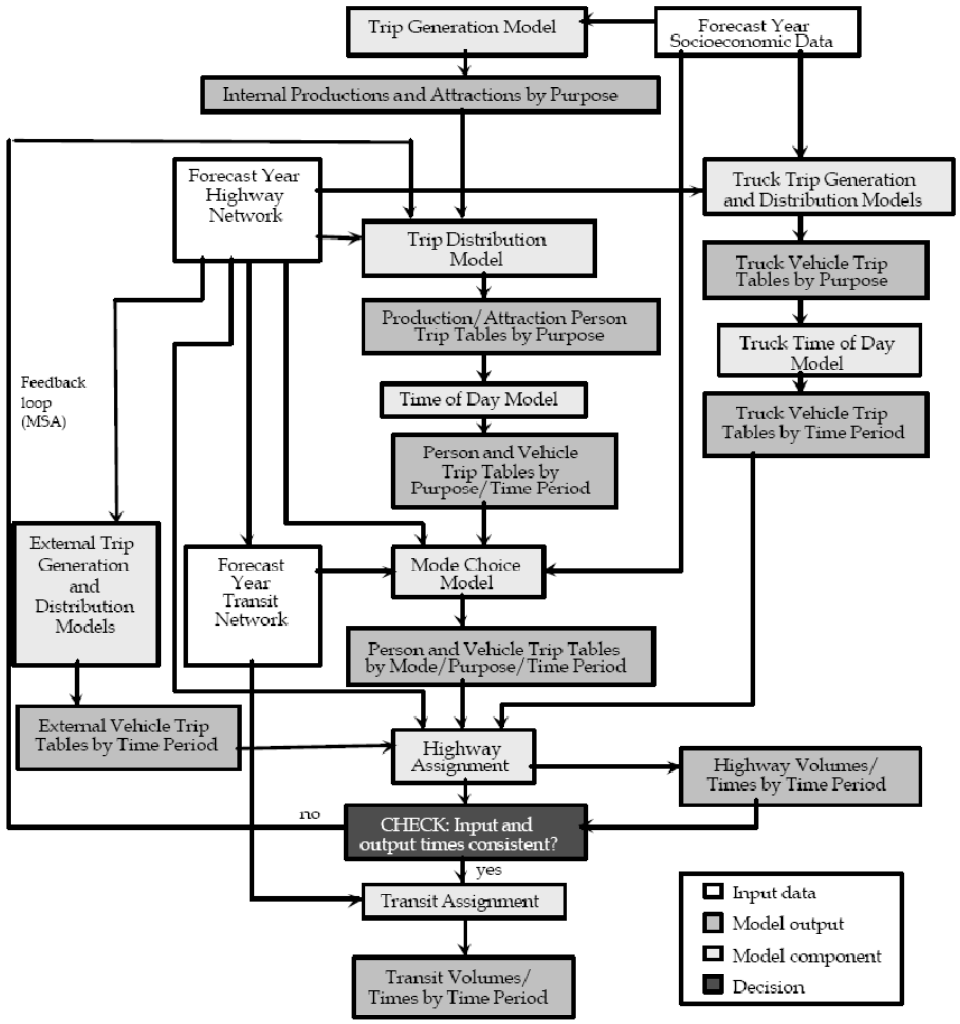


Figure 2 – TransCAD Planning Model Used by the Southeast Michigan Council of Governments [Volpe, 2004]

Over the past 20 years, significant efforts have also been devoted to the development of alternative travel forecasting methods attempting to use traffic flow counts to generate synthetic O-D data that would reflect traffic condition observed across a network during a specific period. Development of these approaches has been heavily influenced by the desire to leverage the increasing amount of data provided by traffic surveillance systems. Another benefit of these approaches has been to facilitate the use of traffic simulation models to predict network traffic demands and network performance under various scenarios.

The objective of travel demand forecasting methods is not to develop O-D data that perfectly reflects actual travel patterns, but data that would reflect current or future travel patterns with reasonable accuracy to allow efficient decision-making. Perfect matches are not expected given the difficulty to predict with exactitude what may happen in the future, as well as all the factors leading individuals to travel to a specific location at a specific time using a specific route. All that is typically needed are estimates of travel patterns precise enough to allow adequate determination of the potential effects of proposed system improvements on network operations so that the projects best satisfying system development objectives can be identified and programmed for implementation.

Descriptions of the various families of techniques that have been developed for the generation of O-D matrices and the assignment of flows to a transportation network are provided in Appendix A. This information is provided primarily with the intent to help readers unfamiliar with travel forecasting techniques to understand the potential complexity and range of approaches available for the estimation of O-D matrices and the assignment of flows on a network.

2.2. Use in Transportation Operations

While O-D data is traditionally associated with transportation planning activities, such data is also frequently being used in a range of transportation operations activities. The most prominent uses include:

- Analysis of traffic (turning) behavior at intersections.
- Optimization of traffic signal timings.
- Analysis of freeway operations at freeway merge, diverge and weaving sections.
- Corridor traffic management.
- Emergency evacuation traffic management.
- Vehicle routing applications.
- Modeling of traffic demand in simulation models.

Analysis of traffic behavior at intersections: One of the key elements in intersection analysis procedures, whether signalized or controlled by stop signs, is to know the proportion of vehicles turning left, going straight and turning right from a given approach. Such information is akin to O-D data as it expresses travel desires between an origin point upstream of the destination and a destination point downstream of the intersection. At stop-controlled intersections, the same information is used to determine delays associated with various movements and assess whether operational problems at the intersection may warrant a change in geometry or the type of traffic control used.

Optimization of traffic signal timing: For signalized intersections, O-D data is used to determine the level of conflicts between movements and determine the most efficient phasing and road geometry arrangements to minimize stops, delays, or other performance measures. While advances in communication and computer equipment has promoted the introduction of real-time traffic-responsive traffic signal control systems, the need for many systems to operate with up-to-date traffic demand estimates has created a need estimate O-D patterns in environments in which conditions may change from one interval to the next.

Analysis of freeway operations at freeway merge, diverge and weaving sections: Merge and diverge sections are typically associated with on and off ramps. Weaving sections are areas where two or more traffic streams traveling in the same direction cross. Such sections are typically located between closely spaced on and off ramps. The analysis of traffic behavior at these locations heavily depends on knowing the proportion of freeway traffic remaining on the freeway past the off ramp and the proportion freeway traffic downstream of the on ramp that did not originate from the freeway.

Corridor traffic management: Similar to the analysis of intersections or freeway sections, knowledge of traffic flow patterns is essential for efficiently managing urban corridors. In recent years, there has been a notable push for the integrated management of freeway/arterial corridors, where decisions about flow control on the freeway are based not only on the potential impacts on freeway traffic but also on the potential effects on surrounding arterials, and vice versa. To effectively manage such corridors, it is essential to know where major traffic flows originate and where vehicles intend to travel to. This information is not only essential for correctly simulating flow patterns but also for adequately evaluating traffic routing alternatives.

Emergency evacuation traffic management: Knowledge of flow patterns is important for the development of efficient emergency evacuation procedures [Liu *et al.*, 2007]. Flow patterns observed during emergency situations may be significantly different from the patterns normally observed during weekdays and weekends. Flow patterns may further change significantly over relatively short intervals. In such a context, information about the latest observed flow patterns is crucial for allowing traffic managers to adjust signal control policies to the changing traffic needs. This information can also be used to project near-future traffic demands on individual roads and proactively manage the expected influx of traffic, either through traffic management control adjustments or routing suggestions, to reduce delays, improve system throughput, and provide a much smoother evaluation procedure.

Vehicle routing applications: Vehicle routing applications are probably the most obvious examples of O-D data uses. Without information about the intended destination of a vehicle, no routing recommendation can be made. In this case, the origin of a trip is typically taken to be the current location of the vehicle, while the destination is provided by the driver of the vehicle. The challenge here is to base routing decisions on information adequately reflecting current traffic conditions or reflecting the conditions that are expected to exist when a vehicle is to reach a particular link.

Modeling of traffic demand in simulation models: Many simulation models rely on O-D matrices supplied by their users to determine the traffic demand to be simulated. In these models, flows between pairs or origin and destination zones are read from the supplied demand matrix and then assigned to specific links on the network based on the results of a routing algorithm. This is the modeling approach used by Paramics [Portrait Software, 2007] and AIMSUN [TSS, 2001], two of the leading microscopic traffic simulation models. While VISSIM [PTV, 2005], another leading simulation model, can simulate traffic demand by propagating vehicles across a network using input flow rates at entry links and turning flow percentages at intersections, it specifically requires the coding O-D flows if dynamic traffic assignment behavior is to be simulated.

3. Origin-Destination Data Collection Methods

Various methods are currently employed for collecting or generating origin-destination data for transportation projects. These methods can be categorized into the following three broad groups:

- **Direct data collection methods**, in which origin-destination information is obtained by surveying travelers.
- **Indirect data generation through application of the traditional transportation planning process**. These methods typically seek to develop O-D matrices reflecting the observed socio-economic characteristics of each defined transportation zone within a network of interest.
- I**ndirect data generation through the application of synthetic matrix generation methods**. In this case, an origin-destination matrix is developed with the objective to replicate observed traffic flows on a set of links across a network.

Each of these approaches, together with the estimation techniques typically associated with them, is described in more details in the sections that follow.

3.1. Direct Data Generation Methods

Traditional methods for collecting O-D data include methods in which information about trips is obtained directly from the travelers. From an historical perspective, these methods have typically focused on very limited geographical areas [Hagen *et al.*, 2006]. Their primary utilization has been for the analysis of flow patterns along corridors. Some studies with larger geographical scope have also been conducted in support of planning activities by metropolitan planning organizations. Studies on scale larger than an urban area are however very rare.

Below is a description of the survey methods typically used for the direct determination of O-D matrices [Cambridge Systematics, 1996; Hagen *et al.* 2006]:

- **Phone interviews:** A sample of the population is interviewed by phone about their travel habits and. The results of the interviews are then compiled to extract general flow patterns.
- **License plate surveys:** The license plate of vehicles traveling the survey location is recorded by fieldworkers or automated instrumentation. Vehicle owners are then determined using data from the state's Department of Motor Vehicles and are sent a mail-back survey. For small study areas, trip patterns could also be inferred by matching vehicle detections obtained at different locations, such as toll detection records from vehicles using RFID tags.
- **Roadside interviews**: Vehicles traveling along specific roads are stopped and asked questions about their trip.
- **Roadside handout surveys:** Postcards are distributed to motorists passing a specific location, or to a sampling of households within a given region, with instruction to fill out the card and return it. For convenience, postcards can generally be mailed back using pre-paid business reply mail. An example of an O-D survey card is shown in Figure 3.
- **Combined roadside interview and handout surveys:** Fieldworkers stop some or all vehicles passing the survey location to conduct short interviews with the driver. When the interview is completed, they hand out self completion mail-back survey forms.

Survey Control #____

Please take a moment to answer a few questions about the trip you were making today when you received this card (excluding any return trip).

Please record your responses on the attached card OR contact our Web site at *www.i595survey.com*. You must have the survey control number (see top right) to complete the survey online.

Information should be provided only for the trip you were making when you received this card.

1. **Where did your trip begin? (the last place you entered your vehicle prior to receiving this card, excluding short stops for gas or food)**
   Street Address ____________
   Nearest Intersection/Landmark ____________
   Town ____________ State/Province ________ Zip ________
2. **At what type of place did your trip begin? (Choose only one)**
   ☐ Your Primary Residence ☐ Workplace ☐ Store ☐ Airport
   ☐ Your Seasonal Residence ☐ Hotel/Motel ☐ Recreation Area
   ☐ Other (please specify) ____________
3. **Where did/will your trip end? (the first place you exited the vehicle after receiving this card, excluding short stops for gas or food)**
   Street Address ____________
   Nearest Intersection/Landmark ____________
   Town ____________ State/Province ________ Zip ________
4. **What type of place is your trip end point? (Choose only one)**
   ☐ Your Primary Residence ☐ Workplace ☐ Store ☐ Airport
   ☐ Your Seasonal Residence ☐ Hotel/Motel ☐ Recreation Area
   ☐ Other (please specify) ____________
5. **If you have traveled or will travel on I-595, where did you get on? (Choose only one)**
   ☐ US 1 ☐ Ft. Lauderdale Int. Airport ☐ I-95 ☐ US 441/SR7
   ☐ Fla. Turnpike ☐ Davie Road ☐ University Drive
   ☐ Pine Island Road ☐ Nob Hill Road ☐ Hiatus Road
   ☐ Flamingo Road ☐ 136th Avenue ☐ I-75/Sawgrass Xway
   ☐ Did not use I-595
6. **Where did or will you get off I-595? (Choose only one)**
   ☐ US 1 ☐ Ft. Lauderdale Int. Airport ☐ I-95 ☐ US 441/SR7
   ☐ Fla. Turnpike ☐ Davie Road ☐ University Drive
   ☐ Pine Island Road ☐ Nob Hill Road ☐ Hiatus Road
   ☐ Flamingo Road ☐ 136th Avenue ☐ I-75/Sawgrass Xway
   ☐ Did not use I-595
7. **What was the purpose of your trip? (Choose only one)**
   ☐ Work Commute ☐ Business Related ☐ Going Home
   ☐ Shopping ☐ School
   ☐ Recreation ☐ Other (please specify) ____________
8. **How many people were in the vehicle, including the driver?**
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 or more
9. **What type of vehicle were you in?**
   ☐ Passenger vehicle/motorcycle ☐ Pick-up truck/van/SUV/minivan
   ☐ Truck (2+ axles, more than 4 tires)
   ☐ Other ____________
10. **How many vehicles are available to your household?**
    ☐ 1 ☐ 2 ☐ 3+ ☐ None
11. **What is your annual household income?**
    ☐ Less than $20,000 ☐ $20,000-$39,999 ☐ $40,000-$74,999 ☐ $75,000 and above
12. **How many workers (age 16 and older) are in your household?**
    ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 or more ☐ None
13. **How many people are in your household?**
    ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 or more
14. **If a low cost and fast transit alternative were available for this trip, would you consider using it? Please answer both.**
    Buses in special lanes ☐ yes ☐ no
    Trains (like Metrorail or Tri-Rail) ☐ yes ☐ no
15. **Are you a South Florida resident?**
    ☐ Permanent ☐ Seasonal ☐ Not a South Florida resident
16. **Please add any comments on how we can improve transportation in South Florida.**
    ____
    ____
    ____

Please complete, fold, and mail this form as soon as possible. No postage is necessary. Thank you very much for your cooperation! You do not need to mail it if you completed the Web survey.

Figure 3 – Florida DOT Mail-Back Questionnaire for the I-595 Vehicle Trip Length Survey [Hagen et al. 2006]

- **Online surveys.** Travelers contacted at home or at a roadside location are asked to complete a web-based survey about their travel habits.
- **Travel Diaries.** Selected travelers who agree to participate in the survey are provided with a diary to document their travel behavior within a specific time period. The diary is then returned to the surveying agency at the end of the survey period.

Table 1 summarizes the main advantages and disadvantages associated with each of the method mentioned above. Typically, phone interviews are conducted when it is desired to obtain information about regional travel patterns. In such a case, sampling rates exceeding 5 percent of regional households are rarely considered. Roadside interviews, roadside distribution of mail-back postcards and license plate surveys are typically conducted when it is desired to obtain information about the travel patterns of vehicles traveling on certain roads or in and out of a specific area.

Table 1 – Comparison of OD Survey Methods [Easa, 1993; Hagen et al., 2006]

Method	Advantages	Disadvantages
Phone interviews	• Ability to obtain additional information on trip characteristics. • Does not require stopping traffic. • High response rate. • Sample rate can be adjusted to meet study requirements. • Suitable for large areas.	• Persons interviewed may not fully recall details of their trips • Requires trained personnel to conduct the interviews • May requires a large number of personnel depending on the scope of the study
Roadside interviews	• Response rate usually much higher than with other methods, which reduces the potential for bias. • Personal contact is made between surveyors and respondents, which create an opportunity to obtain additional information about trips. • Sample rate can be adjusted to meet study requirements. • Collected data available for analysis much sooner than with other methods. • Ability to obtain information about trips passing specific locations.	• Requires stopping traffic. • May not be used at locations with high traffic volumes, particularly during peak hours. • Because of the potential for delays, interviews must be kept short, which may limit the amount of information collected. • Least safe of all survey methods. • Requires trained personnel to conduct the interviews. • May requires large number of personnel depending on the scope of the study. • Pulling vehicles over without a legitimate law enforcement reason is not permitted in many states.
Roadside handout surveys	• Generally less expensive than other methods. • Ability to obtain additional information on trip characteristics. • Minimal impact on traffic depending on distribution method used. • Ability to screen for certain types of respondents. • Ability to obtain information about trips passing a specific location.	• Requires stopping traffic to distribute postcards. • Care is required to distribute cards to a representative group of trips. • Socioeconomic bias may exist. • Response rate tends to be low. • Limited opportunities to conduct follow-ups. • Pulling vehicles over without a legitimate law enforcement reason is not permitted in many states.
License plate surveys	• Safest method as it does not require stopping traffic. • No traffic delays at survey locations. • Number of field personnel typically less than other methods. • Mail-back questionnaire can be more extensive than interviews in terms of questions asked. • Use of videotaping information or automated license plate readers allows night surveys. • Ability to obtain information about trips passing a specific location.	• No personal contacts between surveyors and potential respondents, which reduces opportunities to answer questions or explain aspects of the survey. • It is critical that questionnaires be mailed to potential respondents within a short time period after the license plates are observed (1-2 days). This is however often difficult because of the need for multi-agency coordination and the potential difficulties in identifying license plates. • Mail survey can have a low response rate and high potential for response bias. • People driving rental or lease cars are not surveyed. • Peoples driving someone else's car may not be surveyed unless they are given the questionnaire by the owner of the vehicle.
Web surveys	• Less expensive than other methods as they do not require costs for design, printing, postage, telephone calls, call personnel or data entry. • Ability to check validity of data as they are provided by travelers.	• May need incentive to entice travelers to fill out the questionnaire. • Socioeconomic bias may exist as drivers without internet access or computer skills are unlikely to respond.
Travel diaries	• Ability to record detailed information about multi-purpose trips.	• Depends on travelers to accurately report all travel information. • Potential bias in sample as it primarily relies on persons willing to participate in survey. • Fairly expensive.

3.2. Indirect Data Generation through Application of Transportation Planning Process

Generation of O-D flow patterns within the traditional transportation planning process is generally associated with the first two steps of the process: trip generation and trip distribution. Within each step, various approaches exist to develop relevant trip data, as outlined below.

3.2.1. Trip Generation Models

Trips originating from or going to a specific zone are usually predicted through the application of trip-generation models. Mathematical formulations used for accomplishing this prediction can be categorized into three families of models:

1. Regression models.
2. Trip-rate analysis models.
3. Cross-classification models.

Regression models estimate trips originating or ending in a zone through the application of equations linking a zone's trip production and attraction to a given set of variables. Variables quantifying the socioeconomic characteristics of a zone are typically used for the predictions. Frequently used variables include population, number of household, median income, average car ownership, etc. While various regression models have been proposed to estimate trip origins and destinations in relation to zonal characteristics, the models most frequently used generally belong to the family of linear multiple-regression models. Such models typically take the following form:

$$P = \beta_1 \mathrm{x}_1 + \beta_2 \mathrm{x}_2 + \ldots + \beta_n \mathrm{x}_n + \varepsilon \qquad [1]$$

where: P = Trips produced or attracted.
x_n = Prediction parameter n.
β_n = Coefficient associated with n^{th} prediction parameter.
ε_i = Error term.

Trip rate analysis models determine the expected number of trips originating from or destined to a zone by considering trip-production and trip-attraction rates associated with specific trip generators within each zone. As an example, Figure 4 illustrates the trip production and attraction rates associated with various commercial land use areas in the San Diego downtown area [City of San Diego, 2003]. Such trip rate tables are typically developed based on trip generation studies conducted by regional government agencies, the Institute of Transportation Engineers (ITE), and other qualified sources. Using these rates, the total number of trips originating from or destined to a zone can be estimated by compiling the trips associated with each category of trip generator or attractor.

Cross-classification models can finally be thought of as extensions of trip rate models. Instead of associating a single trip generation rate to a specific characteristic, such as the square footage associated with a specific land use, the rate is varied according to one, two or more other parameters. An example is given in Figure 5, where home-based non-work trips are estimated based on the density of the residential area, the number of vehicles available per household and the number of persons per household.

COMMERCIAL-RETAIL	
Convenience Market:	
Open15-16 hours	37 trips/1,000 sq. ft.
Open 24 hours	52 trips/1,000 sq. ft.
Lumber Store	24 trips/1,000 sq. ft.
Restaurant:	
Quality	32 trips/1,000 sq. ft.
High Turnover (sit-down)	27 trips/1,000 sq. ft.
Fast Food (with or without drive-through)	35 trips/1,000 sq. ft.
Shopping Center:	
Neighborhood	48 trips/1,000 sq. ft.
Community	28 trips/1,000 sq. ft.
Regional:	
Less than 500,000 sq. ft.	0.65 [Ln(T) = 0.756 Ln(x) + 5.25]
500,000 sq. ft. or more	0.63 [Ln(T) = 0.756 Ln(x) + 5.25]
Specialty Retail Center (Strip Commercial)	18 trips/1,000 sq. ft.
Supermarket	60 trips/1,000 sq. ft.
FINANCIAL INSTITUTION	
Excluding drive-through	26 trips/1,000 sq. ft.
With drive-through	31 trips/1,000 sq. ft.
Drive-through only	34 trips/lane
INDUSTRIAL	
Industrial/Business Park	13 trips/1,000 sq. ft.
Large Industrial Park	7 trips/1,000 sq. ft.
Small Industrial Park	12 trips/1,000 sq. ft.
Warehousing	4 trips/1,000 sq. ft.
LIBRARY	14 trips/1,000 sq. ft.
LODGING	
Hotel (w/convention facilities/restaurant)	9 trips/room
Motel	8 trips/room
Resort Hotel	7 trips/room

Figure 4 – Example of Trip Generation Rates [City of San Diego, 2003]

Detroit				
HBW	Autos/Household			
Workers/HH	0	1	2	3+
1	1.306	1.179	1.430	1.215
2	1.660	2.633	2.257	2.762
3+	0.000	10.000	3.172	4.049

Outside of Detroit				
HBW	Autos/Household			
Workers/HH	0	1	2	3+
1	1.222	1.173	1.411	1.339
2	3.197	1.832	2.345	2.495
3+	5.000	3.504	3.459	3.761

SEMCOG Region				
HBW	Autos/Household			
Workers/HH	0	1	2	3+
1	1.235	1.174	1.416	1.309
2	2.558	1.996	2.324	2.550
3+	5.000	5.310	3.417	3.847

Figure 5 – Examples of Cross-Classification Trip Generation Rates [Taylor and Feng, 2007]

3.2.2. Trip Distribution Models

Trip distribution models are mathematical functions that relate trip interchanges between transportation zones to the socioeconomic characteristics of the zones and their estimated trip production and attraction levels. Two basic types of models exist for executing this distribution:

- Growth factor models.
- Theoretical models.

Growth Factor Models

Growth factor models are extrapolation techniques. These models try to proportion the relative growth in trip production and attraction between zones using existing trip productions and attractions as models for distributing future trips. Examples of growth factor models include:

- Uniform factor model.
- Average factor model.
- Fratar model.

Growth factor models usually focus on inter-zonal trips as their formulation does not allow trips occurring entirely within a given zone to be estimated. Estimation of trip distribution between zones for a future year typically relies on a base-year estimate of trips between the transportation zones of interest. Inter-zonal trips for a given target year are then estimated by multiplying the observed base-year trip patterns by growth factors based on the anticipated land-use changes or other criteria over the projection horizon. Depending on the method used, various cycles of projections and adjustments could be executed until a stable O-D trip matrix is obtained.

Among the models mentioned above, both the uniform and average factor models are currently rarely used. The most popular model is the Fratar model, which generally takes the following form:

$$T_{ij} = (P_i\ G_i)\frac{t_{ij}\ G_i}{\sum x\ t_{ix}\ G_x} \qquad [2]$$

where: T_{ij} = Projected estimate of trips between zones *i and j.*
t_{ij} = Current estimate of trips between zones *i and j.*
P_i = Current number of trips produced by zone *i.*
G_i = Growth factor for trips produced by zone *i* based on anticipated land use changes.

Similar to all growth factor models, application of the Fratar model begins with a base O-D flow matrix. The application of growth factors to this matrix produces a first estimate of trips expected to occur between two zones. Because the model does not distinguish between trips produced and attracted by a given zone, values obtained for T_{ij} and T_{ji} are generally averaged. Following this first estimate, iterative adjustments are then made until the estimated number of trips produced by each zone in the resulting O-D matrix matches the number of trips expected to occur in the horizon year.

The Fratar model suffers from three major drawbacks. The first is its inability to consider the addition of new zones beyond the base year, such as what would happen with a new residential development. In this case, all base year interchange volumes associated with these new zones would be zero and would not be changed by the application of growth factors. The second drawback is that convergence to the target-year trip generation totals is not always possible. Finally, the model is not sensitive to the travel costs between zones, which significantly affect trip distribution in reality. For these reasons, application of the model is typically restricted to situations in which no information about travel time or travel cost between zones is available and to situations for which other models cannot be applied.

Theoretical Models

Theoretical trip distribution models are based on various mathematical formulations designed to represent the degree to which trips produced in one zone are attracted by other zones. The most commonly known models in this category include:

- Gravity model.
- Intervening opportunities model.
- Entropy maximization models.
- Multinomial logit models.

One of the most widely used theoretical models is the **gravity model**, mainly because of its simplicity and accuracy. It is based on a loose analogy to Newton's law of gravity. It assumes that interactions between transportation zones decline within increasing distance between them, as measured using distance, travel time or cost, but also increase in direct proportion to the amount of activity within each zone. From a mathematical standpoint, this model takes the following form [Papacostas and Prevedouros, 2001]:

$$T_{ij} = P_i \frac{A_j F_{ij} K_{ij}}{\sum(A_j F_{ij} K_{ij})} \quad [3]$$

subject to:

$$\sum P_i = \sum A_j \quad [4]$$

where: T_{ij} = Estimated trips between zones *i and j.*
P_i = Trips produced by zone *i.*
A_j = Trips attracted by zone *j.*
F_{ij} = Friction factor for impedance (usually travel time) between zones *i* and *j.*
K_{ij} = Socioeconomic adjustment factor for trips produced by *i* and attracted by *j.*

Developing a gravity model is a trial-and-error process that requires considerable care. Calibration of the model generally focuses on identifying the appropriate friction factor representing the reluctance, or impedance, of persons to make trips of various durations or distances. Adjustments of the factor are typically made incrementally through successive iterations until the frequency distribution of trip lengths produced by the model closely matches the frequency distribution observed from travel surveys or demonstrates an acceptable shape and average trip length.

Another important consideration is how to handle unexplained and unacceptable differences between observed and estimated travel patterns. Rather than conducting extensive research to try to find an explanation for all such phenomena, the accepted practice is to factor the model estimates to match observed patterns. With the gravity model, and often with other models, this adjustment is done through the introduction of a socioeconomic adjustment factor (parameter *K*). These factors are developed for individual trip interchanges and assigned values that adjust the estimated trips for the interchanges of concern to match the observed values.

Intervening opportunity models are based upon the idea that the probability of choosing a particular destination, from a given origin and for a particular trip purpose, is proportional to the opportunities for trip purpose satisfaction at the destination and inversely proportional to all such opportunities that are closer to the origin [Zhao *et al. , 2001*]. From a mathematical standpoint, these models typically take the following form:

$$T_{ij} = P_i \frac{e^{-LV_{(j-1)}} - e^{-LV_{(j)}}}{1 - e^{-LV_{(j)}}} \qquad [5]$$

where: T_{ij} = Estimated number of trips between zones *i and j.*
P_i = Trips produced by zone *i.*
L = Probability of accepting a destination opportunity.
$V_{(J)}$ = Total destination opportunities over all *J* destinations.
$V_{(j)}$ = Total destination opportunities from origin zone *i* to the j^{th} ranked destination.
$V_{(j-1)}$ = Total destination opportunities from origin zone *i* to the $(j-1)^{th}$ ranked destination.

Intervening opportunity models assume that trip makers consider potential destinations sequentially, in order of their impedance away from the origin. The probability that a trip will terminate at one of a group of destinations is equal to the product of two probabilities: the probability that an acceptable destination closer to the origin has not been chosen and the probability that an acceptable destination exists in these destinations.

Although opportunity models are based on somewhat sophisticated principles, they are not often used in practice. Some of the possible reasons for this limited use include:

- The theoretical basis is not very well known and more difficult to understand.
- The theoretical and practical advantages of opportunity models over gravity models are not so significant as to warrant their replacing gravity models.
- Lack of suitable software to calibrate and use them.

Multinomial logit models are used to forecast discrete choices. They are extensions of the binomial choice model to cases in which more than two alternatives are considered. In this case, the probability of selecting a particular destination zone is based on the number of trip attractions that are estimated for the destination zone relative to the total attractions in all possible destination zones. Multinomial logit models typically take the following form:

$$T_{ij} = P_i \frac{e^{-U_{ij}}}{\sum_x e^{-U_{ix}}} \qquad [6]$$

where: T_{ij} = Estimated number of trips between zones *i and j.*
P_i = Trips produced by zone *i.*
U_{ij} = Disutility associated with traveling from zone *i* to zone *j*, typically function of travel time, distance, cost or other factors.

The above equation essentially estimates the probability of making a trip to destination zone *j* based on travel cost to this zone relative to the travel costs to all other zones. Such a calculation is, in essence, conceptually similar to the gravity model.

Unlike previous models, **entropy maximization** models are not behavioral models. They do not attempt to predict trip distribution by modeling the human behavioral aspects related to choosing a destination but rather attempt to determine a distribution of trips which is most likely to occur when assuming that each tip occurs independently of others. It is assumed that the likelihood of a particular trip distribution matrix to occur is proportional to the number of ways the matrix can be obtained. Since entropy maximization models generally assume that the number of trips in a network remains constant, the matrix estimation problem thus becomes to find the set of trips t_{ij} that would satisfy the following expression [Paramahamsan, 1999; Agrawal *et al.*, 2005; Samanta and Majumber, 2006]:

$$Maximize\ Z(T_{ij}) = P_i \frac{T!}{\Pi_{ij} T_{ij}} \qquad [7]$$

where: T = Total number of trips in network.
T_{ij} = Estimated number of trips between zones *i and j.*

3.3. Synthetic Matrix Generation Models

While it is possible to directly measure the travel volume between two points, estimating the trip matrix for an entire network is generally a very expensive and time-consuming endeavor. As a consequence of these costs, various methodologies have been proposed to generate O-D matrices reflecting observed flow movements within a transportation network. The proposed synthetic methodologies can be categorized into two major groups [Dixon and Rilett, 2005]:

- Methods attempting to calculate O-D flows using simple behavioral rules.
- Methods attempting to use traffic surveillance data as input to the estimation models.

Estimation methods associated with the first group typically attempt to combine aggregated home and roadway survey data to estimate demand for travel associated with origin and destination zones, and then to use simple behavioral assumptions to estimate the associated trip matrix. One example of behavioral assumption may be to use a gravity model to distribute trips along routes of various lengths. Methodologies within this group are, however, often considered simplistic, as it is frequently assumed that one or two parameters can adequately describe travel behavior.

Estimation methods associated with the second group are far more frequently cited when referring to synthetic matrix generation models. Over the past few decades, the increasing availability of traffic surveillance systems has fueled interest in the development of methods attempting to take advantage of data provided by such systems. Surveillance data can not only be obtained at relatively low cost when the surveillance systems are already in place, but can also cover multiple periods extending over a single day or multiple days. Such systems also offer the advantage of collecting data while not disrupting normal travel patterns, which is not the case with many direct O-D survey methods. To date, research efforts have primarily focus on using traffic counts from loop detectors. However, efforts targeting the use of cordon traffic counts, intersection turning movements, travel time probe vehicles, and automated vehicle identification data are also frequently documented [Dixon and Rilett, 2005; Nie and Zhang, 2008].

According to Hazleton (2008), methods developed for inferring O-D matrices from traffic counts can be divided into two types:

- Static matrix estimation methods, where it is most often assumed that a single set of link counts is available, and which are typically augmented by highly relevant prior information such as an outdated O-D matrix [Cascetta, 1984; Bell, 1991; Tebaldi and West, 1998; Hazleton, 2000; Sherali *et al.*, 2003; Li, 2005; Doblas and Benitez, 2005].

- Dynamic matrix estimation methods, based on sequences of consecutive traffic counts taken at, say, 5 to 15 minute intervals [Cremer and Keller, 1987; Cascetta *et al.*, 1993; Sherali and Park, 2001; Lin and Chang, 2007].

Most of the methods based on link flow data that have been proposed to date rely on the use of an initial O-D matrix or a link choice proportion matrix (Van Zuylen and Willumsen, 1980; Maher, 1983; Cascetta and Nguyen, 1988). This prior matrix may be obtained from a traditional distribution model, such as the gravity model, or from matrices that have been estimated in previous network analyses. When such prior information is not available, neutral seed pattern matrices in which all the entries are assigned values of 1 can be used.

A key assumption in many traffic-count based O-D estimators is that the proportional relationship between the traffic counts and the O-D parameters, often known as link choice proportions, is known a priori [Dixon and Rilett, 2005]. Historically, however, the link choice proportion matrix has been difficult to measure directly. As a result, most approaches approximate this matrix using assignment models, where the assignment parameters are estimated simultaneously with the O-D parameters, or exogenously [Van Zuylen and Willumsen, 1980; Cascetta *et al*., 1993]. The former case is generally seen as applicable for congested conditions, while the later is most applicable for uncongested conditions.

Key to all traffic-count based matrix estimation methods is how differences between observed flows and estimated flows resulting from the assumed O-D matrix are minimized. Proposed approaches generally consider whether the network of interest is congested or not [Chen et al, 2005]. For uncongested networks, proportional assignments can be used for estimating O-D matrices. In this case, route assignments are assumed to be independent of the estimation process and can be obtained based on the observed travel times and appropriate route choice assumptions. Within this context, various statistical methods have been used to develop methodologies for minimizing the differences between observed flows and predicted flows in a given network. These methodologies include:

- Generalized least squares, in which the unknown parameters are estimated based on the minimization of the squared distance between the observed and estimated link volumes [Robillard, 1975; Maher, 1983; Cascetta, 1984; Bell, 1991; Hazleton, 2000; Ashok and Ben-Akiva, 2000, 2002; Nie *et al.*, 2005].
- Least absolute norm (LAN) estimator [Sherali *et al*., 1997].
- Entropy maximization [Van Zuylen and Willumsen, 1980; Bell, 1983].
- Bayesian inference [Maher, 1983; Tebaldi and West, 1998; Castillo *et al.* 2008].
- Constrained maximum likelihood [Spiess, 1987; Cascetta and Nguyen, 1988].
- Information minimization [Van Zuylen and Willumsen, 1980; Cascetta and Nguyen, 1988].
- Genetic algorithms [Baek *et al.*, 2004].

One example of application of a synthetic matrix generation methodology for uncongested network can be found in the Paramics microscopic simulation model Portrait Software, 2007]. In this case, simulation is used to estimate the link flows associated with a specific O-D matrix. At specified intervals, changes are made to the existing O-D matrix to try to minimize the cumulative error between the simulated and observed link flows. Depending on user options, the search algorithm tries to minimize either the arithmetic mean of the GEH distance or the square root of the arithmetic mean of the squared difference between the modeled and observed flows for each link for which an observation is available.

Adjustments to flows are done either at periodic intervals or each time a vehicle enters a link. In both cases, the objective is to use the differences between the simulated and observed flows to determine a corresponding adjustment to the flows within the O-D matrix. Because the presence of congestion can result in changes in O-D flows that are not reflected in observed link output flows as a result of congestion queuing, it is generally recommended to conduct the matrix estimation process at a reduced flow level for which congestion is unlikely to be a concern.

For networks with congestion, the proportional assignment assumption is no longer valid as route choices and O-D matrices become interdependent [Chen et al, 2005]. Because of this, it becomes necessary to incorporate a route assignment model into the estimation process. A possible solution is to use a bi-level programming approach, in which the upper level problem uses one of the statistical error minimization technique describe above to select the most proper O-D matrix, while the lower level endogenously determine the route assignments according to user or system equilibrium principles. In some cases, this bi-level programming level has been converted into a single-level optimization problem by assuming that information provided from a complete set of traffic counts constitute an equilibrium flow pattern. However, this approach is subject to the ability of obtaining a consistent set of traffic counts.

4. Issues with Current O-D Data Uses

Over the years, significant progress has been made in the development of techniques capable of generating O-D flow data representative of flow patterns observed in real networks. While early forecasting and estimation methods primarily focused on aggregate zonal flow patterns under static demand assumptions, available methods have gradually evolved towards considering individual trips in stochastic and time-dependent dynamic decision environments [Daganzo, 2007].

Despite these advances, numerous issues remain with how O-D data are estimated and used for the evaluation of transportation networks. While early travel forecasting and routing models can be considered simplistic, more recent models can be fairly complicated to implement in practical settings, particularly models attempting to estimate O-D data and provide flow assignment in dynamic settings. Many of these models can only be implemented through the development of efficient computer software.

In theory, the most recent computer-based travel forecasting models can predict almost anything on a multi-modal transportation network in minute details. However, despite the ability of modern computers to perform complex operations, a number of fundamental problems remain that may undermine the validity of the outputs produced by demand forecasting models:

- Available forecasting models are often dependent on the provision of large amounts of input data. For instance, Daganzo (2007) indicates that a forecasting model of a large city with a reasonable spatio-temporal resolution could easily require more O-D entries than there are people in the city. When input data is not available, there is often a tendency to make assumptions and provide “best guess” estimates to the forecasting model. This results in travel forecast depending on the judgment of the person in charge of running the model.

- Most of the synthetic O-D estimation techniques assume that the input data they use are reliable. However, this is not always the case. For instance, it has been demonstrated that unless inductive loops are maintained and calibrated at regular intervals, the data provided by these detectors can be subject to error rates of up to 41 percent [Turner *et al.*, 1999; Gajewski *et al.*, 2002]. Faulty counts could also occur as a result of failures in monitoring equipment or communication between the equipment in the field and the data collection server. Some of these failures can be particularly difficult to detect if the collected data are not continuously reviewed. There is therefore a probably that faulty data may be fed to synthetic O-D methods, thus causing significant impacts on the accuracy of the resulting O-D flow estimates. A similar problem would also exist with methods relying instead on prior O-D data, as such data may also be marked by some inaccuracies [Lin and Chang, 2005, 2006].

- Driver navigation is an unpredictable gaming activity. This problem arises because rational drivers often try to anticipate the congestion level along their possible paths. To accurately anticipate congestion levels, rational drivers ideally need to know the decisions of other rational drivers who will contribute to the congestion they will be experienced along their path. In addition, these other drivers may face the same conundrum in reverse, as they also have to try to guess the decisions of others drivers. While existing traveler information systems could provide information about congestion level, no information is typically available regarding future traffic conditions. In most cases, drivers thus make their travel decisions partly based on past experiences and partly based on available current traffic information while knowing that there always remain a potential for travel conditions differing than what was expected. Because of this high dependency on individual driver behavior, forecasting models may have very limited reliability in predicting travel patterns [Nie and Zhang, 2008]. This problem is further compounded by the fact that drivers may not always follow recommendations given by navigation systems.

- Oversaturated networks tend to behave chaotically. Dagazo (1996, 1998) has shown that the output flows of congested networks are hypersensitive to the input demand, making the networks difficult to predict. As congestion levels increases in cities throughout the United States and the world, networks are increasingly operating in oversaturated modes that are difficult to manage.
- A known limitation of the user-equilibrium principle is that although a user-equilibrium is sufficient to determine total link flow uniquely, under certain technical conditions it is not sufficient to determine route flow uniquely. This may lead to situations in which route flow solution are selected arbitrary, without any specific behavior assumption or mathematical condition to support the choice [Bar-Gera and Luzon, 2007]. Even though this problem has been known for years, very little has been done to estimate its extent. Research conducted by Bar-Gera and Luzon on a Chicago network found that it is almost always possible to find one user-equilibrium solution along swappable routes between and origin and destination in which all the flow is assigned to one route and another one in which the entire flow could be assigned on another link.
- In many recursive prediction models, the quality of flow predictions is dependent on the presumed stochastic flow demand evolution process. However, modeling within-day flow variations is not always easy, particularly during major transitions between off-peak and peak periods, in which flow conditions can change significantly in relatively short intervals. Consequently, many prediction methods model the deviation from historical demand patterns as a stochastic process rather than the variations of the travel demands themselves [Nie and Zhang, 2008].
- Due to the complexities introduced by real-time traffic dynamics and system characteristics, analytical function forms that adequately capture traffic realism typically do not exist. To generate exact analytical solutions, many dynamic traffic assignment models thus compromise on key characteristics of the problem, primarily the traffic flow modeling aspects, raising issues of realism. Simulation-based models can capture the traffic dynamics robustly, but mathematical properties cannot be derived for them [Peeta and Zhou, 2006]
- Real-time model application often requires performing a certain set of operations within a given time frame. Because synthetic O-D estimation methods and dynamic traffic assignment techniques are generally computationally intensive, this significantly limits their application in real-time settings.

The above elements clearly outline the difficulty of developing accurate flow pattern information with existing estimation methods. Most of the methods in use today attempt to infer O-D data from surrogate data. While the estimation techniques have become significantly more complex over the years through attempts to better capture traveler behavior, there is still no guarantee that the resulting O-D data will adequately match real travel patterns. This is heavily due to the fact that travelers make trip decisions based on a wide array of factors, with individual factors having varying importance from one traveler to the next, and often from one time period to another.

While traffic counts and other surveillance data can be used to infer O-D travel patterns, the resulting patterns are usually nothing more than attempts to fill an O-D matrix with data that would allow a network to be loaded with travel demands that would produce the same link flows as those observed in reality. While individual link flows may be reproduced, there is no guaranty that the estimated flow patterns truly replicate driver behavior. For instance, the same network loading can often be obtained using alternate combinations of short, medium and long trips.

While a practical solution to the above issues appears to be in the execution of direct travel time surveys, this approach is also generally considered impractical on a large scale when using traditional survey methods. Experiences from past surveys indicate that existing direct O-D data collection methods can be very costly, both in time and monetary aspects. Depending on the survey being executed, individuals may be required for conducting interviews, distributing mail-back surveys, entering collected data into suitable electronic databases, and performing some data analyses. The potential for low response rates and potential inability to obtain temporal trip information with a resolution adequate for forecasting traffic variations within a day can further be added to the problem.

Table 2 – Cost Efficiency of Sample Travel Surveys [Hagen et al., 2006]

Performing agency	Year	Sample size	Response rate	Average cost per survey	Total cost
Household telephone interviews with mail-back activity diaries					
Metropolitan Transportation Commission (San Francisco Bay)	1990s	9,400	49%	$84	$1,000,000
Caltrans Office of Travel Forecasting and Analysis	1990s	13,500 weekday 900 weekend	50% precontact 69% of agreed precontact	$104	$1,494,000
Southern California Assocations of Governments	1990s	16,000	50% precontact 69% of agreed precontact	$94	$1,500,000
Roadside handout surveys					
Vermont Agency of Transportation	1994	Average of 1676 card distributions per site	23.9%	$14-15 per usable response	n/a
Roadside interviews					
Vermont Agency of Transportation	1994	Average of 502 interviews per site	95.2%	$12-13 per usable response	n/a
License plate surveys with mail-out/mail-back questionnaires					
Amtrak	1992	15,100 5,800 7,300	30% 28% 22%	$16	$75,000 per site
Caltrans District 4 (San Francisco area)	1994	18,000	30%	$8-9	$150,000
Caltrans, AMBAG and Three Counties	1994	44,500	15%	n/a	n/a
Caltrans District 7 (Los Angeles) and CTS	1990s	1,721 4024	11.7% 12.5%	n/a	$60,000
Caltrans District 8 (Riverside area) and SBAG	1990s	21,000 23,000	22% 24%	n/s	$7,000 $10,000
Caltrans District 12 (Orange County) and Orange County	1990s	7,450	11%	$9-10	$68,700
Santa Barbara County Association of Governments	1990s	3,361	24%	n/a	n/a

Table 2 provides some information about response rate and costs of various O-D surveys conducted in the past 15 years [Hagen *et al.*, 2006]. As can be observed, the listed surveys generally produced relatively low response rates. The highest response rate, 95%, was for the survey using roadside interviews. Surveys using mail-back questionnaires typically produced response rates ranging from 10% to 50%. Survey costs also vary significantly, from an average of 8 to 16 dollars per individual survey for methods based on license plate recording or roadside interviews, to up to 100 dollars per individual phone interview. Recent interviews with transportation planners indicate that the cost estimates shown in Table 2 are still reflective of current O-D survey costs despite the fact that the illustrated examples are for surveys that were conducted over 10 years ago.

The data clearly indicate that obtaining large samples of O-D data using traditional survey methods can be relatively inefficient and cost-prohibitive. For instance, collecting data for a sample of 100,000 trips may require mailing 200,000 to 400,000 questionnaires, or phoning as many persons, at a cost that can easily exceed a few million dollars. Many transportation agencies go around this problem by simply imposing a cap on the funds that can be expended on data collection, and thus, by effectively limiting the amount of data to be collected. Because of high costs, surveys are also typically executed only once every few years, if at all. As an example, the Tri County Planning Commission in Lansing, Michigan, has not conducted an OD survey since the 1960s because of limited budgets. This is probably typical of small metropolitan planning organizations. Planning organizations for large metropolitan areas may execute surveys in intervals ranging from once every five years to once every ten years. In such cases, however, there is still no guarantee that the collected data will satisfy all needs. In particular, the long intervals between data collections often leave agencies with no other choice than to perform planning analyses using outdated data characterizing travel behavior that was observed within a relatively limited time widow, with “best guesses” often added to fill in gaps in data.

5. New and Enhanced Applications Enabled by IntelliDrive O-D Data

IntelliDrive applications are based on the projected ability of vehicles to communicate wirelessly with roadside equipment and other vehicles. In the context of O-D data collection, the primary benefit offered by IntelliDrive systems is the potential to transform individual vehicles into recording instruments. For instance, onboard instrumentation could be used to record the location of a vehicle at pre-specified intervals, such as every second or every time a vehicle enters a new link. This information could then be used to trace the path followed by a vehicle. If instrumentation further allows the speed of the vehicle and various other vehicle status parameters to be recorded, various trip performance measures could be estimated, such as the number of stops made and the delay incurred. Speed profiles could also be built and used to determine where delays were incurred along a given trip. If the intended destination of a vehicle is known, it then becomes possible to suggest routes to drivers and to project where vehicles may be heading and where congestion may appear in a network.

In this report, O-D data does not only refer to the knowledge of where a vehicle has started a trip and where it intends or has terminated a trip. O-D data also refers to the ability to collect information about trip between its origin and destination point. While knowing where vehicles travel from and to is important to establish regional travel patterns, knowing the paths that vehicles take to reach their destination helps determine preferred routes and assess network congestion levels.

Because of concerns regarding the privacy of travelers, current IntelliDrive data collection protocols are recommending that vehicles cannot be the tracked over long distances and that any data collected from IntelliDrive vehicles do not include any information that may allow the unique identification of the vehicle or its driver. While these recommended provisions may significantly restrict the availability and use of O-D data if implemented, there is reasonable assurance that O-D information may still be accessible. One option considers obtaining driver approval for accessing O-D information through a service agreement's "opt-in" clause in which individual driver would allow to be tracked in exchange for some benefit.

Assuming that O-D data can be retrieved from IntelliDrive probe vehicles, the following subsections describe the impacts of availability of such information on transportation planning and system operations activities.

5.1. Impacts on Transportation Planning Activities

The ability to use IntelliDrive probe vehicles to collect O-D data is expected to have significant impacts on transportation planning activities. As indicated earlier, a primary transportation planning task is to determine regional travel patterns. With respect to current travel demand estimation practice, the primary benefits provided by IntelliDrive systems would be the ability to track vehicle movements across a network and collect direct information about trips being made. In turn, the ability to track vehicles could translate into the following benefits for transportation planning activities:

- **Increased trip sample rate.** Current travel forecasting methods typically rely on limited samples. As indicated earlier, location-based surveys relying on mail-back postcards have historical response rates varying between 10 and 30 percent of all vehicles passing a specific location. Surveys seeking to asses regional travel patterns rarely seek to interview more than 5 percent of household in a region, in addition to being executed only once every few years. Similarly, the development of synthetic O-D matrices based on traffic flow counts is function of the number of traffic detection stations available. For budget reasons, permanent counters are often only installed on freeways and some major roads. This result in flow data being collected from only a fraction of all the roads in a network. With IntelliDrive probe data, the amount of information collected about trips made in a network would primarily be function of the number of equipped vehicles. If all vehicles were IntelliDrive vehicles, it would theoretically be possible to collect trip data from every trip made within a network, regardless of where and when the trip is made. While such a scenario is not likely in the near future, even a small percentage of IntelliDrive vehicles could yield increases in trip sample rate when compared to current practice. In this case, a major benefit would be the ability to continuously collect data, rather that only during a brief survey period collecting data only within specific time windows across a few days.

- **Improved network coverage.** IntelliDrive probe vehicles offer an opportunity to collect information from every roadway in a network. As indicated above, because of deployment and maintenance costs, traffic surveillance systems often only cover major roadways. This restricts the usability of traffic flow counts to estimate travel patterns along primary travel roads. With IntelliDrive vehicles, information about traffic conditions could be collected from every link on which a probe vehicle travels. This would allow collecting information from every type of road, including minor arterials, collectors and residential streets.

- **Improved ability to analyze network specific elements.** The ability to track IntelliDrive vehicles between a trip origin and destination points would provide new opportunities for trip analysis. For instance, it may become possible to compile statistics about trips using a specific link, a specific link at a specific time, or a specific sequence of links. This would enable transportation system planners to develop statistics about where the vehicles observed to use a specific link tend to originate from and where they tend to go.

- **Increased accuracy in estimating existing travel demand patterns.** The ability to compile trip data from a large fleet of vehicles, from any type of road in a network, and from any time period, should allow refinements in travel demand analyses. While travel forecasts will always retain a certain degree of uncertainty, the improved analytical abilities provided by the collection of large volumes of direct trip data should allow the development of travel patterns that may better reflect existing traffic conditions and travel patterns. In this case, the highest degree of improvement may be for cases in which IntelliDrive probe data can be used to replace synthetic O-D data generation from traffic flow counts.

- **Improved ability to track trends.** The ability to continuously collect trip data from probe vehicles would provide an enhanced ability to identify trends in travel demand changes, such as seasonal trends in travel patterns and gradual changes from one year to the next. There would also be an opportunity to segment changes by time-of-day, geographical area, specific type of road, and specific type of vehicle if this information is available.

- **Ability to collect detailed information about selected trips.** While travel surveys can provide detailed information about trips made by an individual, the information collected is often subject on how well individuals remember their activities. In this case, IntelliDrive systems offer the ability to log detailed reliable information about every portion of a journey. Specifically, recorded vehicle tracking data would allow the identification of every roadway link traveled, the exact time of travel on each link, the average speed of travel on each link, etc. Information about the purpose of a trip may also become available if the driver of vehicle explicitly provides it, such as by keying his destination in a navigation system. Even if data about trip purpose is not available, it may also become possible to infer this information from the identified destination and time of travel, such as for a trip to a fixed work address always executed at the same time.

- **Improved ability to analyze chain trips.** Detailed tracking of vehicle movements would allow the analysis of multi-purpose trips, i.e., trips with multiple stops. Such analysis is currently only possible with the use of travel survey data in which respondent clearly describe trips with multiple stops.

- **Improved ability to analyze road network performance.** Vehicle tracking data could be used to determine the average travel time or average travel speed on individual network links at specific time periods. This information is very valuable in assessing network performance and needs. Currently, travel time data can only be obtained for roadway links on which traffic surveillance equipment has been installed. In these cases, travel times are typically inferred by assuming that the speeds observed where the traffic detectors are located are representative of speeds across the entire link. For links without surveillance equipment, travel times are typically inferred by using formulas estimating travel time as a function of traffic volume and estimated available road capacity. By enabling vehicles to record information about their location every second or every few seconds or to record experienced travel times across roadway links, IntelliDrive systems would allow more detailed analyses of link traffic performance than what is currently possible. In particular, data could be collected from every link in a network and for every time period. This data could be used to develop new formulas for estimating link travel times that may capture more accurately some of the impacting factors that may vary from link to link.

- **Improved ability to estimate vehicle emissions.** Transportation planning organizations are frequently required to estimate the level of vehicle emissions within a region to evaluate compliance with environmental regulations. Such evaluations are currently typically conducted using models that simply estimate emissions by considering average travel speeds, total miles traveled and information characterizing the local fleet of vehicles. In this case, availability of second-by-second tracking data would enable the use of more detailed vehicle emission models better able to capture changes in driving behavior and to improve the accuracy of the emission estimates.

5.2. Impacts on Traffic Management Applications

The projected impacts on traffic management applications of O-D data collection by IntelliDrive probe vehicles depend on the application being considered. Below is a summary of expected impacts on various aspects of traffic management operations:

- **Modeling of traffic demand in simulation models**. Traffic demand modeling in many of the leading simulation models is in the form of an O-D matrix. This is for instance the case of the Paramics and Aimsun microscopic traffic simulation models. In both models, methods are provided to allow synthetic O-D matrices to be developed based on information characterizing observed traffic flow counts and observed turning percentages at intersections. While the VISSIM simulation model further offers the option to model demand in the form of traffic flow rates on entry links and turning percentage at intersections, the coding of O-D flows is required if dynamic routing is to be simulated. In this case, the ability of IntelliDrive probe vehicles to track vehicles would greatly simplify the task of generating O-D travel matrices for simulation scenarios, in addition to increasing the accuracy of the modeling and simulation results. Instead of using trip patterns mathematically derived to match link-based flow statistics, travel patterns could be developed by directly compiling statistics about observed trips. IntelliDrive O-D data could also be analyzed with respect to time or vehicle type to provide O-D matrices for specific time periods, specific vehicle types, etc.

- **Analysis of traffic behavior at intersections**. The evaluation of traffic behavior at signalized and stop-controlled intersections heavily depends on knowledge of whether approaching vehicles are intending to go straight, turn left or turn right. This information is typically used to assess levels of conflicts between movements at the intersection and the performance of proposed traffic control plans. Currently, directional flow patterns are typically obtained through manual field surveys in which individuals count vehicles from each approach going in each direction during representative time periods. Because of the costs associated, surveys are typically executed only once every few years. Automated means of counting vehicles also exist, such as license plate readers and video tracking systems, but they are used infrequently because of their high setup costs. In this case, IntelliDrive probes would enable the automated collection of data about traffic movements across every intersection in a network on a 24-hour basis. As a result, up-to-date demand information for any portion of the day or any day of week would always be available. In addition, directional flows could be compiled as a function of vehicle type, thus allowing for a better representation of the impacts of specific vehicle types on traffic performance.

- **Optimization of traffic signal timings**. Similar to the operational analysis of intersections, the optimization of traffic signals heavily depends on information about how many vehicles intend to go straight, turn left or turn right. In systems used by small cities, signal timings are typically set to provide adequate control for an average high demand scenario determined by analysis of historical data. Due to the cost of conducting surveys, several years often elapse between the re-optimization of signal timings to account for changes in traffic demands. In this case, IntelliDrive systems would provide an automated means of collecting data about traffic movements across an intersection. Information about incurred delay could also be collected if second-by-second data is recorded. This would enable a better tracking of changes in traffic conditions and identification of when signal timings at individual intersections may need to be adjusted.

  In addition to fixed systems, medium to large cities are increasingly relying on the use of signal timings that have the capability to automatically adjust to actual traffic demand. In these systems, adjustments primarily depend on observed changes in flow rates approaching an intersection, or the detected presence or absence of a vehicle on an approach. Dynamic information about the proportion of vehicles turning right, turning left or going straight is currently only available at intersections with exclusive lanes, and at intersections where video detection systems have the capability of detecting directional flow movements within an intersection. In this case, IntelliDrive probe vehicles would allow up-to-the-minute information about directional flow rates to be collected for every intersection. This information could also be compiled according to vehicle types or other classification permitted by the collected data. However, these benefits may not be realized until a certain proportion of vehicles are

IntelliDrive equipped, as a low vehicle sampling may yield significant uncertainty regarding the true representativeness of the IntelliDrive-derived statistics.

IntelliDrive has the potential to yield additional benefits in the development of network traffic signal control. For instance, knowing the intended destination of vehicles would allow for forecasting the most likely route that individual vehicles may take. These forecasts could be used to track waves of vehicles and proactively adjust the signal timings ahead of these waves. While this is not a new approach, the improvement over current practice would be the ability to obtain information about potential vehicle paths. Currently, traffic projections are typically development by propagating flow rates or observed groups of vehicles across a network. With IntelliDrive systems, individual vehicle paths based either on past records or current stated destination would be used. As a result, potential gains in accuracy of traffic projections may be obtained.

- **Analysis of freeway operations at freeway merge, diverge and weaving sections**. Similar to signalized and stop-controlled intersections, the analysis of freeway merge, diverge and weaving sections depends on information regarding where vehicles are coming from and where they are going In this case, IntelliDrive systems offer the ability to get real-time information about directional flow movements. This information could then be used to analyze current traffic performance at specific freeway sections and determine whether unusual conditions exist.

- **Corridor traffic management**. Information about the origin and destination of vehicles would be particularly beneficial for corridor traffic management. In existing corridor management applications, past flow data or simulation results are used to determine the best flow allocation strategy across available alternate routes and the best traffic control on each route. This means that only static or reactive strategies can typically be considered. A first contribution of IntelliDrive O-D probe data would be to allow for improved modeling of travel behavior within a corridor. Instead of developing travel patterns based on flow counts using synthetic O-D data generation methods, travel patterns could be directly obtained from the vehicles traveling the corridor and segmented according to vehicle type, time of day or any other available variable. A second contribution, should the intended destination of vehicles be available, would be to allow proactive traffic control along the corridor. Instead of simply reacting to observed changes traffic, travel path could be suggested to individual vehicles to improve system performance. Traffic control strategies could also be adjusted ahead of anticipated changes in traffic patterns to reduce stops and delay and further improve system performance.

- **Emergency evacuation traffic management**. The implementation of emergency evacuation plans could significantly benefit from the availability of information about the intended destinations of vehicles. Similar to corridor management applications, this information could be used to determine the expected path of vehicles following an evacuation order. In this case, path information could be fed to a simulation model or other forecasting tool to identify the location of potential traffic problems and to proactively develop solutions for these locations before the problem appears. Path information could further be used to recommend the most likely route that an individual vehicle should take for leaving an area subject to an emergency evacuation order based on network traffic flow projections. These recommendations may not only be used to minimize traffic time for individual travelers but also to manage traffic flows with the objective to improve system performance and minimize potential problems.

- **Vehicle routing applications**. Collection of O-D data from vehicles traveling within a corridor or network offers the potential to benefit vehicle routing applications. Drivers currently have the option of using on-board navigation systems to obtain routing information to their intended destination. In some of the more advanced systems, routing information may also consider known incident locations, historical traffic data or recent travel time information reported by traffic surveillance systems or other travelers. From a traffic management standpoint, one potential benefit of collecting information about the intended destinations of vehicles is the added ability of predicting traffic flows and forecasting operational hotspots. This information could be used to provide routing suggestions to drivers based not only on current traffic conditions but also on projected conditions along their path. Alternatively, routing suggestions could be provided not to minimize the travel time of individual travelers but to instead optimize network performance. Monitoring of whether or not drivers follow issued recommendations could also be used to determine the effectiveness of routing recommendations and to use this information in network flow projections for more realistic predictions.

6. Benefit-Cost Ratio of New and Enhanced Applications Enabled by O-D Data

Sections 5 presented potential benefits with respect to transportation planning and system operations that can be expected with the availability of O-D trip information in IntelliDrive data sets. While obtaining some operational benefits is an important criteria, application deployments are generally assessed based on the benefits they provide against their deployment and operational costs. A measure frequently used for this purpose is the benefit-cost ratio. A ratio above 1 indicates that an application generates benefits that compensate for its costs. Conversely, a ratio below 1 indicates an application that does not generate enough benefits to cover its deployment and operation costs.

To date, very few studies have attempted to establish benefit-cost ratios for proposed IntelliDrive applications. This is because accurate ratios for IntelliDrive applications are difficult to capturefor a number of reason:

- IntelliDrive applications are heavily dependent on communication and computer technologies. Because these technologies change rapidly, it is difficult to assess exact deployment and operation costs for applications that may still be several years from reaching the implementation stage.
- Many benefits expected from IntelliDrive systems are difficult to assess prior to an actual deployment due to a lack of prior application experience. For instance, while it is expected that many IntelliDrive applications will improve traffic safety, the exact impacts on crash rates can only be guessed. There is also significant difficulty in assessing how the applications may reduce crash risks, as near collisions often are not reflected in statistics.
- Many tests conducted so far have simply focused on proving the viability of the IntelliDrive concept. Since these tests have primarily focused on limited deployment in more or less controlled environments, there is still no clear understanding as to how various applications may operate within a full scale IntelliDrive system deployment.

Other factors specific to the use of O-D data that further contribute to the difficulties of estimating benefit-cost ratios for applications using this information include:

- There is still significant uncertainty as to what will be allowed to be collected with respect to driver privacy safeguards.
- O-D data can easily be added to currently proposed probe vehicle data collection systems. As such, very little cost may be incurred to add the desired data collection capability.
- Systems collecting real-time O-D data do not currently exist. Simulation is therefore the only method currently available for assessing potential impacts on applications and system benefits. However, simulation results are highly subject to the quality of their calibration to real-world conditions. Inappropriate calibration could thus cast a significant shadow on the validity of generic cost-benefit ratios based on simulation results alone.
- A significant benefit of including O-D data in IntelliDrive data sets is the ability to replace synthetic O-D trip matrices by matrices developed using real-world observations. While this change may not induce operational changes in applications using O-D data, it has the potential to improve the quality of the evaluations being conducted and decisions made upon the results of these evaluations. A difficulty is thus to quantify the value of improvements in data quality and decision-making.

- Network-specific elements may affect the benefits provided by the ability to automatically collect O-D trip data from IntelliDrive probe vehicles. For transportation agencies without active O-D data collection programs, the availability of O-D data from IntelliDrive probe vehicles would represent a net gain in data collection and analysis capabilities. For agencies already collecting some O-D data, the benefits will be a function of the incremental gains achieved in data collection and data accuracy. Some benefits may also be attributed to the ability to replace existing costly manual data collection procedures.
- The benefits provided by applications using O-D data are likely to be affected by network-specific elements. For instance, while one network may offer travelers many alternate routes along heavily traveled corridors, other networks may only offer limited options, if any, due to geographical or other constraints.

One of the few studies attempting to establish benefit-cost ratio for IntelliDrive is a recent study by the Volpe National Transportation Center performed for the U.S. Department of Transportation (Volpe National Transportation Center, 2008). This study conducted a systematic quantification of the costs and benefits of the proposed IntelliDrive program in the United States over its expected life cycle using well-accepted procedures for discounting values in future time periods to present values. Table 3 presents the benefit-cost ratios that were estimated for various categories of applications over an assumed 40-year period. The study found that about 95% of the benefits from IntelliDrive system would result from reduced crashes, with the remaining benefits stemming from improved mobility and other positive private and societal impacts. However, not enough information was available to estimate the benefits of several applications.

Table 3 – Estimated Benefits and Costs of IntelliDrive Applications
[Volpe National Transportation Center, 2008]

Application / Cost Element	Safety Benefits	Mobility Benefits	Costs
Signal Violation Warning	11.0	0.1	
Stop Sign Violation Warning	2.7	0.0	
Curve Speed Warning	14.6	0.1	
Electronic Brake Lights	13.6	0.2	
Ramp Metering		0.3	
Traffic Signal Timing		0.3	
Winter Maintenance		0.4	
Traveler Information		0.9	
Total Benefits	**41.8**	**2.4**	
Roadside Equipment			9.3
Onboard Equipment			12.4
Network Backhaul, O&M			3.7
Governance & Program			1.0
Application-Specific Costs			0.8
Total Costs			**27.3**
NET BENEFITS: 16.9 **B/C RATIO: 1.6**			

*Data in billions on 2008 dollars

When considering all societal impacts, it is estimated that the IntelliDrive initiative may generate net benefits of about $41.8 billion for a full system deployment cost of $27.3 billion, yielding an overall benefits to costs ratio of 1.6 to 1. Sensitivity testing further indicated that these results are robust to the choice of discount rate and time period selected, but that sizable increases to assumed input values for the costs of the onboard equipment could reduce the benefit-cost ratio to below 1.0.

Within Table 3, applications leveraging O-D trip data would primarily have benefits falling within the mobility category. As indicated earlier, the estimated mobility benefits are significantly lower than the expected safety benefits. However, the figures shown in Table 3 can only be considered as preliminary conservative figures. As indicated in the research report, the estimated ratios do not yet include:

- Envisioned future enhancement of several applications, e.g. the use of fully adaptive traffic signal control.
- Additional applications that may be developed, including private-sector applications.
- Any estimate of safety benefits related to un-reported crashes.
- The full value of emissions reduction benefits stemming from reductions in crash-related congestion.
- The mobility benefits associated with improved traveler information systems.
- Benefits to enterprises outside of transportation, particularly meteorological forecasting.
- The potential to achieve a fuller measure of benefits more quickly through the use of aftermarket OBE and/or retrofitting of older vehicles.
- Extension of the IntelliDrive concept to public transportation and commercial vehicles.

Based on this observation, the ratios of Table 3 are likely to be revised upward as more evaluations are conducted into to the potential benefits of various applications. In particular, while the estimates of Table 3 indicate that mobility applications yield lower benefits, they do not indicate that such applications are not worth pursuing. Because safety and mobility applications may rely on the same underlying infrastructure, their estimated benefits can be viewed in addition to the safety benefits. Since applications using O-D trip data may require very few infrastructure additions, and thus small incremental deployment costs, in a context in which other applications are already deployed, they may still yield high benefit-cost ratios justifying their development.

7. Potential Impacts of Origin-Destination Data on Driver Privacy

The initial IntelliDrive architecture and system requirements were built around the concept that public systems would have direct access to IntelliDrive vehicle data as vehicles pass within range of DSRC roadside radios. Since the data may include ID, speed, direction, destination, time, etc., there have been continuing concerns that this data may be used to compromise driver privacy or used against the driver by law enforcement agents, such as for sending speeding tickets in the mail every month, for tracking driver whereabouts for use in litigation surveillance or criminal investigations, etc. Even with a commitment by managers of the IntelliDrive system that the data would be held private and not provided to law enforcement agencies, a lagging doubt remains within the motoring public that future administrations could change policies and turn the system against the motoring public.

To achieve a high level of acceptance by the motoring public, the IntelliDrive system was designed to make the vehicle and driver's ID anonymous to anyone accessing IntelliDrive probe data. These design changes, while effective, added considerable complexity to the system implementation and resulted in some data value lost. The lost value to the traffic operations centers and metropolitan planning organizations is the ability to follow vehicles from their origin to their destinations for traffic management planning, optimization and control purposes.

This section examines IntelliDrive systems with respect to driver privacy. Specific concerns regarding driver privacy with IntelliDrive applications are first outlined. This is followed by a presentation of emerging driver privacy policies regarding IntelliDrive systems, a description of methods currently promoted for ensuring driver privacy, a discussion of the potential impacts that these methods may have on applications, and a presentation of alternative approaches available to mitigate existing privacy concerns.

7.1. Concerns Regarding Driver Privacy with IntelliDrive Applications

Concerns regarding driver privacy depend on the type of applications considered. There is a significant difference in the acceptability of applications relying on tracking vehicle movements across a single link or a single intersection and applications aiming to track vehicles across long distances.

Vehicle tracking across single links or intersections is at the base of many safety and mobility applications currently being developed and promoted, such as red light violation warning, stop sign violation warning, and freeway on-ramp merge assistance. In both red light and stop sign violation warning applications, real-time vehicle tracking is required to determine the probability that a vehicle may violate the traffic control device in use at the intersection. In more advanced systems, the same information may also be used to assess collision risks with conflicting traffic streams and issue warning message or initiate appropriate avoidance maneuvers. Similar to intersection-based applications, freeway merge assistance applications rely on real-time vehicle tracking to evaluate gaps between vehicles on freeway lanes and determine when a specific vehicle waiting on an on-ramp may safely enter the freeway without generating significant traffic disruptions. What makes vehicle tracking acceptable within these applications is that there is no need to collect information about the origin, destination, and owner of the vehicles being tracked. There is also the argument that since anyone can stand of the side of the road and watch vehicle pass, it thus legally acceptable to track vehicles over similar distances.

Problems with the collection of probe IntelliDrive data arise when there are possibilities for determining the specific origin or destination of a vehicle, or knowing when a vehicle passes a certain point in the network. Safety and mobility applications applied to local intersections and road segments inherently offer protection against surveillance fears by only tracking vehicles across short distances. However, for these applications to be accepted there must be a perception that the collected information at one intersection or from one segment is not being correlated to information collected at other points in a network to infer travel patterns.

The problem of vehicle tracking is not necessarily that drivers are unwilling to be tracked, but rather that they are unwilling to have their personal travel been tracked without their consent. Many fleet drivers are, for instance, already being tracked by their company operators. In this case, tracking may be deemed acceptable, as driving is done for work purposes while at the wheel of company vehicles, with the collected data used primarily for logistics reason and to enforce industry regulations. The fleet drivers may be unwilling to have their movements tracked while driving their personal vehicle during off-duty periods.

Simply stating that drivers are unwilling to be tracked while in their personal vehicle may be also slightly inaccurate. The problem is not that drivers are necessarily unwilling to be tracked but that they are instead wary that collected information may be misused. A particular fear is that the collected information may be used by law enforcement agencies to, for instance, issue speeding tickets. There are already a number of examples of situations in which individual drivers willingly accept being tracked. One of the best examples is individuals subscribing to private traffic congestion reporting services. Many of these services promise drivers to provide drivers with up-to-the-minute traffic information and custom congestion avoidance strategies if they agree to be tracked. In this case, individuals are willing to be tracked if they believe they get something valuable in return. Individuals using Radio Frequency Identification (RFID) tags to pay tolls also willingly accept to be tracked, in this case for the benefit of not having to stop at a toll booth or being able to use a less congested road. Another example is individuals purchasing General Motors vehicles equipped with the OnStar system. In this case, individuals purchase vehicles that can be tracked at any given time by OnStar employee in return for being able to get assistance anywhere they may be or have their vehicle tracked if it is stolen. It can also be considered that individuals are nowadays purchasing cellular phones with embedded GPS allow themselves to be tracked, unless they turn the tracking function off.

Common to all the above cases is the perception that the tracking system is not being misused. Crucial to the acceptability of any IntelliDrive systems would therefore be the perception that the collected information is not being used against them. This will require the development of safeguards in the collection and treatment of IntelliDrive probe data designed to protect the privacy of drivers.

7.2. Emerging Policies Regarding Driver Privacy in IntelliDrive Systems

To address concerns regarding the privacy of travelers, a number of principles and limits have been recently drafted by the National VII Coalition regarding the use of personal information in IntelliDrive applications [National VII Coalition, 2007]. In this case, personal information specifically refers to data that can be used to uniquely identify individuals. For example, a person's origin-destination information is generally considered personal information when it identifies a particular individual. However, when that same data is rendered anonymous, such as through aggregation and summarization, it is no longer considered personal information as long as information allowing the identification of a traveler cannot be extracted from it. In another example, a Vehicle Identification Number (VIN) is considered private information as it identifies a specific vehicle. However, the first six digits of a VIN would not be considered as private information as it only identifies a vehicle model.

The principles proposed by the National VII coalition were designed to reflect fair information practices and to ensure that IntelliDrive applications are implemented in a way that is properly respectful of reasonable privacy expectations. Below is a summary of the nine principles that are proposed:

1. **Respect for privacy and personal Information**. IntelliDrive-derived personal information should be acquired, retained, disclosed, and used only in ways that protect the privacy of individuals. Whenever possible, applications should be designed to only collect and process anonymous information.

2. **Information purposes.** Personal information should be acquired, used, disclosed and retained only for valid purposes. A user of personal information should:

    - Inform an individual about the purposes for which the information is collected, used or disclosed before collecting it to allow this individual to decide whether or not to agree to the proposed use of his personal information.
    - Use and/or disclose personal information to third parties only for valid purposes about which the information subject has been informed.
    - Retain personal information for only as long as the information serves a valid purpose.
    - Limit the storage of personal information to a specified duration that should reflect the period of time necessary to fulfill the purpose for which personal information was collected.

3. **Data acquisition**. In acquiring personal information, an information user should:

    - Assess the potential impact on the privacy of individuals.
    - Collect only information that is reasonably expected to support current or planned activities.
    - Collect information consistently according to established guidelines and to permission notices that the user has provided to individual from which the information is collected.

4. **Notification of data collection.** Before personal information is collected, the user of the information should provide effective advance notice to each individual from which the data is collected about:

    - What personal information is collected.
    - Why the information is collected.
    - How the information will be used.
    - What steps will be taken to protect the confidentiality, integrity, and quality of the information.
    - Any opportunities to remain anonymous.
    - The consequences of providing or withholding personal information.
    - How long the information will be retained.
    - Rights of recourse and redress.

5. **Fair information use.** Personal information should be used only in ways that are compatible both with the notice provided by the user and with the individual's reasonable expectations regarding how the information will be used.

6. **Information protection and retention**. IntelliDrive systems should be designed to implement advanced security and other technologies to protect personal information against improper collection, disclosure or misuse. Personal information users and information administrators should only retain personal information that is relevant to a valid purpose and only for as long as, and to the extent that, the information is protected against improper access, disclosure or use. Particular attention should be given to:

   - Maintaining the security of personal information.
   - Protecting the confidentiality of personal information against improper access.
   - Assuring the quality and integrity of personal information collected or maintained.

   Personal information users and administrators should further have data storage procedures that assure appropriate and secure disposal of personal information when:

   - There is no longer a valid purpose for retaining the personal information.
   - A stated or required time limit on data retention has been reached.
   - Data transmission has been completed.

7. **Openness.** Personal information users and information administrators should be informed about privacy issues and the best ways to protect personal information derived from IntelliDrive applications. Personal information subjects should further be able to rely on personal information users to receive adequate information about the purpose of the data collection and options available to ensure that privacy rights are respected.

8. **Participation.** In addition to receiving information regarding how personal information is collected and used, each personal information subject should be able to protect his or her own privacy. Personal information users should provide each individual with opportunities to:

   - Access personal information about himself or herself.
   - Correct any inaccurate personal information about the personal information subject.
   - Object to improper or unfair personal information use.
   - Choose to remain anonymous, and not provide personal information.

9. **Accountability.** A user of personal information should respond to inquiries and complaints about interference with privacy interests or misuse of personal information. If an individual has a complaint that he or she has been harmed by improper collection, retention, disclosure or use of his personal information, this individual should have appropriate means to raise and resolve the complaint.

The following further describe limits on uses of personal information by specific individuals or agencies associated with specific transportation application areas. These limits establish in effect boundaries in the utilization of personal information.

1. **Public-sector transportation system management**. Public-sector entities may only collect and retain anonymous safety and traffic related data for applications aiming to enhance transportation functions. Vehicle operators/owner shall not be required to provide personal information for such functions.

2. **Public-sector commerce and toll collection**. Public-sector entities may collect and use personal information to the extent that personal information subjects have provided consent.

3. **Public-sector regulation and commercial vehicle permitting.** Public-sector entities may collect and use personal information to the extent that an individual has provided consent, unless the nature of the regulation or permit requires uniquely identifiable vehicle information for specific applications. In these exceptions, the collected information shall be used only for explicitly stated purposes that are necessary for the application.

4. **Law enforcement and investigation**. No specific information about an individual or vehicle shall be derived from an IntelliDrive application to be used for law enforcement or investigation purposes without a valid warrant. However, anonymous data may be collected and used to assist traditional law enforcement efforts or to analyze transportation problem locations. Specifically, IntelliDrive data shall not be used for recording real-time video or voice of vehicle occupants, associating precise vehicles with times or locations, off-board control of vehicle driving, or maneuvering functions.

5. **Public security surveillance.** IntelliDrive systems will not be designed to gather specific information about an individual driver, occupant, or vehicle for national security purposes.

6. **Private-sector commerce.** Private-sector entities may collect and use personal information to the extent that individuals have provided consent to the use of the data.

7. **Private-sector transportation**. Private-sector entities may use only non-personal information, and vehicle operators/owners shall not be required to provide personal information for such functions.

The above limits do not explicitly forbid the collection of O-D data. The emphasis is on the collection of anonymous data, i.e., data that does not allow associations of individual trips to specific vehicles or persons. This means that the collection of data for estimating travel times along roadway links or turning percentages at intersections is permitted as long as the collected data does not allow the specific identification of vehicles. This could be done by using encrypted vehicle identification numbers or unique identifiers. Only individuals having access to the encryption key would then have the capability to associate a specific vehicle to specific tracking data. Such an approach is already used by systems using RFID or license plate recognition to detect vehicles. In such systems, information about the owner of the vehicle can only be captured by obtaining access to information held by the entity issuing the RFID tag or the state's vehicle registration agency.

One problem with the above approach is the possibility of tracking movements of specific vehicles across multiple periods, even though no information is available about the owner of the vehicle. To prevent this, various approaches have been proposed, such as omitting the vehicle identification number in data reporting functions or assigning unique detection numbers that change with each tracking.

While anonymous vehicle tracking can reasonably satisfy the needs of local applications, significant problems exist when attempting to collect O-D data for transportation planning purposes. Transportation planning activities usually rely on knowledge of traffic movements across a region. This naturally implies tracking vehicles over long distances. While the specific origin of a trip could be masked by preventing tracking for the first few minutes or miles of a trip, the resulting tracking data could still allow the identification of the area from which a vehicle originates, and this information used to facilitate the identification of a specific origin through other means. The same principle may also be applied to mask the destination of a vehicle. This masking can be easily accomplished if the driver enters an intended destination on a routing application. However, if the intended destination is initially unknown, the masking may only be executed during post trip data processing, leaving a certain interval of time during which a specific vehicle could be attached to a specific destination.

7.3. Current IntelliDrive Privacy Methods

The potential issues discussed in the previous section point to the need to develop processes for collecting O-D data that would adequately protect individual privacy rights. As indicated earlier, the acceptability of IntelliDrive systems is heavily dependent on the acceptability of these systems by the traveling public, and more particularly, the perception that the collected information is not being misused.

Current constraints imposed on the IntelliDrive program in the United States by the U.S. Department of Transportation stipulate that IntelliDrive systems (VII Consortium 2009):

- Cannot track an individual vehicle over any road segment longer than 2 km.
- Cannot identify any individual vehicle as violating a traffic law through publicly collected data.
- Cannot identify a vehicle or a vehicle occupant or owner from messages sent to, or through, the infrastructure.

The current approach for data collection using IntelliDrive probe vehicles calls for snapshots describing vehicle status to be generated at preset intervals. As illustrated in Figure 6, each snapshot would contain information describing the time at which the data was captured, the location of the vehicle (latitude and longitude returned by a GPS system), and a series of variables describing the status of various vehicle functions [FHWA, 2006].

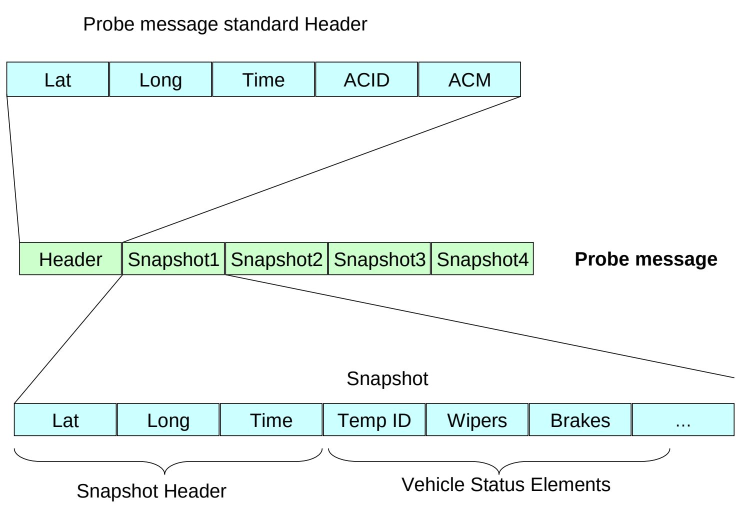


Figure 6 – Currently Proposed Structure for IntelliDrive Messages [FHWA, 2006]

To protect driver privacy, it is currently proposed that IntelliDrive systems be governed by the following principles:

- Over the air probe messages should be encrypted.
- No personal identification data should be attached to messages being transmitted.

- Media Access Control (MAC) addresses used for message transmission should be randomly assigned and changed frequently changed. The current recommendation is to change the MAC address of a vehicle each time communication with an RSE is established.
- All snapshots remaining in a vehicle's memory buffer after a connection with a RSE has been terminated should be deleted.
- All data remaining in a vehicle's memory buffer should be deleted at key off.
- To prevent vehicles from being traced to specific street addresses, no snapshots should be taken for the first 500 meters (1640 feet) of travel. Following this initial blackout, onboard communication equipment would then inhibit data transmission until a first temporary MAC address change has occurred.

A MAC address is required in the header of messages to support communication between the onboard vehicle equipment (OBE) and both other vehicles and roadside equipments (RSEs). Maintaining a constant MAC address for a specific vehicle would be equivalent to assigning a unique identification number to the vehicle. Using constant MAC addresses would then allow to track vehicles movements. For this reason, it was determined that the best approach to ensure driver privacy would be to randomly change the MAC address of a vehicle. Proposed approaches to do this randomization include changing the MAC address each time a vehicle is started, each time a vehicle initiates communication with an RSE, or at specific time intervals. Within this context, messages generated by a vehicle at different times would effectively be treated as messages originating from different vehicles.

One problem with the above approach is that randomizing MAC addresses may critically impact the ability to track vehicles over short distances. In the recent IntelliDrive Proof-of-Concept test program conducted by the U.S. Department of Transportation, vehicles were occasionally observed to unexpectedly drop communication with an RSE. While these vehicles were often able to reestablished connection with the same RSE, the use of a different MAC prevented the RSE to treat data received before and after the communication failure as coming from the same vehicle. In addition, the requirement that all remaining data in the vehicle's memory be deleted after the termination of a communication link caused a significant loss of data. Test data indicates that the probe data delivery efficiency averaged only 84% due to constraints imposed by privacy rules.

To address the above problem, it has been proposed to have a vehicle's OBE generate a random, temporary identification number for all the snapshots generated by a vehicle. This unique number would be changed each time a vehicle comes into contact with an RSE, or after a preset interval in cases in which long intervals may exist between successive RSEs (the current recommendation is to have the identification number reset 120 seconds have communication with an RSE is terminated). This identification number would then allow all messages retrieved by an RSE to be correctly assigned to one vehicle even if there is a temporary failure in the communication link. This would effectively allow the anonymous tracking of individual vehicle movements over short distances while still preventing tracking over long distances.

7.4. Potential Impacts of Current Privacy Methods on IntelliDrive Applications

The current IntelliDrive system architecture does not allow the collection of O-D data with probe data. The biggest impact of this design is the inability to use navigation routing algorithms to optimize travel flow for a large number of vehicles. While individual routes may be calculated by personal or on-board navigation systems, these routes would generally not be coordinated with other systems, which is what system operators may ultimately desire. All O-D data remains within the GPS equipment.

The opportunity lost is if IntelliDrive O-D data remains unavailable so is the ability to know where a group of vehicles are going. Consider for example the following scenarios:

- Special event such as professional football games or summer festivals are often accompanied with swarms of vehicles either going to the event or returning home when it is over. If the routes of the vehicles going to or from the event are known ahead of time, this information could then be used by to modify signal timings along corridors leading to facilitate access to the event and quicken the event's evacuation process. The reduction in system congestion would not only benefits event participants by also non-event traffic in the vicinity of the event.
- The traffic along a corridor comprised of two or more parallel arterials may balanced more efficiently among the available routes if the destinations of the resident vehicles are known. This load balancing cannot be done by individual navigation units. System-wide benefits can only be obtained if the movements of individual vehicles are coordinated by a single system.
- A vehicle leaving home in the morning for work may be offered three different route choices by a navigation system based on actual travel time information. If the selected path is immediately registered with the traffic operations center computer, the route data can then be aggregated into projected network segment load data. The resulting projected travel times for the intended segments could in turn be used to provide more accurate travel time information for the next vehicle to use the navigation system.

In all the above cases, the ability to anticipate the intended travel path of a group of vehicles offers significant potential benefits for enhancing traffic flow management. If O-D data remains unavailable, significant limits may thus be put on the ability to improve traffic flow in urban areas. Navigation systems may not be able to develop travel paths truly reflecting expected traffic conditions at the moment a vehicle is expected to reach a certain location. Traffic management systems may further be restricted to mainly operate in a reactive mode rather than an anticipated mode, forcing them to essentially respond with a lag to observed changes in traffic conditions. This is also without mentioning the loss of flow pattern data for system planning analyses.

7.5. Available Methods to Mitigate Privacy Concerns

An opt-in agreement seems to be an acceptable method for exchanging personal data in return for valuable services. Many other services in common use today frequently collect data from the customer in the act of providing the agreed upon services. Service contracts carefully spell out what data will be collected, how it will be used and under what conditions it will be shared with other entities, if such sharing is permitted. Generally, this is acceptable to the customer because the value of the services provided is perceived to be greater than any risk associated with the data being shared. Some examples of discretionary data sharing include:

- Home and cell phone use – service providers have data indicating the subscriber's general location, time of service, specific numbers called, and duration of the calls.
- Cell phone with GPS – GPS devices added to phones that specifically locate the phone's position and can be used for tracking. GPS can generally be turned off in the phone by the user but frequently is not.
- Personal wireless devices – Wi-Fi and Bluetooth devices broadcast unique MAC address numbers as part of their connectivity protocol (like a fixed phone number). This can be sniffed and monitored by any compatible radio receiver, thus providing the ability to track the device's

user. These devices can also be turned off by their owners when not in use but frequently are not.

- ATM, credit and debit card use – Electronic exchange of account numbers, bank, PIN numbers, time and location of each transaction.
- Airline travel – Requires ID, destination, date/time and flight numbers
- Telematics systems using wireless connectivity; e.g., GM's OnStar – Can exchange data with off-board servers including location, origin and destination, trip histories, time of use, customer ID and account information.
- Toll road transponders; e.g., EZPass – Capture when and where each toll transaction occurred with account information for each customer.

Examples of non-discretionary data sharing further include:

- Camera license plate readers, such as at border crossings, toll plazas, gas stations, traffic signal intersections – captures location, time and ID of each vehicle in view.
- Security cameras, such as at airports, train stations, public buildings, city streets, etc, where gate access control may capture the ID of a traveler along with his picture, or surveillance cameras can be used to track the movements of travelers.

In all of the discretionary cases, the user chooses to "opt-in" to gain the benefits of the services provided when an original agreement is signed or specific services are purchased. What makes the IntelliDrive case unique is that probe data accessibility by public entities and third parties is not discretionary but would be mandatory. Making use of IntelliDrive data discretionary by the motoring public was never seriously considered, again, partially because public policies change with new administrations and decisions like this could be reversed sometime in the future.

Following completion of the proof-of-concept testing of the initial IntelliDrive program, a reconsideration of how mobility applications using probe data would be supported is under review by the IntelliDrive community. Since private wireless technologies that can enable vehicle data collection are already deployed, it may be more practical to purchase data from commercial providers rather than deploy an alternate government-funded system to gather data directly. Traffic management centers and metropolitan planning organizations would then have the option to buy data from service providers that would be rendered anonymous prior to being transferred to the state agencies. In such a scenario, the trusted relationships that are already established between drivers and service providers by virtue of their opt-in service agreements add value for their users through improved traffic information, situational awareness of weather, events, construction work and so forth.

It appears that the change in the IntelliDrive architecture towards discretionary data may resolve several concerns with the existing design:

- No federal deployment of IntelliDrive infrastructure required
- Privacy issues resolved with opt-in status
- IntelliDrive complex certificate management system simplified
- Competition would bring innovation, efficiency and low costs
- More rapid deployment

8. Case Study: Potential Benefits of Origin-Destination Data on Routing Applications

To illustrate the potential benefits of collecting O-D data from IntelliDrive vehicles, a case study evaluating the benefits of collecting such data for a dynamic routing application is analyzed. This evaluation is conducted using the Paramics microscopic traffic simulation model and evaluates how O-D data can be used to enhance the ability to reroute vehicles around and incident, as well as how transportation system operations can benefit from such an ability.

Without routing systems, drivers facing non-recurring congestion caused by an incident are left to their own judgment as to whether they should stay on their initially planned route or seek an alternate route. In many cases, this decision is influenced by how familiar a driver is with the surrounding road network and whether he believes that his destination can be reached with reasonable ease through an alternate route. The perception of how long the congestion might last will also have an impact, particularly in cases where its cause is out of sight. In such cases, drivers have to blindly assess how long they may be caught in the disruption and whether congestion may have also built on alternate routes due to other vehicles attempting to go around the incident. Without outside help, a risk thus exists that a decision to reroute may end up being a wrong decision.

If the current position and intended destination of a vehicle is known, an onboard or centralized navigation system could determine upon receiving an incident warning whether there are benefits in rerouting traffic around the incident. This benefit could be determined on the sole basis of travel time or by considering a series of other factors such as distance and tolls. More importantly, the ability to know where all vehicles are going to would allow a centralized traffic management system to determine which vehicles to reroute and through which alternate route.

While vehicle reroutes can already be triggered in existing transportation networks, there are limitations on what can be achieved. For instance, alternate routes around an incident can be suggested by displaying information on fixed changeable message signs along freeways or portable signs along other routes, if there is enough time for their deployment. With this approach, vehicles only obtain the suggested reroute information when they come within visual distance of the sign. For many vehicles, this may be too late to seek an efficient alternate route, particularly if the available alternate routes are also becoming congested with vehicles seeking to go around the incident.

With IntelliDrive-based notification, drivers can be informed of the incident wherever they are. The greatest benefit may exist for vehicles that are still far from an incident, as the early notification may provide the drivers of these vehicles with a greater number of alternate paths around the incident, and thus with the ability to seek potentially less traveled and less congested alternate routes. By spreading rerouted vehicles across multiple paths, there could further be reductions in the amount of traffic heading towards the incident and reduced congestion on the alternate routes near the incident. This would not only benefit the vehicles being rerouted, but also the vehicles traveling on these routes that are indirectly caught in the ensuing congestion.

8.1. Evaluation Methodology

The potential benefits associated with dynamic IntelliDrive vehicle routing are evaluated by comparing vehicle performance measures for three scenarios:

- Network without an incident.
- Network with an incident and without rerouting application.
- Network with an incident and rerouting application.

Simulations were conducted with the Paramics microscopic traffic simulation software using a modeling of a 40-square mile road network near Novi, Michigan. This network, illustrated in Figure 7, covers the same area that has recently being used by the USDOT for its IntelliDrive proof-of-concept testing. This network includes all freeways and main arterials within the test area. It features a major interchange between four freeways and 172 signalized intersections. This network is particularly suitable for the simulation of routing applications, as it offers travelers multiple alternative routes between various origin and destination nodes. For many O-D pairs, a choice is notably offered to travel either along a freeway or a parallel arterial.

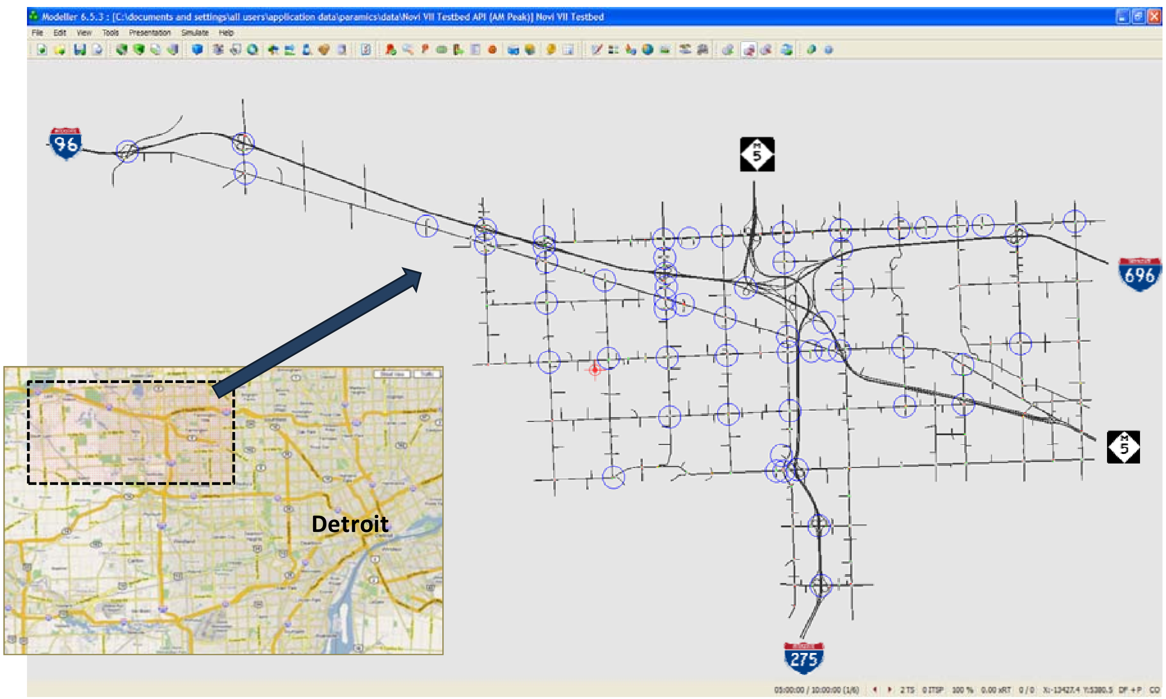


Figure 7 – Paramics Modeling of USDOT IntelliDrive Proof-of-Concept Testbed near Novi, Michigan

For each scenario, network performance is assessed through the values returned by the following statistics:

- Average trip distance.
- Average trip time.
- Average trip progression speed.
- Average trip delay.
- Average stopped delay per trip.
- Average number of stops per trip.

Overall network performance for each scenario is assessed by aggregating performance measures across all simulated vehicles. To account for the stochastic nature of Paramics simulation processes, evaluations are based on a compilation of statistics across six replications of each scenario using different random number seeds. While the number of replications is relatively small, it is deemed sufficient for this analysis to assess the variability of simulation results and identify general trends. For each scenario, average performance measures are produced by first averaging statistics for all simulated vehicles within each simulation run. The average statistics produced for each run are then averaged across the six completed runs to produce an overall estimate.

In addition to overall network performance statistics, statistics associated with vehicles directly and indirectly affected by the incident were also compiled and compared for the two scenarios involving an incident. For these comparisons, efforts were also made to compare statistics averaged across six replication runs. Because of the stochastic nature of the simulation processes, such comparisons involved a fair amount of data processing. In stochastic simulation models, a slight change in network geometry or simulated demand is often sufficient to significantly alter network behavior. Such changes typically lead to the implementation of fairly different trip sequences, resulting in vehicles traveling along a specific O-D pair being given completely different identification numbers. For the scenarios under consideration, assessing the impacts associated with rerouting or not rerouting vehicles around an incident has no impact on the vehicle identification numbers assigned by Paramics, as the routing changes are implemented after a vehicle has been generated and assigned to travel along a particular O-D pair. This allows direct comparisons of simulation results for scenarios with and without reroutes based on a specific random number seed. However, changing the random number seed directly affects the release sequence of vehicles. Because of this change, the identification of the groups of vehicles affected by the incident had to be re-executed for each random number seed.

8.2. Incident Scenario Modeling

This section presents the modeling of the incident scenario that was used to assess the benefits of having access to O-D data to enable dynamic rerouting of IntelliDrive vehicles around an incident. This modeling comprises five main elements:

- Modeling of underlying traffic demand.
- Modeling of IntelliDrive vehicles.
- Modeling of incidents in Paramics to simulate impacts on traffic.
- Modeling of how the incident is perceived by the routing algorithm.
- Travel cost calculation.

8.2.1. Underlying Traffic Demand

The simulated traffic demand for the scenarios being considered models a representative morning peak pattern. Figure 8 illustrates the equivalent hourly flow rates simulated for each 15-minute period between 6:00 and 11:00 AM. These flows are based on hourly intersection traffic flow counts obtained from the Southeast Michigan Council of Governments (SEMCOG). These counts, executed between 2000 and 2006, covered approximately 400 sites. From 6:00 to 8:00, the demand is assumed to gradually increase, reaching a peak entry flow across all origins. The demand then gradually reduces between 8:00 and 10:00 AM, before dropping to mid-morning minimum levels after 10:30. Within this five-hour period, specific origin-destination matrices were developed for each simulation hour (for instance 6:00 to 7:00, 7:00 to 8:00, etc.). This modeling thus produces not only varying flow rates across a simulation period but also varying travel patterns.

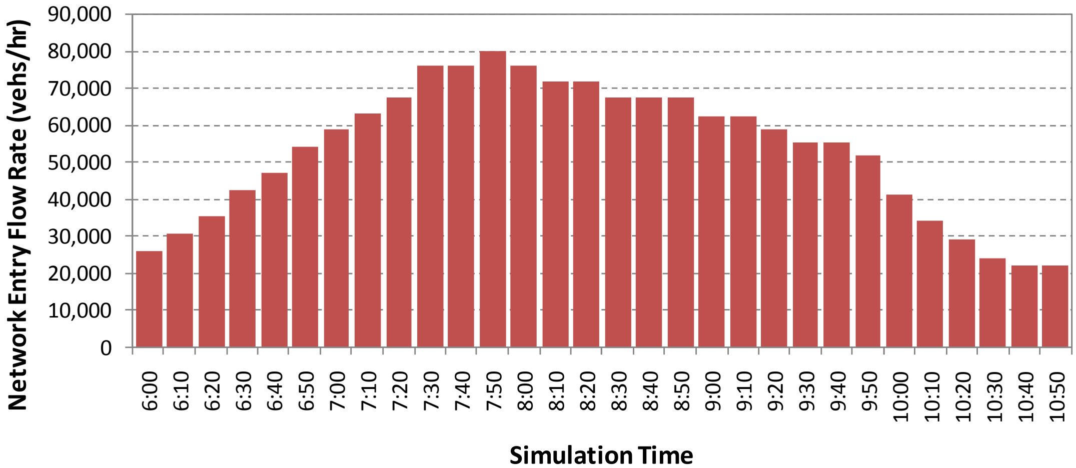


Figure 8 – Simulated Traffic Demand

While developing the demand model, efforts were made to calibrate the simulated demand to observed flows across the network. However, these efforts did not seek to obtain a perfect match. The rationale behind that decision is that the intent of the evaluation only sought to assess impacts within a realistic morning traffic demand pattern. For this reason, accurately calibrating the simulated traffic flow to actual traffic conditions would not have yielded significant advantages. Enough calibration was conducted to obtain realistic congestion patterns, particularly along heavily traveled routes.

The development of each origin-destination matrix was executed by the Paramics Estimator module. This module establishes a matrix by gradually altering assigned O-D flows to allow individual link flows to match observed flows on links for which this information is available. This adjustment was made with the objective to minimize the square root error between observed and simulated flows. After a matrix was produced, manual adjustments were then made to prevent unrealistic flows from being assigned to zones for which such flows would not exist.

In addition to the variable demand pattern, traffic flow is simulated with a five-minute information feedback loop. Every five minutes, Paramics recalculates the travel cost across each link. These costs are then used to calculate the route that individual vehicle entering the network should follow. Within this context, vehicles entering the network five minutes after the occurrence of an incident would then start to respond to the added travel times on some links, much like what may happen when drivers are informed of an incident through radio reports. While this is an additional option, the feedback loop was not setup to affect vehicle that have already started their route. In this case, vehicles that have already left their origin are assumed to ignore any changes in network conditions. The only exception, as described later, is for IntelliDrive vehicles responding to the occurrence and clearance of the simulated incident.

8.2.2. Modeling of IntelliDrive Vehicles

Each vehicle in the simulation generated by Paramics is designated as an IntelliDrive or non-IntelliDrive vehicle. Most of the scenarios considered in the analyses only deal with vehicle populations composed either entirely of non-IntelliDrive vehicles (0% market share) or IntelliDrive vehicles (100% market share). However, vehicle populations containing both IntelliDrive and non-IntelliDrive vehicles can be defined. In such cases, vehicles are randomly assigned an IntelliDrive or non-IntelliDrive status upon generation based on a proportion defined in the simulation setup files.

During a simulation, non-IntelliDrive vehicles are routed according to Paramics' default routing algorithm, while IntelliDrive vehicles are routed according to custom-built functions seeking to replicate Paramics routing decision while implementing additional features. These functions, which were developed using Paramics' Application Programming Interface (API), are described in more detail in Appendix A. Comparative tests have shown that the routing algorithm used by the IntelliDrive vehicles generally produces the same routing results as Paramics when using the same link travel costs. Differences are observed in less than 2 percent of the cases and can typically be traced to routing difficulties created by complex intersection road geometries, such as intersections with Michigan Left-Turns, where a vehicle turns left by first turning right and then making a U-turn slightly downstream of an intersection.

8.2.3. Modeling of Incident Impacts on Traffic

For the evaluation, a 15-minute full closure of the ramp linking Northbound I-275 to Eastbound I-696 is modeled. The location of the incident is shown in Figure 9. Since Paramics only allows an incident to block a single lane and one incident to be placed on a link at a given time, a full closure of the I-696 ramp is simulated by placing the incident at the boundary of the two links, as shown in Figure 10. As illustrated, the first incident is placed at the end of the first link on the curb lane, while the second incident is placed at the beginning of the second link on the second lane. As can be seen, such a placement results in an effective closure of the freeway ramp.

The incident is assumed to occur at 7:00 AM exactly and to end at 7:15 AM, with the freeway ramp remaining completely blocked during this 15-minute period. Figure 11 illustrates the propagation of the queue that forms upstream of the incident at 5-minute intervals using the Paramics Hotspot Viewer tool. This tool illustrates the location of queues of vehicles using circles with radii corresponding to the number of vehicles in the queued present on individual links. In this case, circles are only shown for queues of at least 20 vehicles. Queues extending over multiple links are shown with a series of circles representing the portion of the queue on each link.

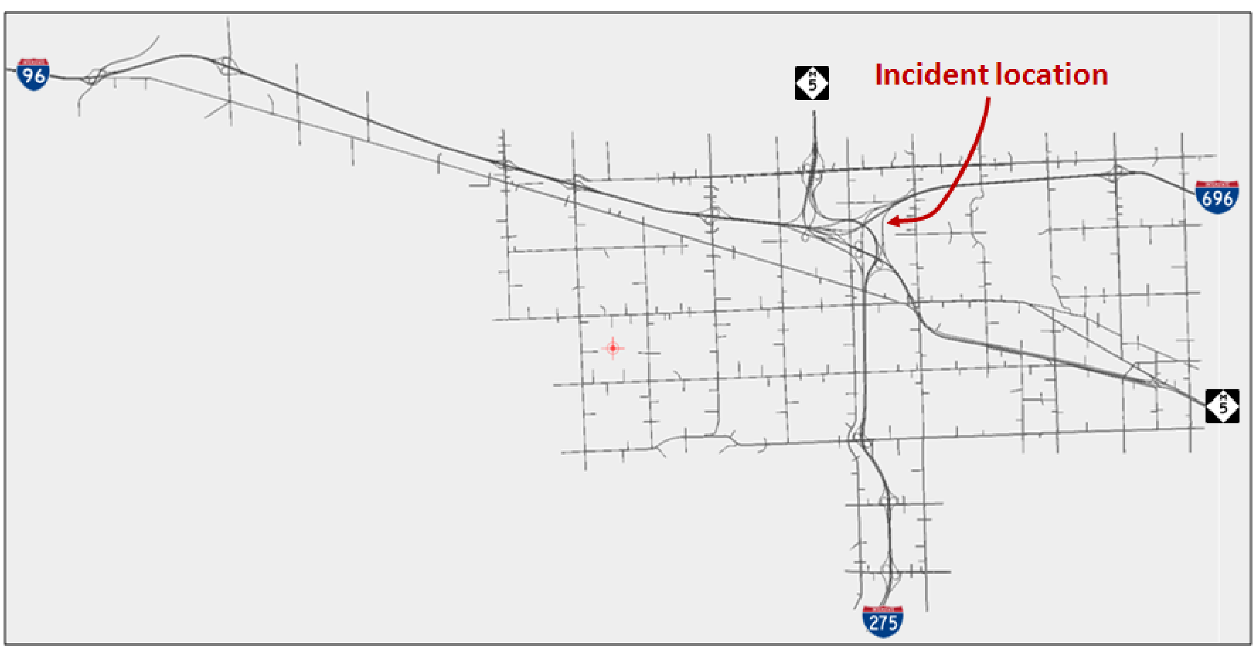


Figure 9 – Location of Simulated Incident

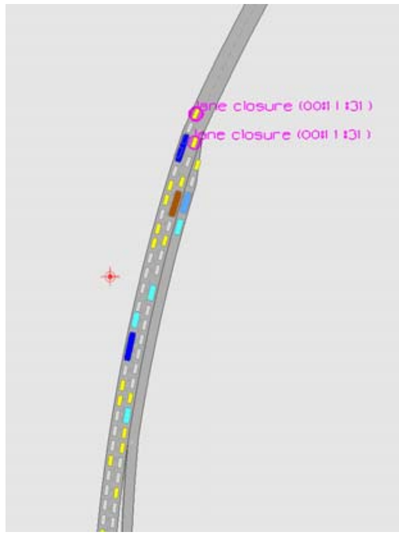


Figure 10 – Placement of Vehicles to Model Full Ramp Blockage

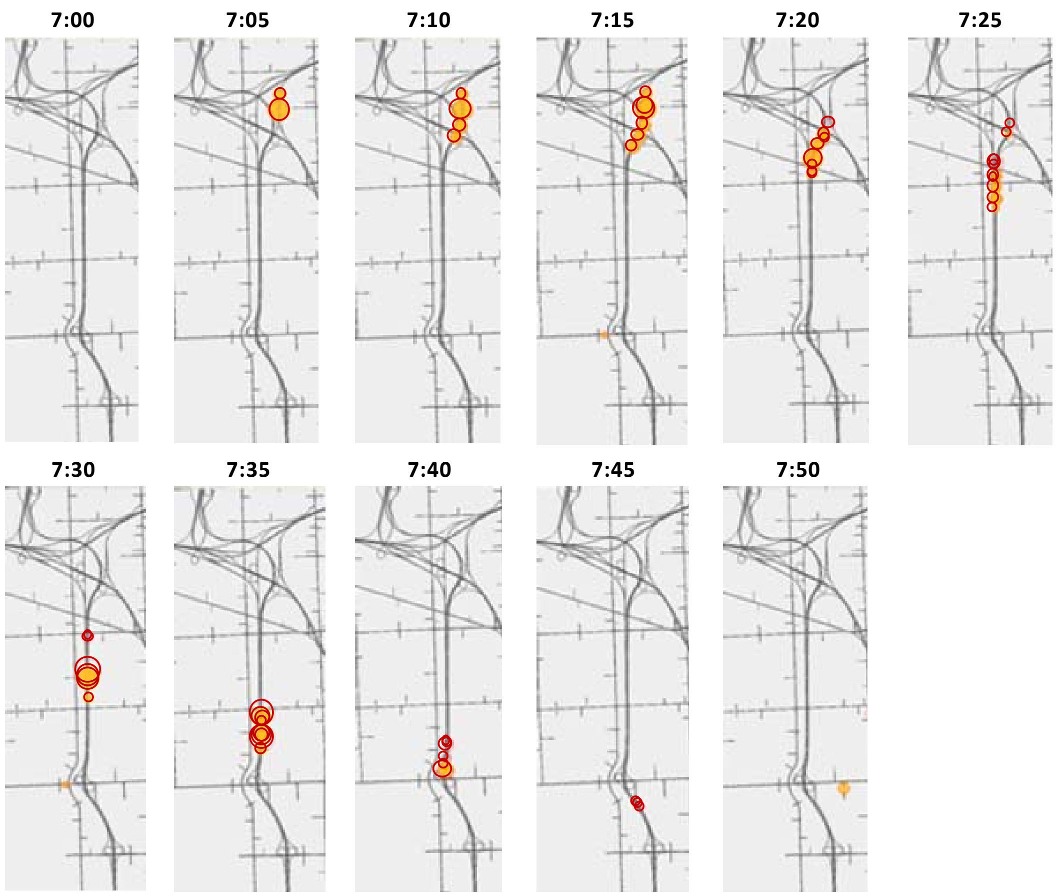


Figure 11 – Propagation of Traffic Disruptions in a Simulation Run without Active Navigation

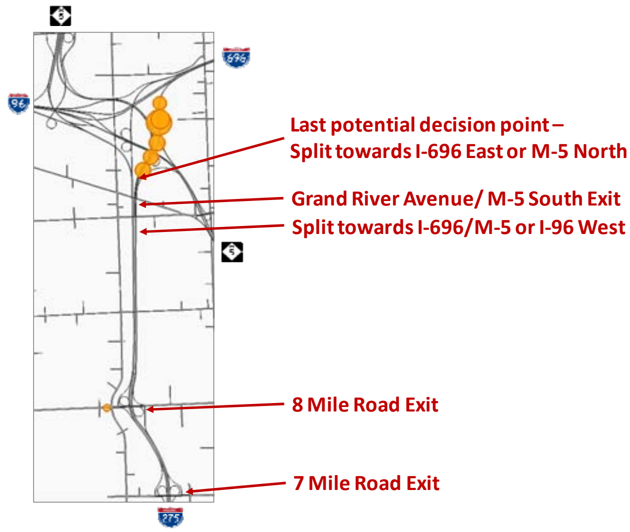


Figure 12 – Rerouting Decision Points along I-275

At 7:15, the queue extends about 1.6 km (1 mile) behind the incident and includes about 600 vehicles on both the freeway ramp and two feeding sub-ramps. Referring to Figure 12, which illustrates potential decision points along the freeway on which the traffic disruptions propagate, the back of the queue at 7:15 is located just downstream of the last decision point allowing approaching vehicles to seek alternate routes.

After the incident has been cleared, the front of the queue starts moving upstream while vehicles keep joining the back of the queue. At approximately 7:23, the front of the queue reaches the location where the back of the queue was observed at 7:15 when the incident ended. However, by 7:23 the actual back of the queue has moved further upstream by about 0.6 mile (1 km). Traffic shockwaves keep moving upstream and creating disruptions up until about 7:50 at locations as far as 3.5 miles (6.0 km) upstream from the initial incident location.

8.2.4. Response of IntelliDrive Vehicles to Incident

Only IntelliDrive vehicles are assumed to be able to navigate around the incident. Figure 13 illustrates the incident definition used to model the response of an IntelliDrive system to the incident. While the simulated incident is set to occur at 7:00 AM (simulation time 25200 seconds), it is assumed in this case that IntelliDrive vehicles are only notified of its occurrence at 7:01 AM (simulation time 25260 seconds), i.e., one minute after the incident has happened.

```
Number of Incidents 2
1  716:717      25260     26220        10000.
2  715:716      25260     26220        10000.
```

Figure 13 – Incident Modeling in Paramics IntelliDrive Setup File

The 1-minute response delay is an assumption that was made to account for the time it may take to identify and validate the incident and for the application server to notify all IntelliDrive vehicles of the incident. Shorter or longer processing delays could be assumed in alternate scenarios based on the situation considered. In particular, scenarios involving vehicle-to-vehicle communication and automated crash sensing may allow information to be propagated to vehicles close to the incident much quicker than applications requiring the information to be processed through a central computer server. However, use of a central server may still be required to communicate with vehicles that are still far from the incident.

The end of the incident notification is further expected to occur at 7:17, two minutes after the end of the incident. Similar to the start of the incident notification, a delay may be attributed to the time needed to notify the application server of the end of the incident and to subsequently broadcast the incident to IntelliDrive vehicles. A portion of the three minutes may also represent a buffer to allow some of the queue that has built up to dissipate before allowing vehicles to route back to the link.

As shown in Figure 13, a cost multiplication factor of 10,000 is associated to the link on which the incident is located. This factor is applied by the routing algorithm if the vehicle is projected to travel on the link on which the incident is located while the incident is active, i.e., only between 7:01 and 7:17 (simulation times 25,260 and 26,220 seconds). This has the effect making travel across this link very prohibitive and thus pushes vehicles to seek alternate routes.

At 7:01, all vehicles in the network are informed of the incident. Vehicles will then reassess their route the next time they transfer from one link to another. As the modeled network is primarily comprised of short links, this induces an additional delay of a few seconds for some vehicles. Vehicle will be rerouted along the path with minimum cost available to them, which may or may not be a path allowing them to reroute around the incident. At 7:17, a similar scenario occurs. In this case, vehicles are informed of the end of the incident and will reassess their projected path the next time they will transfer from one link to another. This may result in vehicles rerouting back towards their initial travel path if this proves to be the lowest cost alternative or continuing along an alternate path.

As indicated, not all vehicles will be able to obtain an alternative path. Vehicles having already passed the last decision point by the time they are notified of the incident will have no other choice than to wait in queue until the incident is cleared. Since IntelliDrive vehicles are programmed to reevaluate their route when transferring from one link to another, this means that vehicles having passed the location shown in Figure 5 will typically not be able to reroute. Vehicles upstream of this point will have a number of alternative choices that will depend on their current location and intended destination.

8.2.5. Impact of Incident on Travel Cost Calculation

Vehicle routing by IntelliDrive and non-IntelliDrive vehicles is done using the same travel cost model. The cost model used for the simulated scenario is:

$$Travel\ Cost = \sum_{link\ i} \left[f_{cost\ i} \times f_{incident\ i} \times \left(TT_i + 0.05\ Dist_i + 0\ Toll_i \right) \right] \qquad [8]$$

with:

$$f_{incident\ i} = \begin{cases} 10{,}000 & if\ T \geq 25{,}260\ and\ T < 26{,}220 \\ 1 & ortherwise \end{cases} \qquad [9]$$

where: *Travel Cost* = Network travel cost
T = Simulation time (seconds)
TT_i = Travel time on link *i* (seconds)
$Dist_i$ = Travel distance on link *i* (meters)

$Toll_i$ = Toll to travel on link *i*
$f_{cost\ i}$ = Cost multiplication factor for link *i*
$f_{incident\ i}$ = Incident cost multiplication factor for link *i*

This model considers both link travel time and distance. A travel distance element is considered in the cost calculation to avoid situations in which a vehicle may adopt a much longer alternate path only to save a few seconds. In this case, the use of a 0.05 weight factor for the distance was determined to allow routing decisions to remain primarily based on travel time.

As explained in Appendix A, the incident cost multiplication factor has been added to the Paramics modeling to allow for simulating the response of IntelliDrive vehicles to information about the incident. In this case, a factor of 10,000 is applied to the cost of travel on the link with the incident to discourage IntelliDrive vehicles from using the link. This cost is applied not for the exact duration of the incident, but for the period during which an incident warning message is assumed to be broadcast by the IntelliDrive system. In this case, the factor is applied from one minute after the start of the incident (7:01, or 25,260 seconds) until two minutes after the conclusion of the incident (7:17 or 26,220 seconds).

8.3. Performance Measures Considered

For the evaluation, the following performance measures are considered:

- Trip distance – Length of trip from an origin to a destination.
- Trip cost – Cost of travel from an origin to a destination as calculated by Equation 8 in Section 8.2.5.
- Trip travel time – Total time spent traveling from an origin to a destination.
- Trip average travel speed – Average rate of travel if individual vehicles were to travel at a constant speed.
- Total delay – Difference between the time taken to travel from origin to destination and the time it would have taken for the same trip while traveling at the posted speed limit on each link and ignoring all delays imposed by traffic signals and other traffic control devices.
- Stopped delay – Total time spent immobilized on a trip.
- Number of stops – Number of times a vehicle stops on a trip, calculated as the number of instances in which the speed drops below 5 mph (8 km/h).

8.4. Vehicle Evaluation Samples

To assess the impacts of vehicle rerouting on traffic flow behavior and system performance, four main groups of vehicles are considered. These groups are identified in Figure 8 and described below:

- **Group 1:** Vehicles queuing on freeway and freeway ramps between 7:00 and 7:15 AM while the incident is active and which are unable to reroute with the active navigation. This sample typically includes vehicles that were informed of the incident too late to change their path and which consequently have no other choice than to wait for the incident to be cleared before being able to continue with their journey. For the scenario considered, this sample includes approximately 100 vehicles.

- **Group 2:** Vehicles queuing on freeway and freeway ramps upstream of the incident between 7:00 and 7:15 AM while the incident is active but which are able to be rerouted around the incident with active navigation. For the current scenario, this sample includes approximately 250 vehicles. All the vehicles in this group are vehicles that were initially projected through the links with the incident.

- **Group 3:** Vehicles queuing on freeway and freeway ramps upstream of the incident after it has been cleared. This represents the vehicles affected by the traffic disruptions shown in the 7:20 to 7:50 time frames of Figure 5 presented earlier. About 3100 vehicles are within this group. These vehicles were identified by isolating from the simulation outputs those experiencing at least 5 seconds of stopped delay on all the links on which traffic disruptions linked to the incident are observed to propagate.
- **Group 4:** All vehicles generated within the network between 6:30 and 8:00 AM. This group is to be used to assess the impact on overall network performance. It includes a total of approximately 68,000 vehicles.

In most of the analyses, it is assumed that either all or none of the simulated vehicles are IntelliDrive vehicles. All of the IntelliDrive vehicles are further assumed to be equipped with a navigation application allowing them to receive information on the incident and to seek an alternate route upon receiving the information. Scenarios considering IntelliDrive market shares between 0 and 100% are only considered for the last analysis.

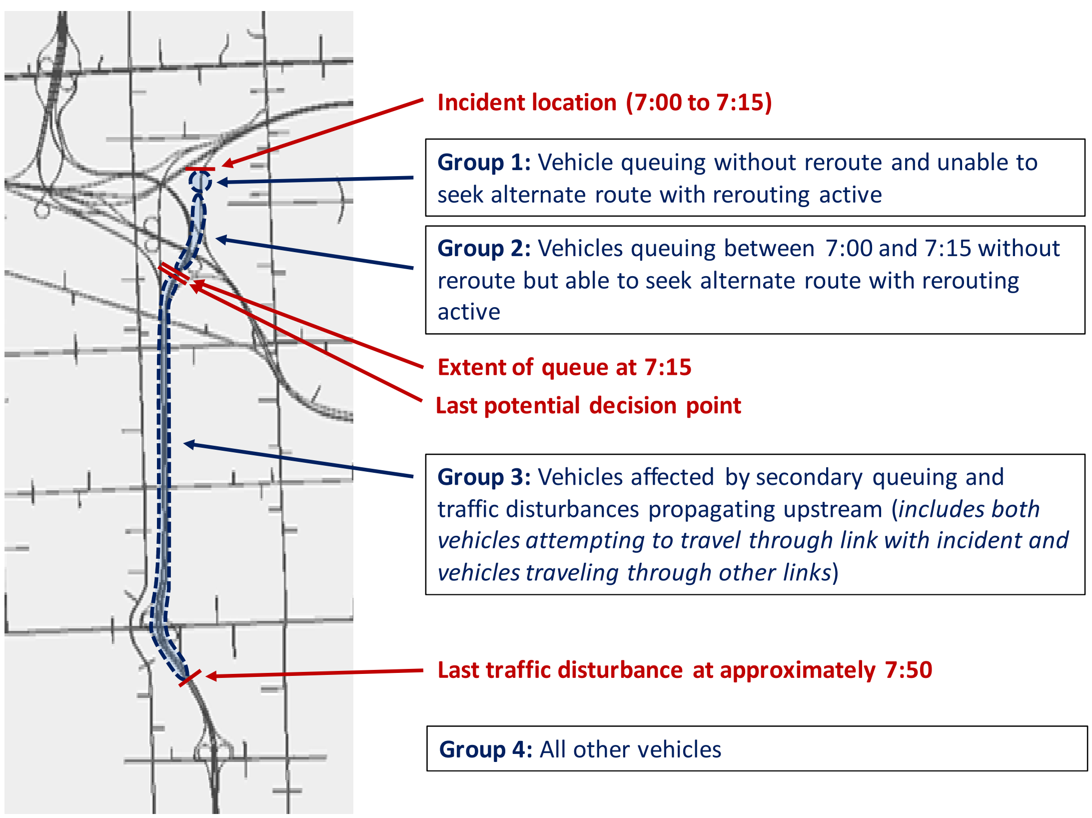


Figure 14 – Vehicle Groups for Assessing Incident Impacts

8.5. Simulation Results

This section presents the results of the simulations comparing network performance with and without incident re-routing. This presentation considers the following elements:

- Propagation of traffic disruptions upstream of the incident.
- Geographical distribution of rerouted decisions.
- Overall network impacts.
- Impacts on vehicles queuing during the incident and unable to reroute (Group 1 in Figure 14).
- Impacts on vehicles queuing during the incident and able to reroute (Group 2).
- Impacts on vehicles affected by the traffic disruptions that propagate upstream of the incident after it has been cleared (Group 3).
- Impacts on vehicles not directly affected by the incident (Group 4).
- Impacts of IntelliDrive market share.

8.5.1. Propagation of Traffic Disruptions with Incident Reroute

Figure 15 illustrates the typical propagation of traffic disruptions created by the incident in simulation runs with active routing. In contrast to Figure 11, which showed the propagation of traffic disruptions without active routing, the traffic disruptions created by the 15-minute freeway ramp closure remain very localized when IntelliDrive vehicles are provided with the ability to dynamically rerouted around the incident based on knowledge of their intended destination.

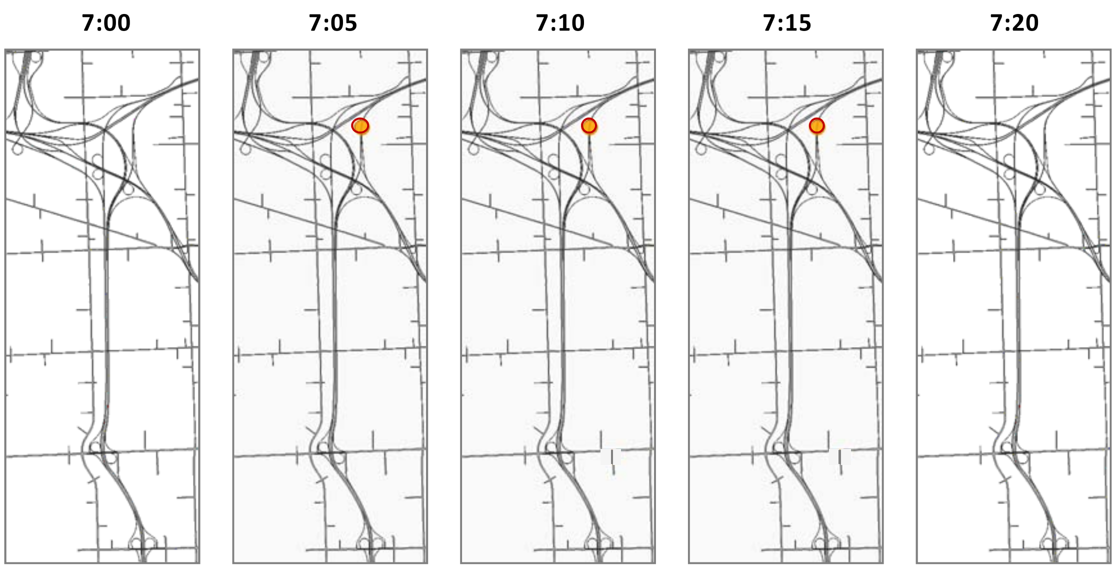


Figure 15 – Typical Propagation of Traffic Disruptions in Simulation Runs with Active Routing

In this scenario, between 81 and 108 vehicles end up queuing behind the incident depending on the random number seed used, with an average of 97 vehicles. These vehicles have all already passed the last potential decision point when the incident occurs and therefore have no other choice than to wait in the queue for the incident to be cleared.

As indicated earlier, vehicles only reassess their routes when transferring from one link to another, after a vehicle has entered the downstream link. This results in the potential trapping of vehicles that may in reality still have an opportunity to take an alternate routes. Evaluations of simulation results indicate that approximately 10 vehicles typically end up being trapped because of the way routing decisions are made. Such a small number should therefore not significantly affect the evaluations.

Under the assumption that all simulated vehicles are IntelliDrive equipped, no vehicle is seen heading towards the incident aside from the trapped vehicles described above. As shown in Figure 15, this results in a queue that remains very contained, does not affect other traffic, and quickly dissipates after the incident is cleared. Contrary to the simulations without active navigation, which show traffic disruptions propagating up to 3.5 mile upstream of the incident until about 7:50, all effects of the incident are observed to disappear within 5 minutes of its clearance in the simulations with active incident reroute.

8.5.2. Geographical Distribution of Rerouted Decisions

Figure 16 illustrates the geographical distribution of the locations where reroute decisions are made, first following notification of the incident occurrence at 7:01, and then following notification at 7:17 that the incident has been cleared. The illustrated data includes the results of six simulation runs and cover a total of 3,274 rerouting attempts.

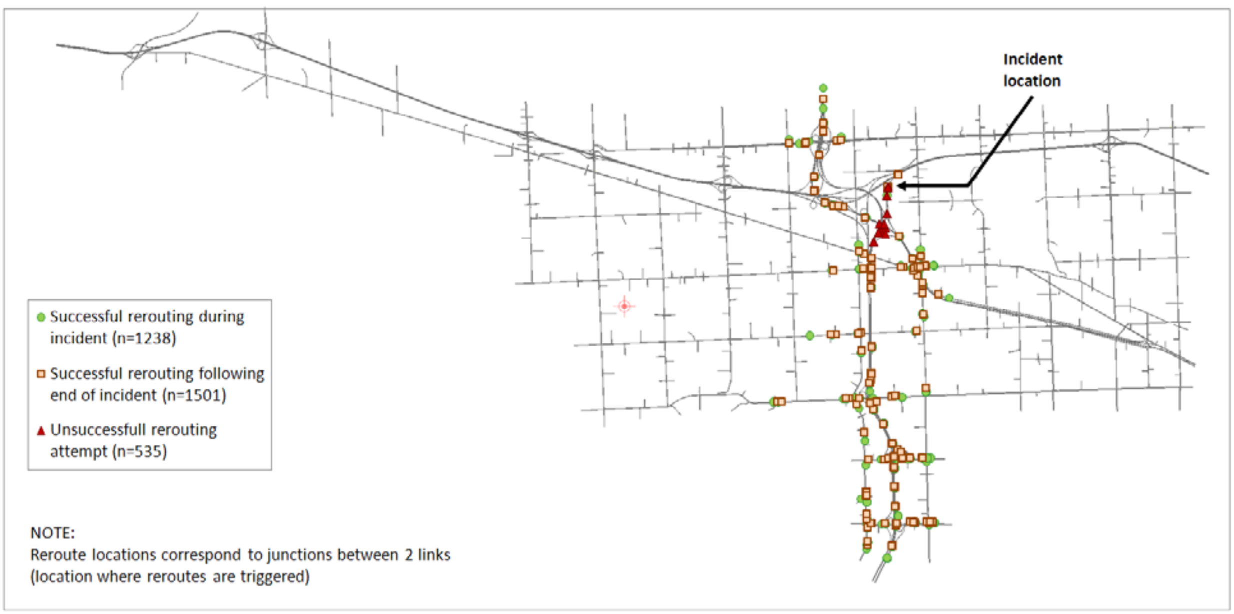


Figure 16 – Geographical Distribution of Locations of Rerouting Decisions

The figure shows one of the greatest potential benefits of leveraging O-D information, which is the ability to inform drivers of road conditions wherever they are. In existing transportation systems, drivers typically only become aware that something may have happened by noticing unusual congestion building up along their route. In most cases, drivers will only seek to use alternative routes after they get caught in the congestion or after they would have been forced off their path by a police cruiser instructed to divert traffic away from an incident. Rerouting decisions could also be made after noticing a reroute advisory displayed on a variable message sign or broadcast through radio stations offering traffic reports.

In the first two cases, reroute would typically occur close to an incident. This creates a potential for having too many vehicles seeking to use the same few alternate routes. Too much traffic on a given route creates a potential for the route to become congested as well. If this occurs, the resulting congestion may be such that all the benefits of attempting to go around the incident may be lost.

Drivers could be informed of an incident further upstream when variable message signs are used. However, there are typically only a few locations where variable signs are used. In most networks, signs are only deployed along freeways. This thus limits their effectiveness to alerting freeway motorists only. While advisory radio can reach vehicle wherever they are, drivers will only respond to broadcasted advisories if they are listening to the right stations. In many cases, drivers only actively seek to listen to traffic broadcasts after they notice something unusual, which is often too late to allow them to avoid major disruptions caused by an incident.

In the simulated scenario, IntelliDrive vehicles are automatically informed of the incident. Motorists are first notified that an incident has happened one minute after its occurrence. Later on, they are informed of its end two minutes after the fact. This provides IntelliDrive vehicles with an opportunity to seek alternate routes regardless of their location. As can be observed in Figure 16, reroute decisions were made not only by vehicles close to the incident, but also by vehicles that were a few miles away from the incident, and in many cases still traveling on local streets.

The further in advance a vehicle is provided with the opportunity to reroute, the greater are the potential benefits. In particular, vehicles that are farther away from an incident will often have a greater choice of potential alternate routes. This may provide them with the ability to travel along routes allowing them to avoid the congested areas altogether, as illustrated in the examples of Figure 17. It may also provide them with the ability to travel along routes that may see smaller increases in traffic attempting to go around the incident and which may thus experience less congestion.

Allowing vehicles to reroute farther upstream from an incident also tend reduce the amount of traffic heading towards an incident. This may result in the building of shorter queues and in traffic impacts that remain contained within a much smaller area. Local traffic on alternate routes may also benefit from a reduction in the number of vehicles seeking to use these routes to bypass an incident if these reductions prevent the onset of congestion or enable traffic to keep flowing relatively smoothly.

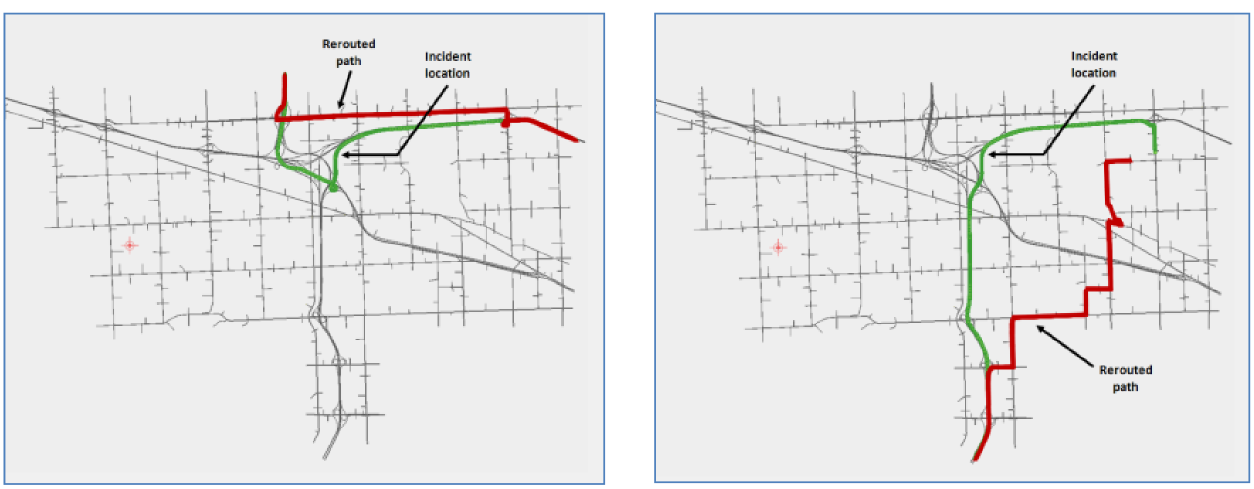


Figure 17 – Examples of Alternate Routes Avoiding the Incident Area

8.5.3. Overall Network Impacts

Figure 18 presents the overall impacts of the incident on network performance. These statistics are based on 6 replications and consider all vehicles initiating a trip between 6:30 and 8:00 AM. The illustrated performance measures include statistics from approximately 71,000 vehicles per simulation run. The figure compares the average trip distance, trip cost, trip time, trip progression speed, total delay, stopped delay and number of stops for the scenarios without an incident, with an incident and no active navigation, and with both an incident and active navigation. The dark mark shown at the top of each bar illustrates the range of simulation results from the 6 replications executed.

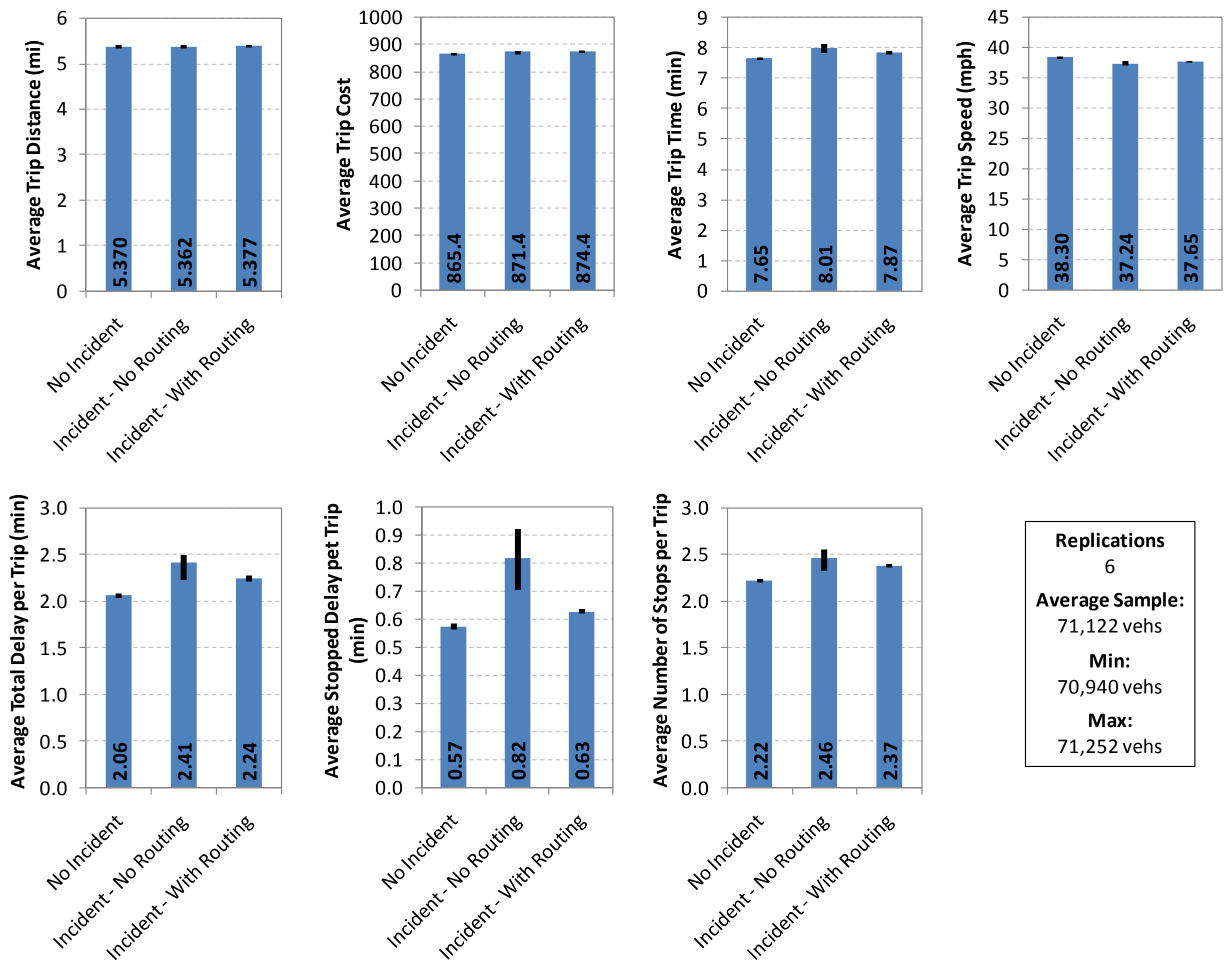


Figure 18 – Overall Network Performance Measures

In each simulation run, between 2203 and 4688 vehicles, with an average of 3517 vehicles, are determined to be directly affected by the incident (vehicles belonging to sampling groups 1, 2 and 3 in Figure 14). Because these vehicles only account for between 3 and 7% of all the vehicles considered in the analyses, the diagrams of Figure 18 show heavily muted responses to the incident and the introduction of active vehicle navigation. Within this context, any noticeable impact that may be observed in the diagrams would thus indicate a probability of much greater impacts for the vehicles directly affected by the incident. The magnitude of these impacts will be determined in the subsequent sections. Despite the fact that Figure 18 may smooth out the impacts of the incident and of the introduction of active navigation, the presented statistics are useful for establishing a frame of reference on network performance. These statistics would also be of interest to network operators, who are typically more concerned with how a system operates as a whole rather than with the performance of individual vehicles.

Comparisons of performance measures between the scenario without an incident and the scenario with an incident and no active rerouting indicate that the traffic disruptions caused by the incident lead to a noticeable increase in the average stopped delay per trip, average trip delay, and overall trip time. The average stopped delay increases by 0.25 min per trip, the total delay per trip by 0.37 min, and the total trip time by 0.38 min. These statistics correspond to increases of 43.7%, 18.0% and 4.9% respectively. The number of stops per trip further edges up by 0.3, which corresponds to an increase of 12.4%. Both the average trip distance and trip cost remain relatively unchanged, with changes of less than 1%. While the impacts appear small in magnitude, it should be remembered that they are multiplied over about 71,000 vehicles. A 0.25 min increase in stopped delay would therefore translate in this case into approximately 17,750 additional minutes of delay, or approximately 295 additional hours of delay.

The above changes not only assess the impacts of vehicles queuing on the freeway upstream of the incident, but also of the increased traffic on neighboring local streets. While vehicles are not actively rerouted around the incidents in the two scenarios being compared, some of the vehicles generated after the start of the incident are still automatically rerouted around the incident by Paramics. This is a consequence of using Paramics' information feedback loop. When vehicles are generated, they determine the path they will follow based on existing link travel costs. Since these costs are updated every five minutes using a rolling average process, vehicles generated after the incident will thus gradually start to react to the congestion caused by the incident, albeit with some lag. This is somewhat similar to what happens in real networks when travelers are informed of unusual congestion. Vehicles that are already on their way are however all assumed to commit to their initially planned route. While the active rerouting application used the same travel costs to determine whether a detour should be made, the application allows vehicles to change their path after they have initiated their trip.

When rerouting is activated, the stopped delay per trip is observed to drop by 23.7% when compared to the scenario without navigation. This further translates into an 8.0% reduction in total delay, a 2.1% reduction in overall trip time and a 5.0% reduction in the number of stops made by vehicles. On an individual trip basis, this corresponds to, on average, a 0.2 min reduction in stopped delay, total delay and travel time. When considering the impacts over all simulated vehicles, this translates on average into a reduction of 228 hours in stopped delay, 230 hours in total delay, and 198 hours in total trip time over the entire network, as well as a total of 8737 fewer stops. Similar to the previous comparisons, there are only marginal changes in the average trip distance and estimated trip cost.

In terms of variability, Figure 18 indicates that the scenario without an incident and the scenario with an incident and active rerouting both exhibit relatively low levels of variability. For these two scenarios, coefficients of variation do not exceed 1.5%. Higher variability, although still relatively contained, is observed for the scenario with an incident and no active rerouting. Coefficients of variation for this scenario reach as high as 7% for the average stopped delay, 3.5% for the total delay and travel time and remain near or below 1% for the other parameters.

For the scenario without an incident, the low variability is explained by the lack of significant congestion in the network, which tends to create relatively stable traffic conditions. When the incident is introduced, the absence of active rerouting causes a significant number of vehicles to queue upstream of the incident. Since queuing patterns are a function of the sequence by which vehicle arrives, any change in arrival pattern can lead to significant changes in how the queue builds up and how far the traffic disruption ultimately reaches, thus explaining the higher variability of simulation results. One of the main consequences of introducing the active rerouting application is to reduce the congestion that builds up around the incident, which leads to more stable traffic conditions and less variability.

To better appreciate the potential benefits of the vehicle reroutes to individual drivers, the following sections take a more detailed looked at the benefits provided by the active navigation application on individual groups of vehicles. The groups considered are those shown in Figure 14 earlier: vehicles trapped in the queue immediately upstream of the incident that are unable to seek alternate route (Group 1), vehicles trapped in the queue that form between 7:00 and 7:15 and able to reroute (Group 2), and vehicles affected by the traffic disruptions that propagate upstream of the incident along the I-275 freeway between 7:15 and 7:50 (Group 3).

8.5.4. Impacts on Queued Vehicles Unable to Reroute (Group 1)

Without active navigation, between 487 and 549 vehicles, with an average of 524 vehicles, are observed to queue on the freeway upstream of the incident between 7:00 and 7:15. With active rerouting, and under the assumption that all vehicles have a routing application installed, many vehicles are able to find alternate route. This results in a drop in the average number of vehicles queuing to only 97 vehicles, with a range from 81 to 113 vehicles depending on the random number seed used..

The inability of certain vehicles to bypass the incident can first be attributed to the assumed 1-minute delay between the moment the incident occurs and the moment that approaching IntelliDrive vehicles are informed of its existence. When the information delay is removed to simulate instant incident notification, the average number of vehicles queuing behind the incident drops to about 50 vehicles. However, such a simulation setup is somewhat unrealistic as it is very unlikely that instantaneous incident notification would be available to motorists. To avoid responding to false warnings, experience has taught system operators to wait for the validation of a reported incident before initiating mitigating actions. Based on this experience, it is expected that a similar validation phase will be imposed to IntelliDrive incident warning applications. This will result in a short lag between the moment an incident is reported and the moment a warning message may be sent out to IntelliDrive vehicles. Since the extent of this lag will depend on specific network design and operating conditions, the use of a 1-minute lag was arbitrarily selected as a reasonable operating parameter.

Another contributing factor to the observed queuing is the location of the incident. Most of the vehicles that end up queuing behind the incident have already passed the last potential decision point allowing them to take an alternate route when they receive notification of the incident. The location of this last decision point is shown in Figure 14. As discussed earlier, this location does not correspond to the junction between two routes but to the upstream end of the link leading to the junction. For simulation efficiency purposes, vehicles assess their routing decisions when they have just transferred from one link to another. Routing decisions may not be made when a vehicle exit a links, as this may create lane assignment conflicts if a new decision results in a different turn decision. When considering the speed limit of the link leading to the last decision point (70 mph, or 112 km/h), it is estimated that modeling results in the potential trapping of vehicles that are up to 14 seconds away from the junction when the incident notification occurs. In terms of queuing vehicles, this decision lag results in approximately 10 additional vehicles being trapped behind the incident.

While vehicles are prevented from making route choices up to a certain distance from the last decision point, this is not far from what may happen in reality if it is considered that navigation systems may need a few seconds to determine a new route following reception of an incident warning. Drivers also often need a few seconds as well to make decisions. If a 14-second lag is considered too long, the negative effects of the adopted modeling could be partly counterbalanced by the use of shorter links. In this case, the link leading to the junction is approximately 1400 ft (425 m) long. However, using shorter links may also lead to simulation difficulties, particularly to vehicles being stuck at the junction of two links due to their inability to perform a number of lane changes in the short distance provided.

Figure 19 compares the average performance measures for the incident scenarios with and without rerouting for the vehicles that are unable to reroute with the active navigation. These statistics reflects the outputs of six simulation runs. The thick bar represents the average across six runs, while the thin line at the top of each bar represents the range of performance values from individual simulation runs.

The graphs indicate relatively marginal changes in performance measures. In this case, a statistical analysis reveals that none of the observed changes are statistically significant at a 95% confidence level. Such a result is not surprising considering that the analysis focuses on vehicles unable to change their routing plans. Most of the observed variations in performance measures can be traced to the stochastic nature of the Paramics simulation processes. Within a simulation, vehicles are inserted not at the upstream end of an entry but at a randomly located position along the link. Changes in the entry position of a vehicle will thus result in some variations in trip distance and trip time. This would be in addition to any other potential stochastic effects associated with the interactions of vehicles with other vehicles and traffic control devices.

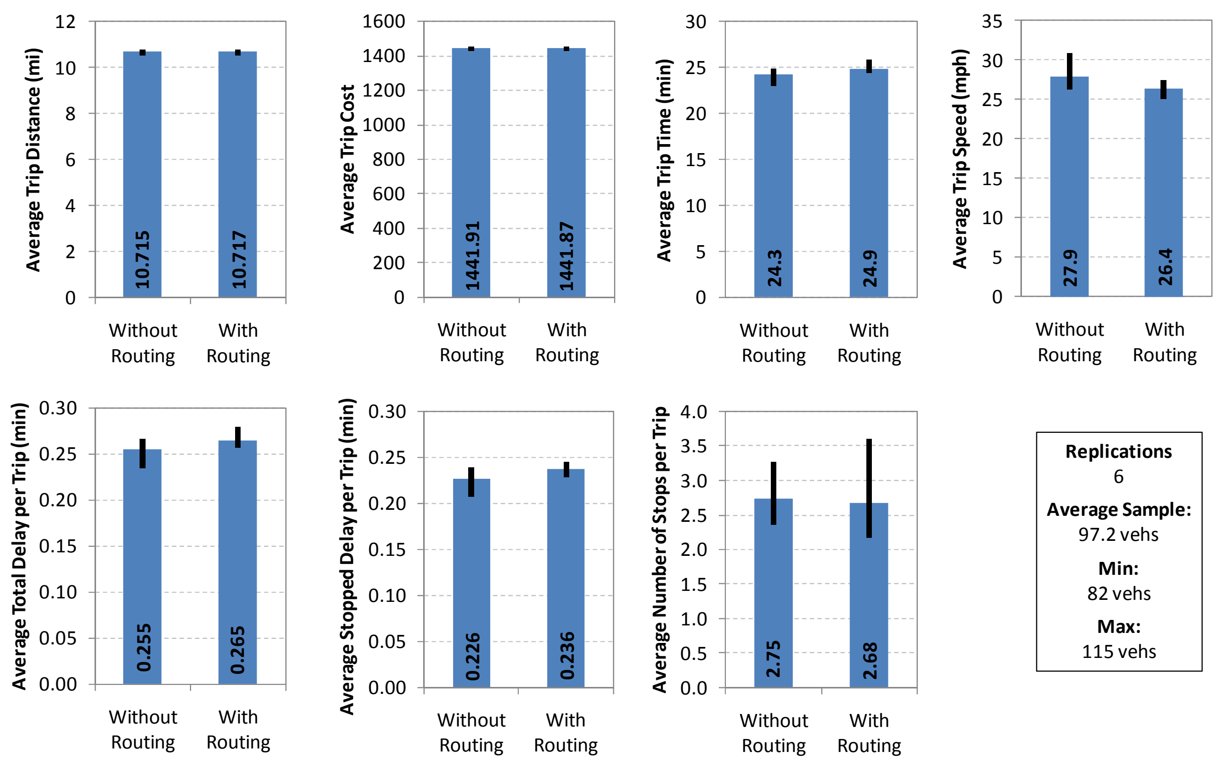


Figure 19 – Performance Measures for Vehicles Queuing Between 7:00 and 7:15 and Unable to Reroute

Figure 20, which illustrates the distribution of impacts on individual vehicles, confirms the conclusions drawn from Figure 19. While the figure compares the results of simulations performed with a specific random number seed, similar distributions were observed with other random number seeds. In this case, it is observed that most of the vehicles that still queue behind the incident with the active navigation experience no noticeable change in trip performance measures when compared to a scenario without navigation. The only performance measure for which a significantly greater variability is observed is the number of stops made along a trip. In most cases, the observed variability between the scenarios with and without navigation can be attributed to the simulation effects described above.

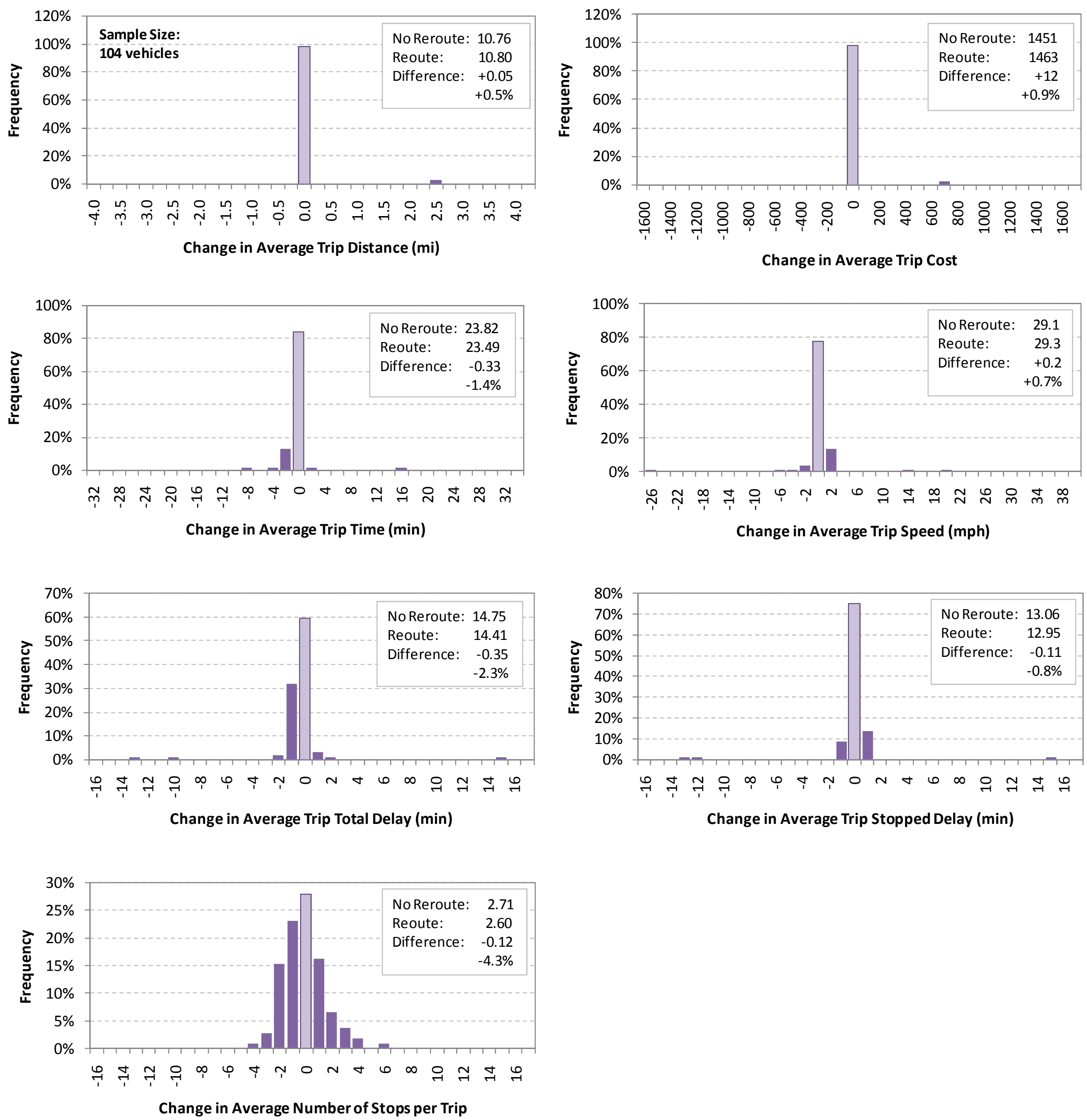


Figure 20 – Distribution of Impacts in a Single Simulation Run for Vehicles Queuing Between 7:00 and 7:15 and Unable to Reroute

8.5.5. Impacts on Queued Vehicles Able to Reroute (Group 2)

Figure 21 displays performance measures for vehicles that queue behind the incident between 7:00 and 7:15 without active navigation but that are successful in seeking an alternate route around the incident with active navigation. With respect to Figure 14, these vehicles belong to the sampling Group 2. The results shown in the figure are a compilation of six simulation runs for each scenario. Depending on the random number seed used, the number of vehicles able to reroute around the incident varies between 458 and 528, with an average of 496 vehicles across all runs.

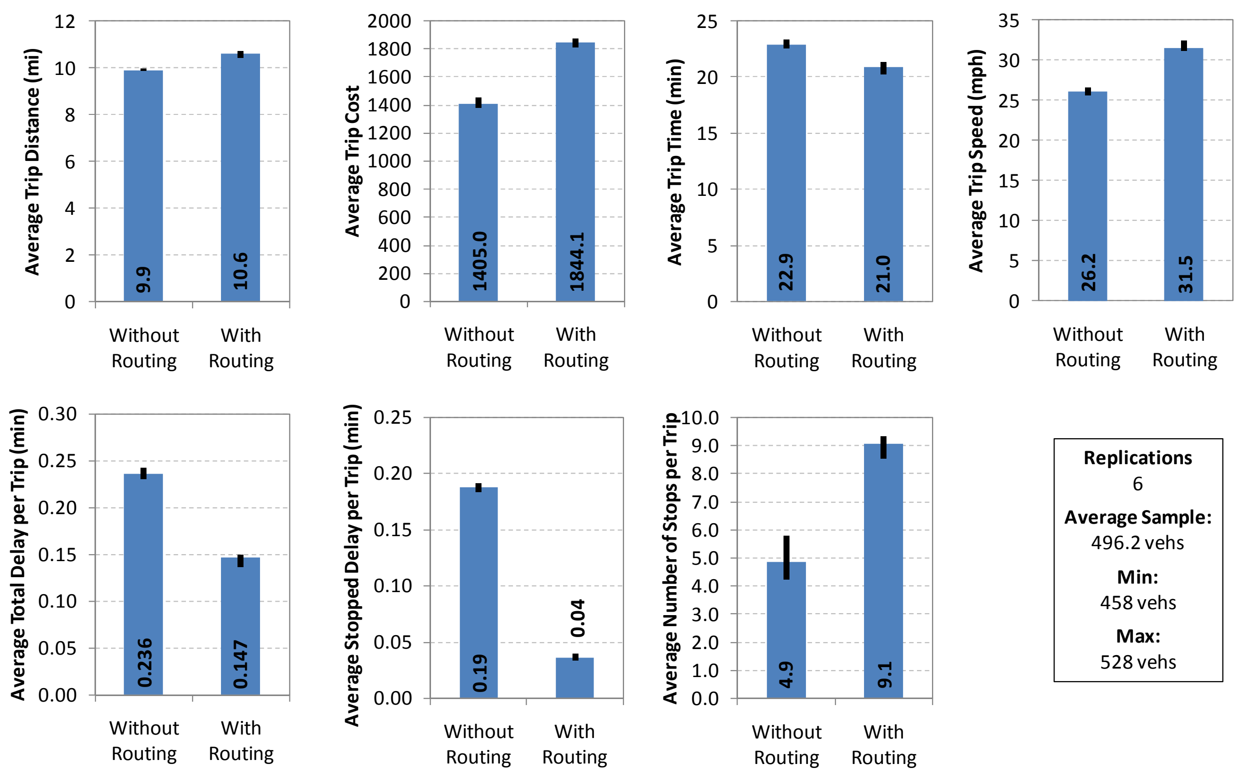


Figure 21 – Performance Measures for Vehicles Queing between 7:00 and 7:15 and Able to Reroute

For the vehicles in Group 2, use of the rerouting application leads to an average reduction of 81.2% in stopped delay per trip and a reduction of 37.9% in total delay. This translates into a 8.4% average reduction in trip time. All these results are statistically significant at a 95% confidence level. In absolute values, these changes correspond to average reductions of 9.1 minutes in stopped delay, 5.4 minutes in total delay, and 1.9 minutes in total trip time. When considering all vehicles within the group, the observed impacts further correspond, on average, to a 75.6-hour reduction in total stopped delay, a 44.4-hour reduction in total delay, and a 16.0-hour reduction in time spent traveling across the network.

While average trip length is observed to increase by about 0.7 mi, or 7.0%, such an increase was expected as rerouted vehicles are pushed to travel along longer routes to go around the congestion created by the incident. The resulting shift from freeway to neighboring arterial roads also explains the 86.5% increase in the number of stops made per trip. In this case, vehicles trade a single stop waiting in queue along the freeway for the incident to clear for a series of stops at signalized intersections.

From a cost standpoint, the comparisons indicate an increase in travel cost with the active navigation. This increase is largely attributed to the increase in trip length. As indicated earlier, trip costs are calculated by adding 5% of the trip length expressed in feet to the trip time in seconds. Distance is included to ensure that vehicles do not venture along significantly longer alternate paths just to save a few seconds. While alternate paths enable vehicles to reduce delays by going around a congested area, some of these savings are partly negated by the use of longer paths requiring longer travel times. Cost increases could then result if the delay savings are not high enough to compensate for the longer travel times. Should travel time alone be considered, an overall reduction in travel cost would be obtained in this case.

Figure 22 more closely examines the operational benefits to vehicles within Group 2. The figure provides the distributions of changes in performance measures associated with individual trips. For illustration purposes, statistics from a single simulation run comparison are shown. As can be observed, there is a relatively wide range of impacts. This is explained by the fact that not all vehicles are affected the same way by the incident. For instance, vehicles approaching the incident after its occurrence stand to benefit more than vehicles approaching a few minutes later.

Similar to Figure 21, the graphs of Figure 22 indicate that rerouting allows all vehicles within the sample to reduce their stopped delay, and most of the vehicles to reduce their total trip delay and trip time. Because of the switch from freeway to arterial road, not all vehicles were able to achieve a reduction in trip travel time. Since the reroute forces many vehicles to shift their travel to an urban environment, many vehicles end up travelling along longer paths on roads with lower speed limits and punctuated with signalized intersections. While stopped delay can be significantly reduced by going around the incident, these savings are partly lost because of the need to travel along longer routes and to additional delays imposed by traffic signals. Overall, however, performance statistics clearly indicate that the ability to reroute is beneficial.

Of the 261 rerouted vehicles shown in Figure 21, 201 vehicles end up on alternate paths that are at least 500 ft longer than their initial planned route. On average, these vehicles travel 1.75 more miles to reach their destination. This was an expected consequence of seeking alternative routes around the incident. These vehicles, which are primarily those reaching the incident soon after its occurrence, save on average 11.5 minutes in stopped delay, 8.1 minutes in total delay and 3.5 minutes in total trip time to reach their destination. On average, vehicles stop 4.0 more times per trip as a result of traveling on signalized urban arterials. Figures 23 and 24 illustrate two examples of vehicle reroutes that resulted in longer trip lengths but that still result in an overall reduction in trip travel time.

Thirty-two vehicles are further shown to have rerouted paths of about the same length as their initial path. As explained earlier, some of these slight variations may be entirely due to simulation processes followed by Paramics. However, because of the geometry of the network, it is further possible that some vehicles truly follow alternate paths with approximately similar length to the initial path. An example of such a situation is shown in Figure 25. Evidence of successful reroute for these 32 vehicles is shown by a 10.7 minute average reduction in stopped delay, a 7.1 minute reduction in total delay and a 4.1 minute reduction in total trip time despite relatively small changes in trip length.

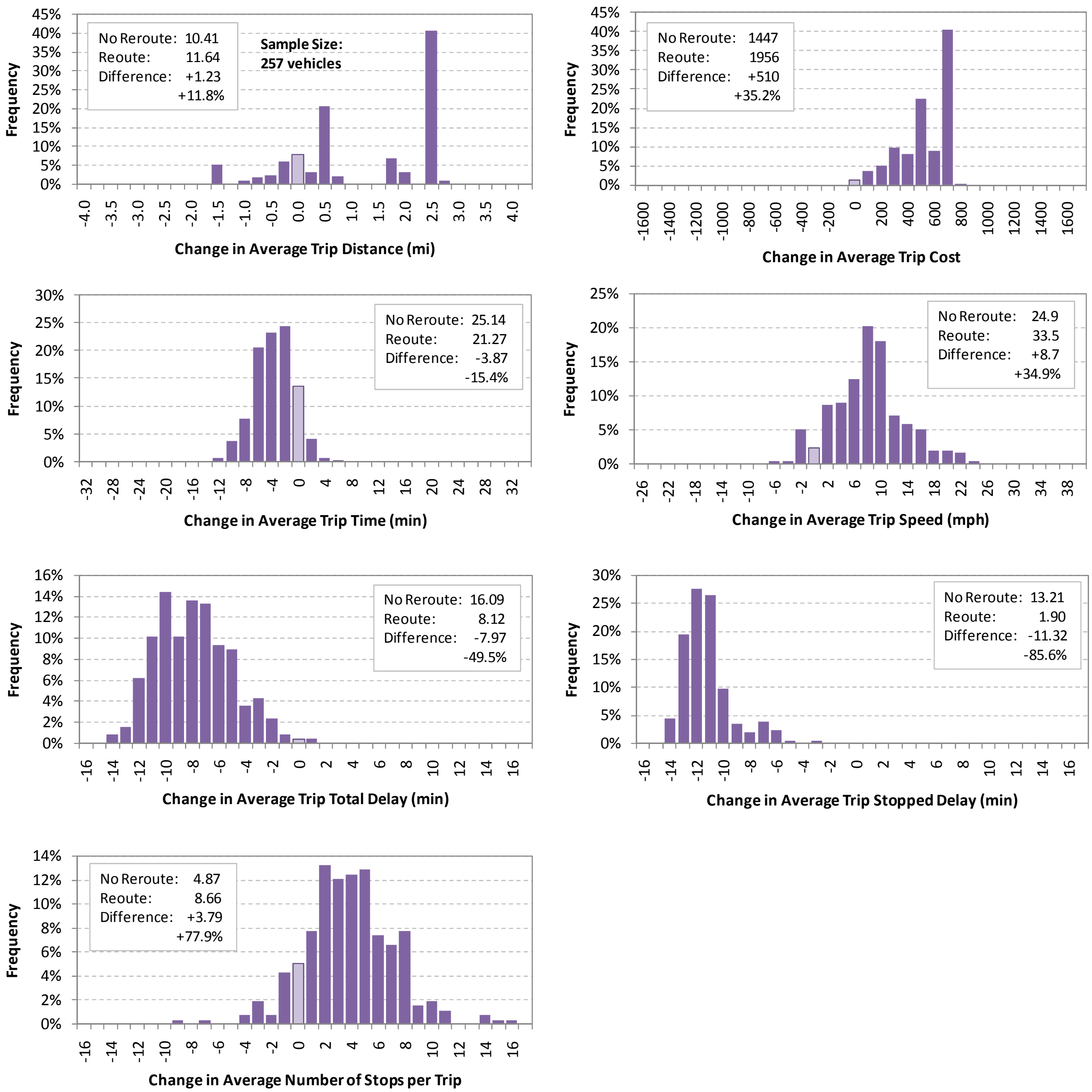
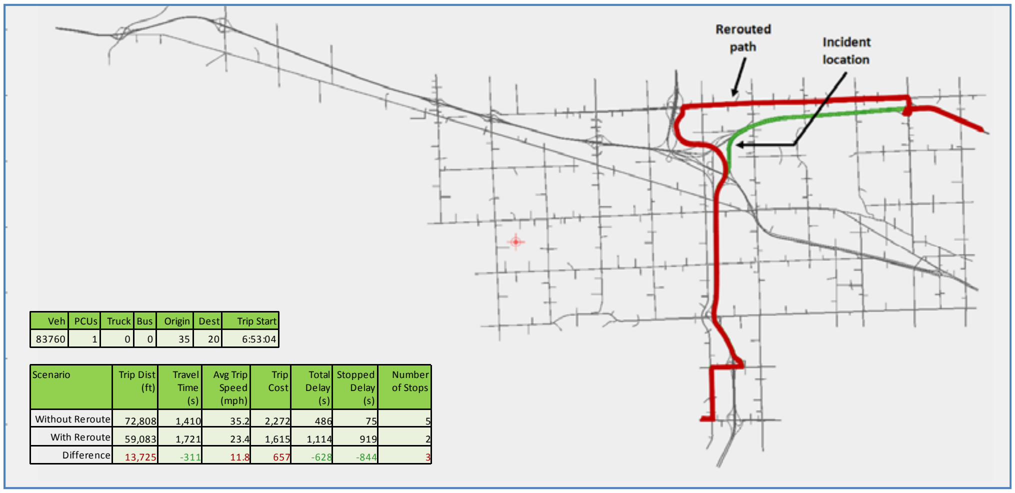


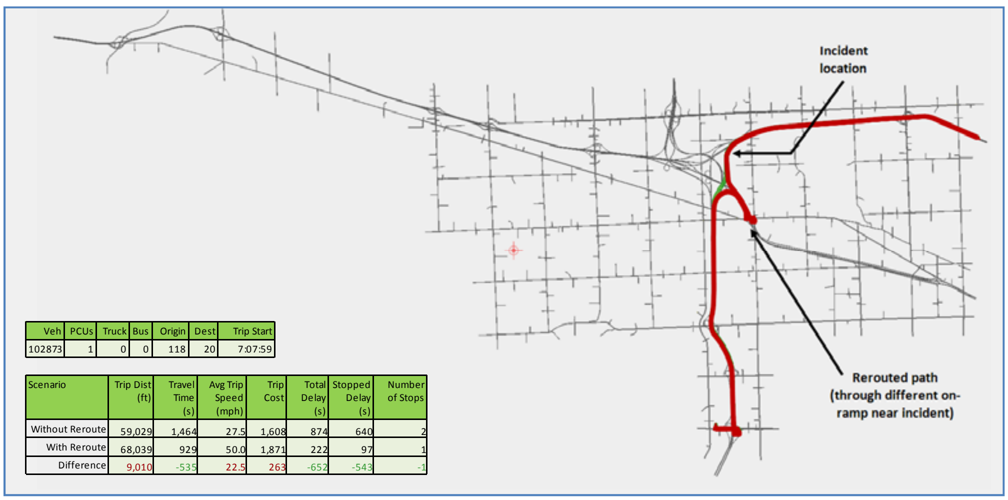
Figure 22 – Distribution of Impacts in a Single Simulation Run for Vehicles Queuing between 7:00 and 7:15 Able to Reroute



Veh	PCUs	Truck	Bus	Origin	Dest	Trip Start
83760	1	0	0	35	20	6:53:04

Scenario	Trip Dist (ft)	Travel Time (s)	Avg Trip Speed (mph)	Trip Cost	Total Delay (s)	Stopped Delay (s)	Number of Stops
Without Reroute	72,808	1,410	35.2	2,272	486	75	5
With Reroute	59,083	1,721	23.4	1,615	1,114	919	2
Difference	13,725	-311	11.8	657	-628	-844	3

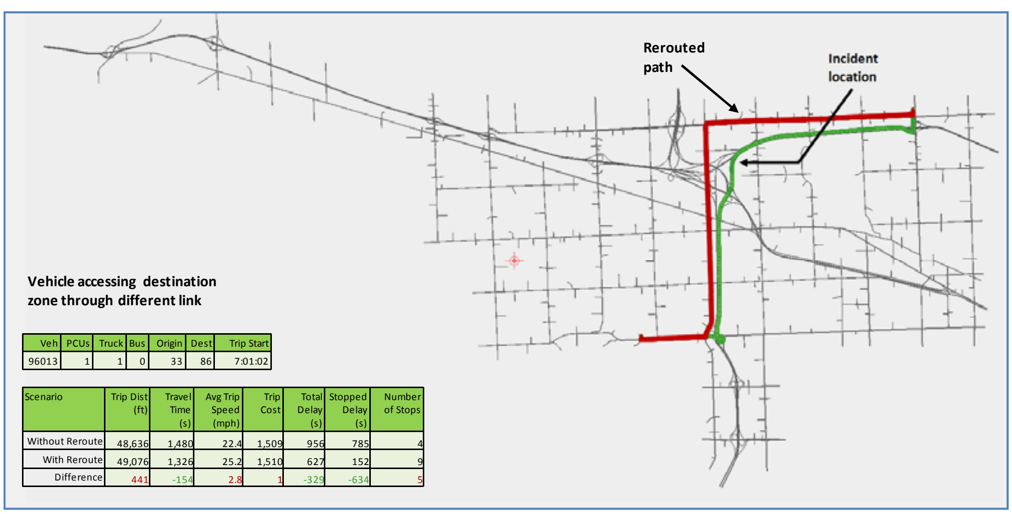
Figure 23 – Example 1 of Rerouted Trip with Longer Trip Length



Veh	PCUs	Truck	Bus	Origin	Dest	Trip Start
102873	1	0	0	118	20	7:07:59

Scenario	Trip Dist (ft)	Travel Time (s)	Avg Trip Speed (mph)	Trip Cost	Total Delay (s)	Stopped Delay (s)	Number of Stops
Without Reroute	59,029	1,464	27.5	1,608	874	640	2
With Reroute	68,039	929	50.0	1,871	222	97	1
Difference	9,010	-535	22.5	263	-652	-543	-1

Figure 24 – Example 2 of Rerouted Trip with Longer Trip Length

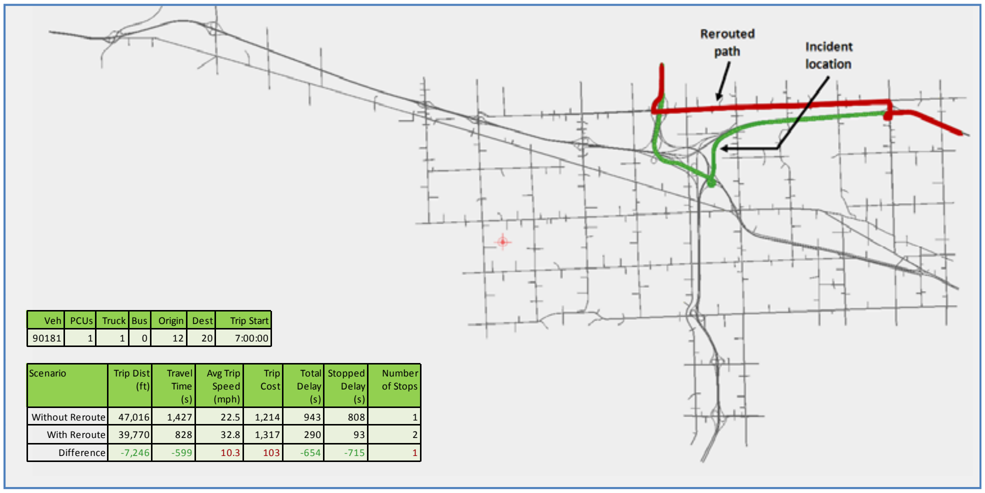


Veh	PCUs	Truck	Bus	Origin	Dest	Trip Start
96013	1	1	0	33	86	7:01:02

Scenario	Trip Dist (ft)	Travel Time (s)	Avg Trip Speed (mph)	Trip Cost	Total Delay (s)	Stopped Delay (s)	Number of Stops
Without Reroute	48,636	1,480	22.4	1,509	956	785	4
With Reroute	49,076	1,326	25.2	1,510	627	152	9
Difference	441	-154	2.8	1	-329	-634	5

Figure 25 – Example of Rerouted Trip with Similar Trip Length

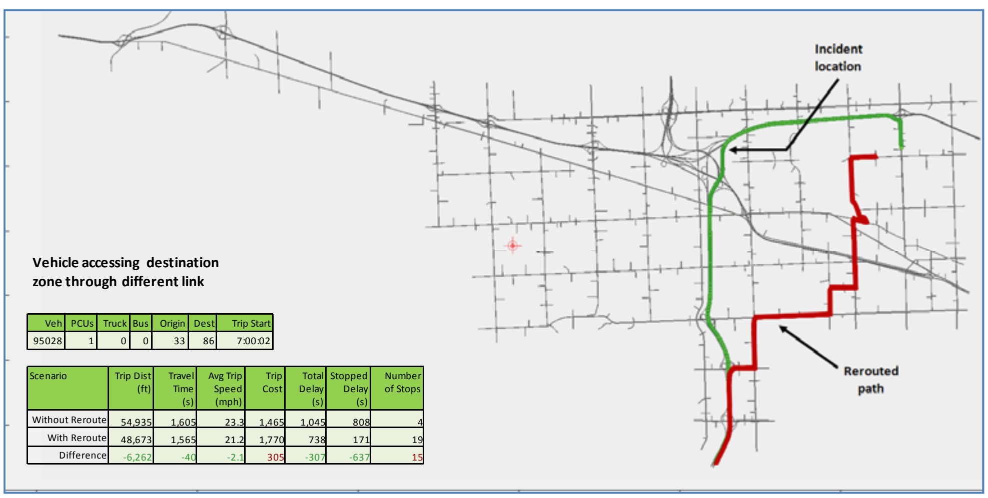
Twenty-four vehicles are finally observed to follow alternate paths with significantly shorter length than their original route. These are vehicles that would normally use the freeway to reach their destination, mainly because of the benefit of higher travel speeds, even though it may result in longer travel distances. Since the incident increases the time required to travel along the freeway, the use of nearby arterials then becomes more attractive, even though it may require stopping at a number of signalized intersections. Examples of such reroutes are shown in Figures 26 and 27. Collectively, the rerouting decisions for the 24 mentioned vehicles result in a 10.5 minute reduction in stopped delay, an 8.0 minute reduction in total delay, an average increase of 2.5 stops per trips, and trips that are in overall shorter by an average of 1.0 mile and 6.3 minutes.



Veh	PCUs	Truck	Bus	Origin	Dest	Trip Start
90181	1	1	0	12	20	7:00:00

Scenario	Trip Dist (ft)	Travel Time (s)	Avg Trip Speed (mph)	Trip Cost	Total Delay (s)	Stopped Delay (s)	Number of Stops
Without Reroute	47,016	1,427	22.5	1,214	943	808	1
With Reroute	39,770	828	32.8	1,317	290	93	2
Difference	-7,246	-599	10.3	103	-654	-715	1

Figure 26 – Example 1 of Rerouted Trip with Shorter Trip Length



Veh	PCUs	Truck	Bus	Origin	Dest	Trip Start
95028	1	0	0	33	86	7:00:02

Scenario	Trip Dist (ft)	Travel Time (s)	Avg Trip Speed (mph)	Trip Cost	Total Delay (s)	Stopped Delay (s)	Number of Stops
Without Reroute	54,935	1,605	23.3	1,465	1,045	808	4
With Reroute	48,673	1,565	21.2	1,770	738	171	19
Difference	-6,262	-40	-2.1	305	-307	-637	15

Figure 27 – Example 2 of Rerouted Trip with Shorter Length

8.5.6. Impacts on Vehicles Affected by Dissipating Queue (Group 3)

This section looks at the impacts of the rerouting application for vehicles that are affected by the traffic disruptions that propagate upstream of the incident on the I-275 freeway. These vehicles all belong to the Group 3 illustrated in Figure 14. Because they are all still upstream of the last potential reroute decision point when they receive the incident notification, these vehicles all have access to alternate routes and all stand to potential benefit from the active navigation application.

Figure 28 compares the average performance measures calculated for this group of vehicles between the incident scenarios with and without rerouting. Similar to other groups, these results are based on six simulation runs for each scenario. In this case, the ability to seek alternate routes around the incident translates, on average, into a 90.0% reduction in stopped delay, a 68.5% reduction in total trip delay, a 30.7% average reduction in total trip time and a 60.7% reduction in the number of stops made along a trip. Since trip distance only slightly increases, the reductions in travel time lead to a small 5.5% reduction in average trip cost. Except for the marginal change in trip distance, all the observed changes in performance measures are statistically significant at the 95% confidence level.

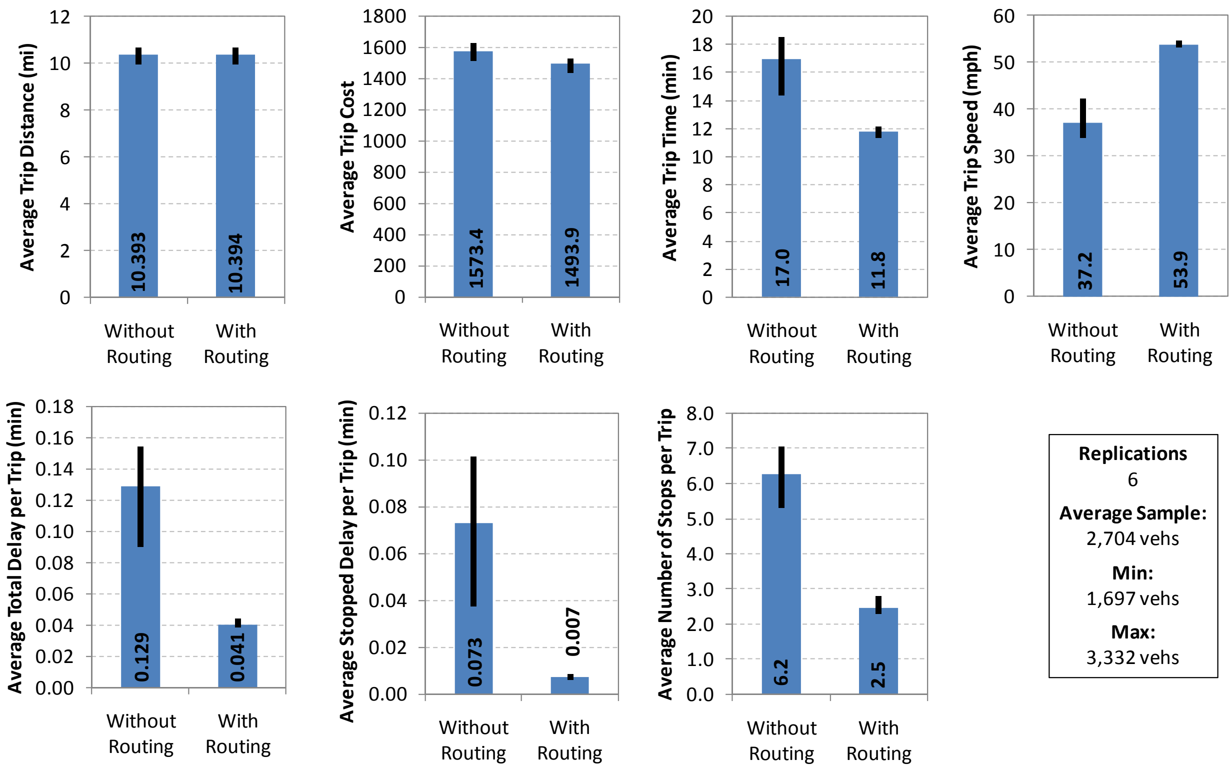


Figure 28 – Performance Measures for Vehicles Affected By Traffic Disturbances on Freeway after 7:15

In absolute values, the above changes translate into a 3.9 minute reduction in stopped delay, a 5.3 minute reduction in total delay, a 5.2 minute reduction in total trip time and a reduction of 3.8 stops per trip. Considering all vehicles within the group, this yields total savings of 177.8 hours in stopped delay, 238.3 hours in total delay, 235.2 hours in total trip time and 10,306 fewer stops.

When compared to Group 2, vehicles in Group 3 achieve on average a greater reduction in total travel time. Because these vehicles are affected further upstream by the congestion created by the incident, they have access to more alternative routes. This translates into an improved ability to choose efficient alternative routes that may not involve detours as long as those experienced by the vehicles caught by the disruptions close to incident. More opportunities also exist for these vehicles for rerouting along routes experiencing smaller increases in traffic and thus imposing fewer delays.

When comparing Figures 28 and 21, it can also be observed that vehicles in Group 3 experience a reduction in the number of stops made per trip with the routing application active while vehicles in Group 2 experience an increase in the number of stops made. This opposing trend is explained by the fact that many of the vehicles in Group 3 make a series of stops on the freeway in the scenario without rerouting while they traverse the disruptions created by the incident. For the same scenario, vehicles in Group 2 typically make a single long stop. When the routing application is activated, vehicles in Group 2 replace their single freeway stop by a series of stops at signalized intersections along neighboring arterials. However, vehicles in Group 3 tend to replace multiple stops on the freeway by a smaller number of stops on the neighboring arterials.

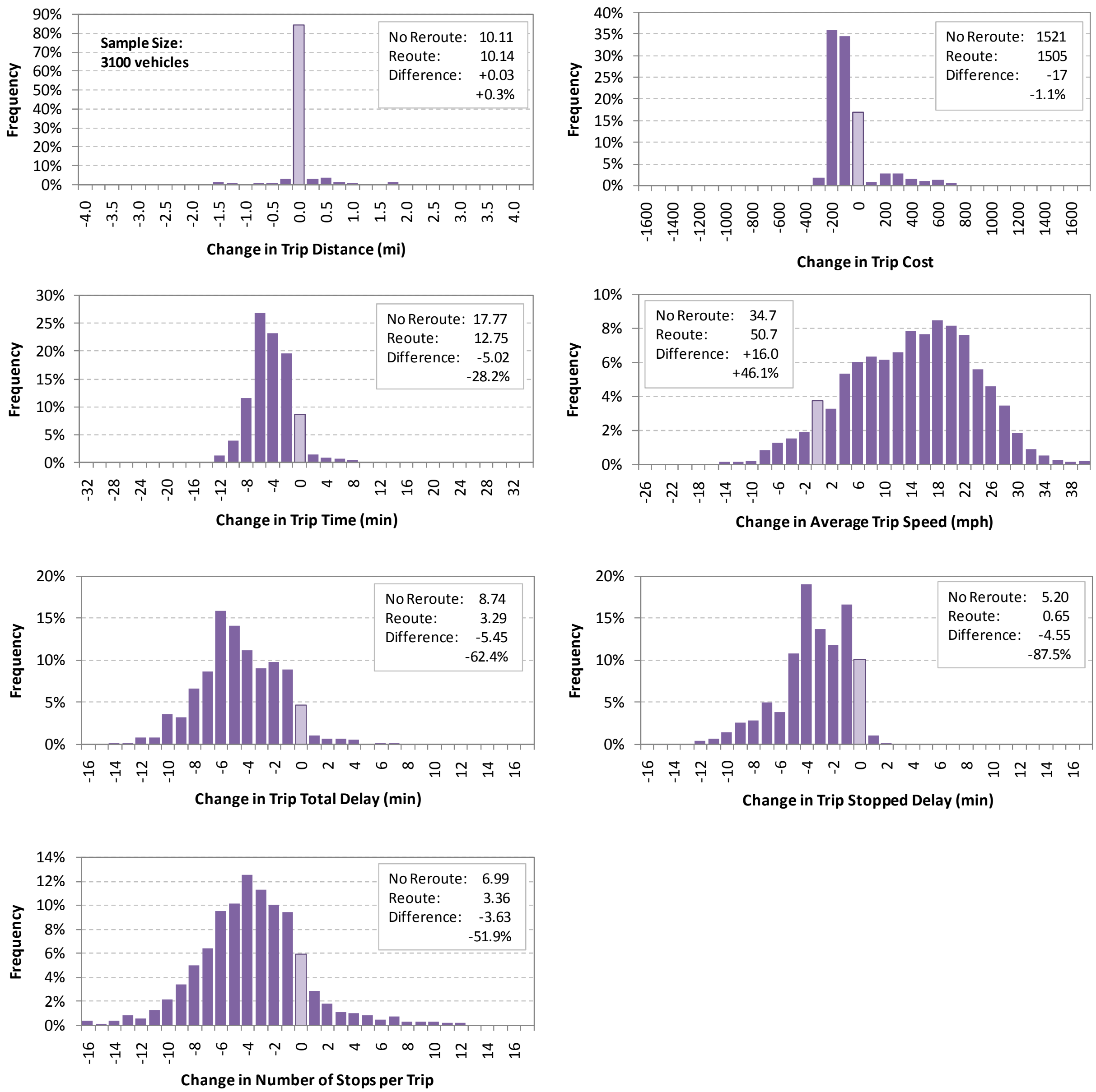


Figure 29 – Distribution of Impacts in a Single Simulation Run for Vehicles Affected By Traffic Disturbances on Freeway after 7:15

Similar to Figure 22, Figure 29 provides the distributions of changes in performance measures associated with individual trips across a single simulation run. For comparison purposes, the results shown in the figure are from the same run used to compile the graphs of Figure 22. A first observation from Figure 29 is that the illustrated distributions generally support the results of Figure 28. The figure shows relatively small impacts on trip length, distributions pointing to reductions in trip cost, trip time, trip total delay, stopped delay and number of stops, and a distribution pointing to an increase in average travel speed.

Aside from illustrating the potential variability of impacts on individual vehicles, the diagrams of Figure 29 further indicate that there exists a probability for individual vehicles not to benefit from a dynamic routing application. For each performance measure, a small number of vehicles are observed to have slightly worse trip performance measures when provided with the ability to dynamically seek alternate routes around the simulated incident. In most cases, these deteriorating results are due to changing traffic conditions along the suggested paths after a reroute decision has been made. This is an expected consequence of trying to provide active navigation in a network in which traffic conditions are constantly changing.

8.5.7. Overall Impacts on All Vehicles Affected by Incident (Groups 1-3)

Figure 30 and Figure 31 combine the statistics for all vehicles affected by the incident that have been presented in the past three sections. When combining statistics for Groups 1, 2 and 3, the rerouting application leads, on average, to a 79.1% reduction in stopped delay, a 55.4% reduction in total delay, a 23.7% reduction in trip travel time and a 43.3% reduction in the number of stops incurred. Trip distance only slightly increases, while the estimated trip cost increases by a marginal 0.9%. Except for the changes in trip cost and trip distance, the estimated impacts on all other performance measures are statistically significant at a 95% confidence level.

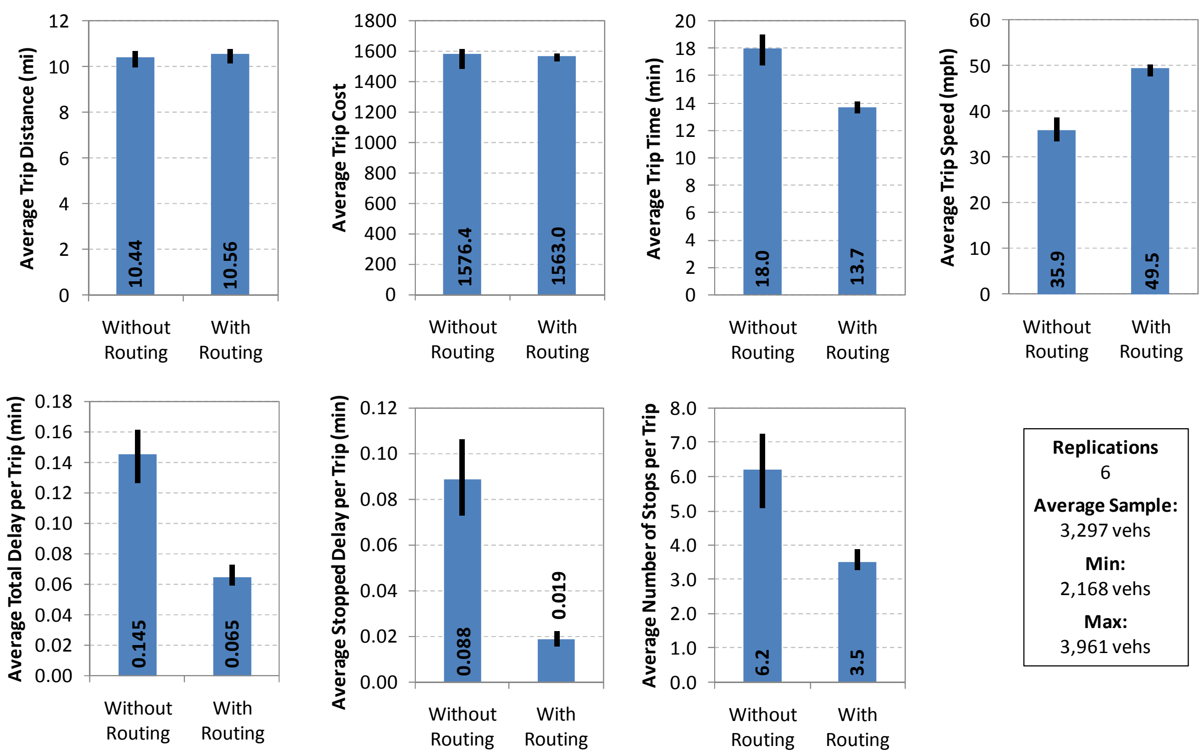


Figure 30 – Performance Measures for All Vehicles Affected by Incident

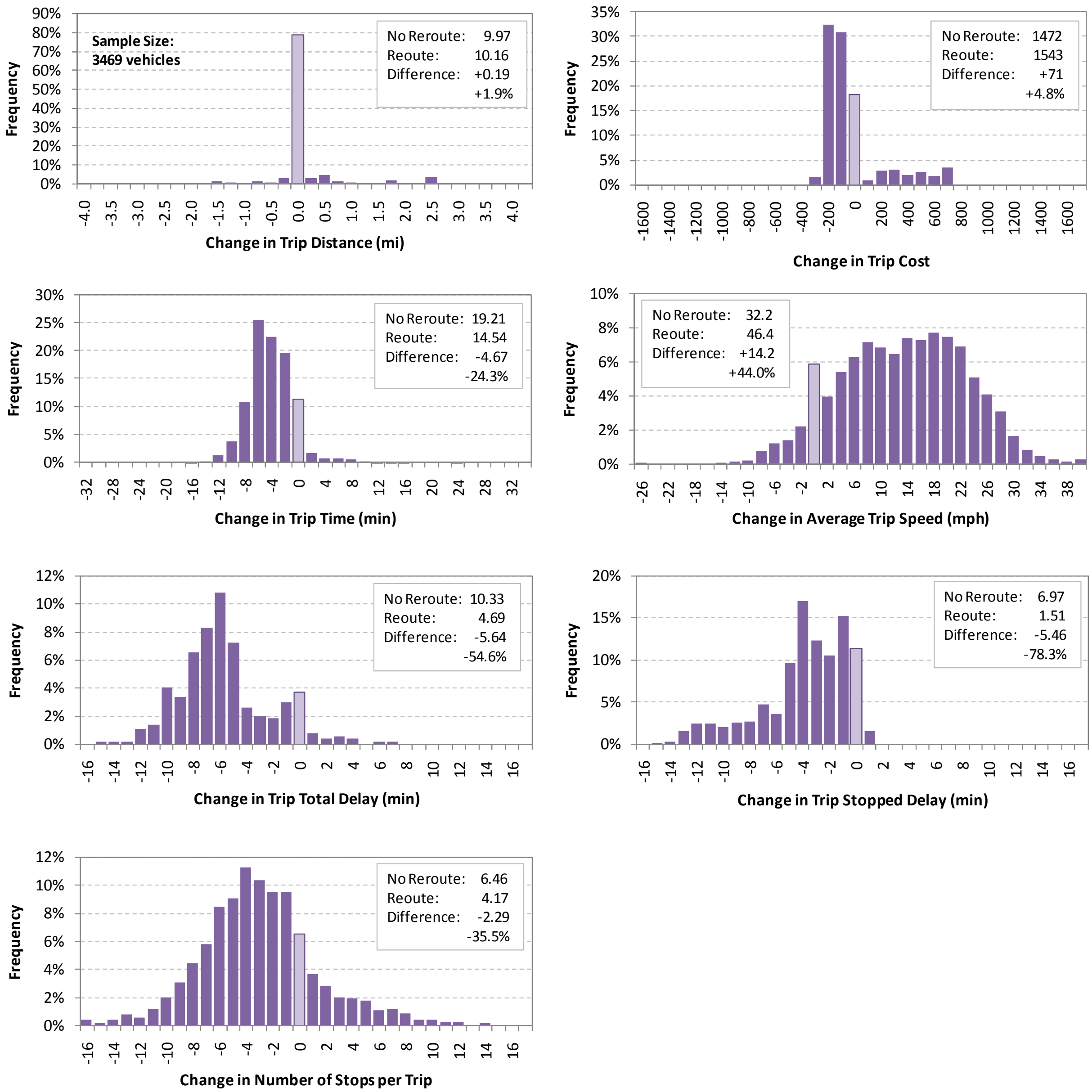


Figure 31 – Distribution of Impacts in a Single Simulation Run for All Vehicles Affected by the Incident

In absolute values, the observed changes translate into a 4.2 minute reduction in average stopped delay, a 4.8 minute reduction in average trip delay, a 4.3 minute reduction in average trip time and a reduction of 2.7 stops per trip. When considering that these trip statistics are for an average of 3297 vehicles, this leads to a total estimated saving of 230 hours in stopped delay, 265 hours in total delay, and 234 hours in vehicle travel time. Overall, these statistics show a net benefit from the ability to use the intended destination of a vehicle to provide alternate routing alternatives around an incident.

8.5.8. Impacts on Vehicles not directly Affected by Incident (Group 4)

The analyses of this section focuses on the vehicles that do not intent to travel through the section of freeway on which the incident occurs or the section on which traffic disruptions caused by the incident propagate. This group considers all the vehicles generated between 6:30 and 8:00, except for those that have been assigned to the sampling groups 1, 2 and 3 shown in Figure 14 and analyzed in the previous sections.

For this group of vehicles, Figure 32 indicates that secondary impacts from the vehicle reroutes remain generally negligible. The largest observed changes are a 3.3% average increase in total trip delay, a 2.1% average increase in the number of stops made and a 1.2% average increase in stopped delay. All other performance measures exhibit changes of less than 1%. Despite the relatively small magnitude of the changes, a statistical analysis indicates that all the observed changes are statistically significant at a 95% confidence level, except for the changes in stopped delay and number of stops.

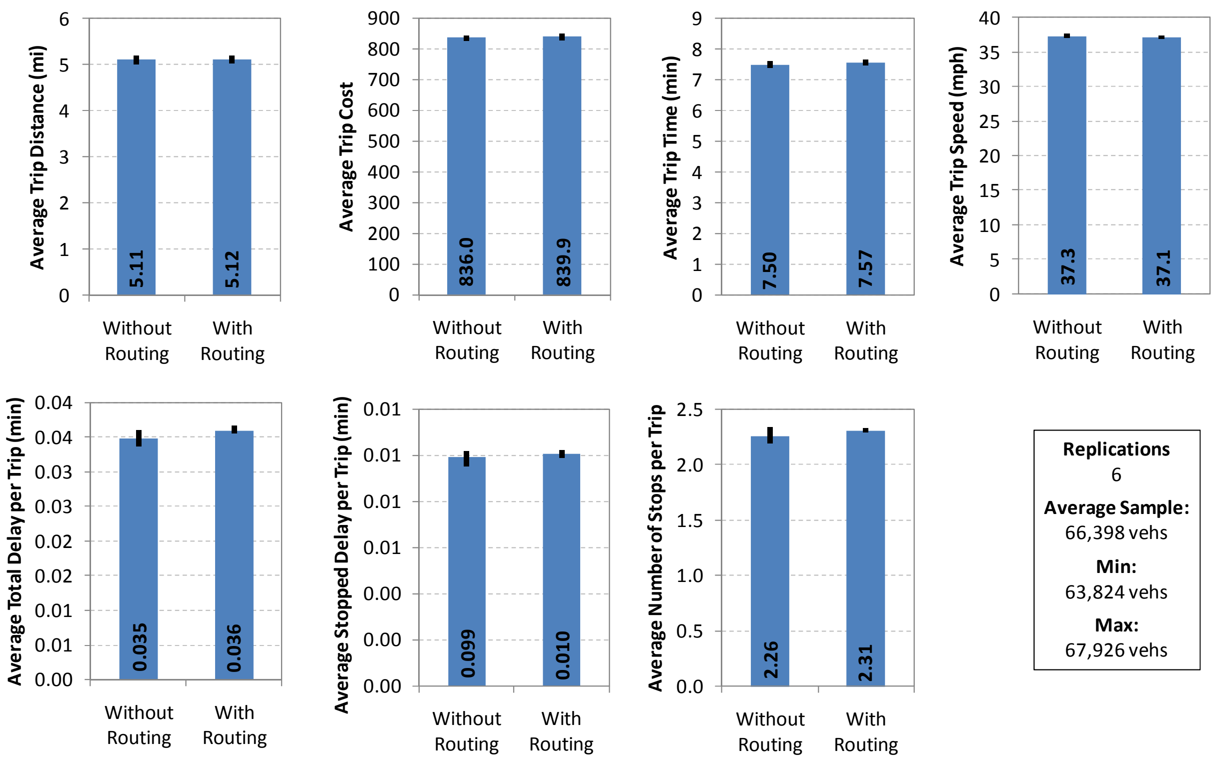


Figure 32 – Performance Measures for Vehicles not Directly Affected by Incident

While it is expected that vehicle reroutes should have negative impacts on local traffic along diversion routes, it may not be possible to develop general trends regarding the magnitude of these impacts. Increases in travel time, delay and number of stops are likely to be network and context specific. For instance, increasing the duration of the simulated incident may force more vehicles to seek alternate routes and increase congestion along these routes as the disruptions generated by the incident extends further upstream along the freeway. Changing the location of the incident may cause a different set of alternative routes to be taken to bypass the incident and change where congestion occurs. Finally, changing the type of traffic demand simulated may further affect traffic behavior and increase or decrease the extent of the disruptions caused by the incident and congestion on local streets.

A particular element not considered in the simulated scenario is the effect of rubbernecking. Rubbernecking characterizes a situation in which drivers traveling in the opposite direction of an incident or on a nearby road slow down to look at what is happening even though there is nothing directly impacting their travel. In many cases, such slow down can be pronounced enough to create congestion in the opposite direction of a freeway or on nearby roads. This may not only result in additional delays experienced by motorists, but also push some additional drivers to seek alternate routes and alter congestion levels on these routes.

Despite the above limitations, the results of Figure 32 show that an effective rerouting scheme seeking to use information about the intended destination of a vehicle can be achieved. A typical scenario in existing transportation networks for such an incident would be to have most of the vehicles attempting to exit the freeway at the same exit ramp, with some vehicles then blindly attempting to find their way through the local street network to reach their destination. In this case, knowledge of a vehicle's current position and intended destination, as well as the location of the incident and of surrounding traffic conditions allow vehicles to be rerouted along the most efficient available detours. This translates into less congestion and traffic disruptions on the local streets, which then benefits the network as a whole.

Further benefits could be obtained if a master traffic management system could project the impacts of suggested reroutes and appropriately balance traffic loads across all available alternate routes. In this case, rerouting decisions would not only consider the benefits to individual drivers, but also the benefits to the overall system. In such a case, some drivers could for instance be pushed along less than optimal routes if it is assessed that such a choice may allow smoother traffic operations.

8.5.9. Market Share Effects

Figure 33 examines the impacts of varying the proportion of vehicles equipped with IntelliDrive instrumentation. Contrary to previous analyses, these results are based on a single replication run. However, the illustrated trends are clear enough to draw general conclusions.

As indicated earlier, only IntelliDrive vehicles are assumed to actively reroute around the incident. Non-IntelliDrive vehicles that have already started on their journey when the incident occurs do not seek alternate routes. On the other hand, non-IntelliDrive vehicles released after the incident has occurred partially respond to the incident. Since these vehicles select their travel path based on information about link travel times that is updated every 5 minutes, there is a gradual awareness of the incident that leads vehicles to seek path around the congestion that is created by the incident. IntelliDrive vehicles use the same link travel time information as non-IntelliDrive vehicles, but are allowed to adjust their intended path at the next possible opportunity after receiving notification of the occurrence or clearance of an incident.

The diagrams of Figure 33 clearly indicate that increasing the proportion of IntelliDrive vehicles translates into additional benefits for the vehicles directly affected by the incident (Groups 1, 2 and 3). As more vehicles have access to the rerouting application, more of them can seek alternate routes. As with many IntelliDrive applications, the greatest incremental benefits appear to be made when the proportion of IntelliDrive vehicles is smaller than 40%. When the proportion exceeds 40%, there appears to be a leveling off of the incremental benefits provided by equipping more vehicles with the rerouting capability.

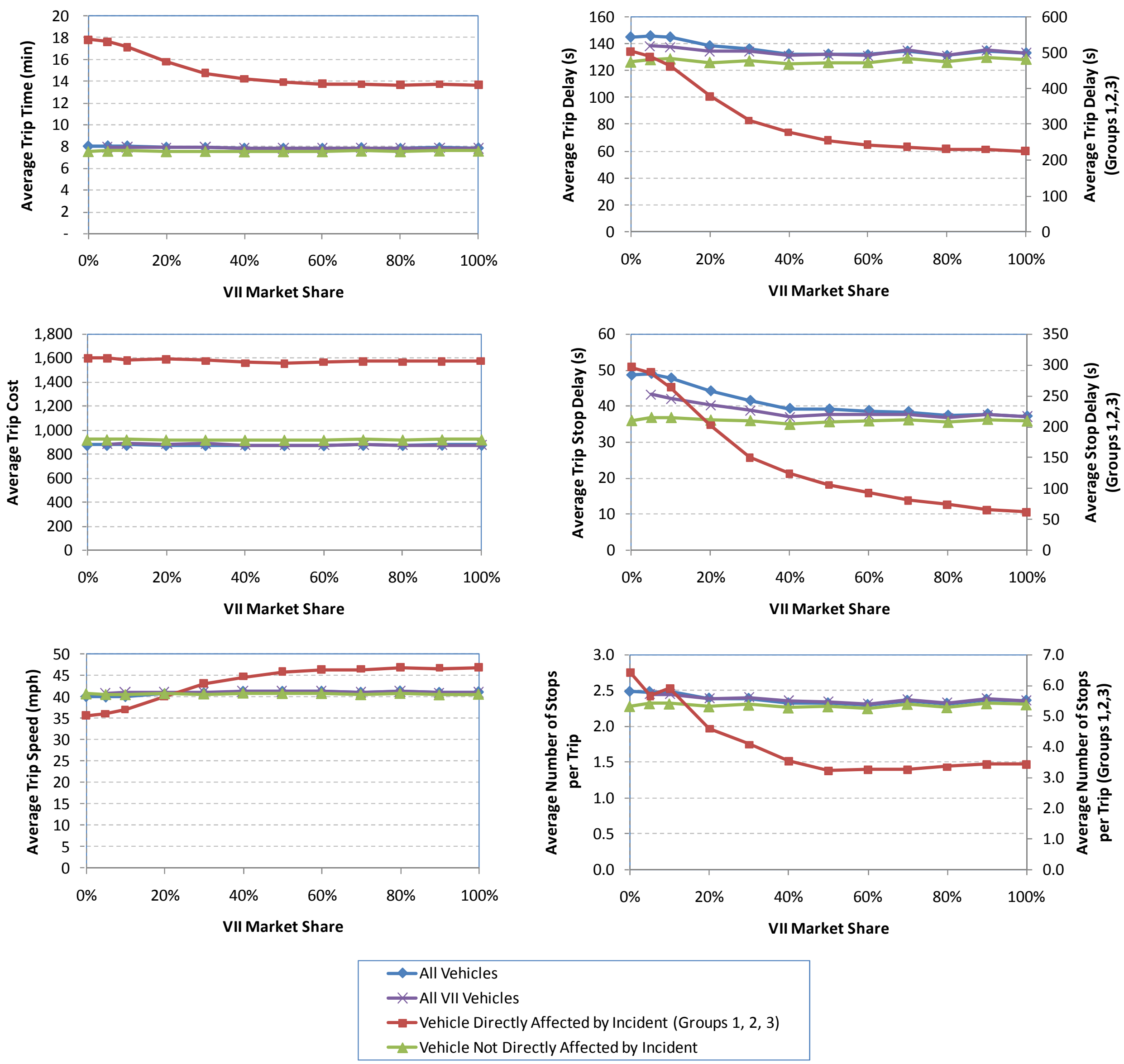


Figure 33 – Market Share Effects

For the vehicles not directly affected by the incident, there are no discernable trends. However, as explained in the previous sections, a different situation could occur if the incident scenario is changed. For a major incident having repercussions throughout a network, or a string of smaller incidents at various locations, a greater proportion of IntelliDrive vehicles may translate into an improved ability for vehicles not intending to travel on the links with incidents to avoid the secondary congestion created by the rerouted vehicles. However, as the proportion of IntelliDrive vehicles increases, additional congestion may be created by allowing all vehicles to seek their own optimal route. For this reason, a balance will then need to be struck between network control objectives and the travel desires of individual drivers. Since an approach considering such compromise has not yet been implemented in the simulation model, it could be considered in a future analysis.

9. Conclusions

The aim of this project was to assess the benefits of including O-D trip information in the data set transmitted by IntelliDrive vehicles. This information not only includes the identification of the starting and end points of a trip but also information that can be obtained through the ability to track vehicles across a network. This information may include the location and speed of a vehicle every second, a record of the links entered by a vehicle during its journey, the time a vehicle has entered each link, the time taken to travel a link, etc.

The primary benefits of enabling IntelliDrive vehicles to report trip information include:

- Ability to collect direct trip information from a large pool of vehicles. This ability would allow for a significant increase in the quantity of direct trip information collected when compared to current practice regarding the execution of travel surveys. It would also remove the need for developing synthetic O-D matrices through the analysis of surrogate data, thus creating a potential of increased accuracy in modeled trip patterns and reliability in study results.
- Ability to collect information about trips occurring anywhere IntelliDrive vehicles go.
- Ability to continuously collect trip information. This may translate into an enhanced ability to determine time-of-day and time-of-week travel patterns, as well as to identify long-term trends in travel pattern changes.
- Ability to use information about the intended destination of a vehicle to provide route guidance.

With respect to planning activities, enabling IntelliDrive vehicles to collect O-D trip data would translate into improved abilities to estimate travel demand patterns, analyze the operational performance of specific network elements, analyze trips with specific characteristics, analyze chain trips, and track trends. From a traffic management standpoint, O-D data from IntelliDrive vehicles would enable enhanced modeling of traffic demand patterns for simulation models, more detailed evaluation of traffic behavior along roadways, the development of signal timing plans better reflecting traffic patterns, and the development of more refined traffic management and emergency evacuation plans. Additional benefits may also be expected for travelers and system operators through the development of dynamic vehicle routing applications.

Due to various factors, generic benefit-cost ratios assessing the potential overall impacts on system operations of applications benefiting from the provision of O-D trip data by IntelliDrive probe vehicles cannot be estimated. Because of a constantly changing technology environment, deployment costs are difficult to assess, particularly for applications that may still be years away from practical deployment. Many applications may also be deployed with low additional costs on infrastructure that may already be planned for other applications. The benefits obtained from specific applications are also likely to be affected by network specific elements. This thus creates a need to assess potential benefits on a network-by-network basis.

While there are legitimate concerns for loss of privacy through the potential for tracking vehicles, options are available to mitigate these concerns. One recommended mitigation approach calls for preventing data collection while a vehicle is within a certain distance of its origin or destination. While this may prevent the analysis of point-to-point trips, it may not overly restrict the analysis of zone-to-zone data. Another proposed approach calls for vehicles to change their identification numbers every time they come into contact of a roadside communication unit or at some other pre-specified interval. While currently favored by many system designers, this approach may be too restrictive, as it would effectively prevent long-distance tracking and trip-based analyses. A potential compromise to this recommendation is to entice travelers to opt-in to the tracking functions in exchange of some services.

A simulation analysis finally examined the network operational benefits that could be obtained from enabling IntelliDrive vehicles to use O-D trip information for dynamic route guidance. The analysis looked more specifically at the operational impacts of allowing IntelliDrive vehicles to dynamically reroute around a major incident completely blocking a freeway ramp for 15 minutes. As expected, vehicle having the ability to be rerouted around the incident generally experienced lower delays than vehicles without the rerouting capability. However, overall individual trip costs did not necessary go down, as vehicles often ended up trading delay reductions for travel along longer routes. One of the most significant benefits of the rerouting application is the ability to reroute IntelliDrive vehicles anywhere they are. Access to O-D data is particularly beneficial for vehicles that are still far away from the incident, as these vehicles may still have access to a range of alternate routes and have an opportunity to pick detours that may be less congested than alternate routes close to the incident. Rerouting vehicles farther away from the incident also reduces the amount of traffic heading towards the incident and the overall congestion on streets around the incident.

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Appendix A – Origin-Destination Flow Assignment Methods

Vehicle routing depends on the availability of information about the origin and destination of vehicles. Based on this information, various techniques can be used to determine the route that specific vehicles may take to travel across a network to their destination. Some of the methods that have been proposed over the years include:

- Minimum path (all-or-nothing) assignment.
- Deterministic user equilibrium.
- Stochastic user equilibrium.
- System optimum assignment.
- Dynamic traffic assignment.

The above models reflect the various technical shifts. Early methods proposed in the 1950s and 1960s were primarily static and aggregate methods designed to be used within the traditional four-step planning method. In the 1970s and 1980s, research primarily focused on developing disaggregate demand models considering individual trips instead of zonal flow rates and capable of producing assignment solutions satisfying network equilibriums. Over the past 20 years, supported by increasing computer power, research on traffic assignment method has primary focused on dynamic problems in which network conditions may change over time. The following sections describe in more detail each of the various assignment approaches mentioned above.

A.1. Minimum Path Assignment

The all-or-nothing assignment technique allocates the entire flow between two zones on the links along the path offering the minimum travel cost based on free-flow travel. In essence, this method assumes that all travelers between two zones actually select the same path. While this approach clearly generates unrealistic flows, it is frequently used because of its simplicity and the fact that it depicts the routes most travelers would be expected to use in the absence of capacity and/or congestion effects.

A.2. Deterministic User-Equilibrium Assignment

Equilibrium assignment techniques explicitly recognize that the cost of traveling across a transportation network depends on the level of traffic flow within the network. For example, it is generally understood that more time may be needed to travel across a congested roadway link than a similar link operating under free-flow conditions. Within this context, deterministic assignment techniques assume that travelers in a transportation system have perfect information about travel times on potential alternative paths within the network, are rational, and behave identically. Equilibrium is found by applying Wardrop's first principle (Wardrop, 1952). This principle states that all drivers choose the route with the lowest travel cost available. Equilibrium is then reached when no driver can unilaterally achieve a reduction in travel time or cost by changing his route.

A frequently cited technique within this group is the **incremental assignment** method. In this technique, a fixed portion of the total demand is assigned to the network at each step, usually according to an all-or-nothing approach. Following the assignment, link travel times are then recalculated based on the new link volumes and used in the next step to assign to the network the next portion of the demand. When many increments are used, results of this technique may resemble an equilibrium assignment. However, this method does not necessarily yield an equilibrium solution due to the use of an all-or-nothing assignment. This may lead to inconsistencies between link volumes and travel times, and, subsequently, to errors in evaluation measures. Incremental assignment is also influenced by the order in which volumes for O-D pairs are assigned, which further raises the possibility of additional bias in the results.

Another well-known deterministic user-equilibrium assignment technique is the **capacity restrained technique**. This technique attempts to account for the fact that roadways have limited capacity and that travel time across roadway links tend to increase as traffic flows near capacity, thus pushing additional travelers to seek other, less costly routes. In this technique, trips are again allocated in increments, with travel times associated with each link adjusted at end of each stop to reflect resulting changes in traffic flows. In this case, however, trips can be distributed over multiple routes. Because it considers capacity constraints, this technique is generally considered most applicable to peak-hour assignment. However, because it is based on a heuristic approach, there is no guarantee that the resulting assignment is a true user-equilibrium.

Currently, the most widely used deterministic user-equilibrium assignment technique is the **Frank-Wolfe algorithm**. This algorithm is widely used in transportation planning software, such as EMME/2 [Chen *et al.*, 2002; Boyce *et al.*, 2004]. This algorithm was originally developed in 1956 to solve quadratic mathematical programming problems. Its popularity is attributed to its modest memory requirements and simplicity, which allows planners to solve networks of realistic sizes. Since the model does not need to store paths, it is further applicable to the analysis of large-scale networks. However, one of its major drawbacks is its slow convergence.

Aside from the above technique, there have been various attempts to use formal mathematical optimization techniques to seek deterministic user-equilibrium solutions reflecting more accurately observed driver behavior. These approaches are generally relatively complex and subject to the degree to which the mathematical model used to represent the transportation network and traffic demand adequately represents their real-world counterpart. For these reasons, the proposed methods have generally remained within the academic realm.

While static assignment techniques have been routinely used for traditional planning applications with somehow acceptable results, they are inadequate for modeling information provision, traffic dynamics and temporal elements of user behavior. This makes their suitability for certain applications, such as evaluating ITS technologies, quite questionable and has resulted in significant research being devoted to producing models more accurately reflecting reality.

A.3. Stochastic User-Equilibrium Assignment

Stochastic assignment techniques recognize that travelers do not have perfect travel cost information, as is assumed in deterministic user-equilibrium techniques. Stochastic assignment techniques treat travel costs as a random variable that can vary among individuals based on their perception, experiences, and preferences. In effect, they are based on the assumption that drivers seek to minimize their perceived travel time and not necessarily their actual travel time.

Stochastic user-equilibrium assignment techniques are generally expected to produce different solutions than deterministic techniques. This generally holds true for networks in which there are substantial differences between actual and perceived travel costs. However, it has also been demonstrated that both deterministic and stochastic equilibrium solutions often tend to become similar for very congested networks [Prashker and Bekhor, 2000]. This is explained by the fact that as congestion increases, stochastic effects in travel time or travel costs become less dominant factors in choosing a specific route for travel.

Stochastic user-equilibrium solutions have traditionally been developed using one of the following two approaches:

- Multinomial logic models.
- Multinomial probit models.

The mathematical formulation of logit models is presented in Section 3.2.2 of the main body of the report. Probit models are similar in concept. Their main difference is in how the probability model is formulated. Logit models are based on logarithm odds while probit models use a cumulative normal probability distribution. Predictions made by a logic and probit model are often very similar. Logit models assume that the factors affecting travel cost are independent and identically distributed, which prevent them from taking into account route correlation. Multinomial probit models do not assume independence and identification distribution of cost factors. However, they encounter serious problems with tractability, which have restricted their application in practical work.

Various alternative logit and probit models formulations seeking to address the problems associated with classical logit and probit models can be found in the literature. Examples include assignment methods based on nested logit, cross-nested logit, paired combinatorial logit, generalized logit and error component logit (Batley and Clegg, 2001). However, because of their considerably greater theoretical and computational complexity, these proposed stochastic assignment procedures have generally seen limited application in engineering practice and have primarily remained in the realm of academic research.

A.4. System Optimum Assignment

User equilibrium is achieved when no traveler can unilaterally reduce his travel costs by moving to another route. In other words, user equilibrium is achieved when travelers are assigned in such a way that for each O-D pair in the network the total travel costs experienced by the travelers, no matter which combination of travel routes and departure times they choose, are equal and minimal.

System optimum assignment assumes that travelers will cooperate in making their travel choices for the overall benefit of the whole system instead of their own individual benefits. Under a system-optimal equilibrium, no individual traveler can switch to a different route without increasing the cumulative total network travel time of all travelers. This is often referred to as Wardop's second principle, which states that at equilibrium the average trip time within a network is minimum (Wardrop, 1952). In this case, individual drivers would not necessarily minimize their own travel time or cost. This assignment method can be thought of as a model in which congestion is minimized when drivers are told which routes to use and faithfully obey the recommendations. While this is not a behaviorally realistic model, it can be useful to transportation planners and engineers trying to manage the traffic towards minimum travel costs.

The comparison between user-equilibrium and system-optimum solutions has long been studied in the literature. For low congested networks, user-equilbrium solutions have been found to approach system optimum flow pattern. However, this similarity is not always reached for congested networks [Prashker and Bekhor, 2000].

A.5. Dynamic Traffic Assignment

Many of the early assignment models were developed in a static way, in which vehicle flows and trip characteristics were assumed not to change over time. Such an approach is generally considered acceptable for regional transportation planning applications where the focus is to gain an understanding of general flow patterns and required roadway capacities at some point in time. However, such a static representation of network performance is not sufficiently accurate for many other applications, such as real-time traffic management and traffic operations modeling. In such cases, a dynamic representation of route choice behavior and resulting network performance is required in which network operating conditions and driver choices may change from one time interval to the next.

Dynamic assignment models introduce time as a variable in the assignment problem. In this case, the objective is not only to determine which route a traveler is to take, but also when a journey will be made. Early models essentially only dealt with the route choice of travelers. Typically, although demand was assumed to vary over time, these variations were considered fixed within the study period. Over time, however, various models introducing departure time as a variable were introduced [Ran and Boyce, 1996; Yang and Meng, 1998; Chen and Hsueh, 1998; Lam *et al.*, 1999]. Other efforts have also attempted to replace the traditional trip-based modeling, in which each trip is treated independently of other trips, by activity-based modeling, in which trips may be part of chains and may be delayed or cancelled due to the postponement of other trips [Lam and Yin, 2001].

The selection of routes within dynamic assignment problems can be approached either from a deterministic or stochastic point of view, and seeking either a user-equilibrium or system optimization. However, the particular difficulty of developing solutions to dynamic assignment problems primarily resides with the added complexity of having to consider time factors in network performance and travel demand loading. Since the time to traverse a link will depend upon the traffic volume encountered on the link, link travel time will also change from one moment to the next. This creates a need to adequately model interactions between travel demand and network performance, more specifically, how changes in traffic demands affect network performance and how changes in network performance affect travel behavior.

As of today, two primary approaches have dominated the methodologies applied to dynamic traffic assignment research [Ban *et al.*, 2008]: approaches relying on the use of microscopic and mesoscopic simulation models and approaches relying on analytical modeling. In the former case, simulation is used to make predictions within an iterative assignment framework. Use of simulation facilitates the capture of complex traffic behavior and significantly simplifies the analysis of traffic signal control strategies. Notable efforts on the use of simulation to solve dynamic traffic assignment problems include development of the DYNASMART [Mahmassani, 1992], DynaMIT [Ben-Akiva *et al.*, 1997] and DYNAMEQ [Mahut *et al.*, 2007] models, as well as work by Varia and Dhinghra (2004).

The second approach primarily relies on macroscopic analytical solutions. Examples of macroscopic analytical solutions that have been proposed include the use of:

- Mathematic programming [Merchant and Nemhauser, 1978; Carey, 1987; Janson, 1991].
- Optimal control theory [Ran and Boyce, 1994; Lam and Huang, 1995].
- Constrained optimization approach.
- Variational inequality [Ran and Boyce, 1996; Friesz and Mookherjee, 2006; Ban *et al.*, 2008; Nie and Zhang, 2008].
- Genetic algorithms [Sadek and Seli, 2004].

Most of the analytical approaches proposed to date may be classified as short period dynamic models aimed at representing traffic conditions within 10-15 minute periods by taking into account queuing and/or spillback effects. In many cases, the stated objective is to develop models that could be integrated into advanced traveler information systems (ATIS), advanced traffic management systems (ATMS) and route guidance systems. However, these proposed models have in general not yet been implemented in practice due to their burdensome computation requirements for large transportation networks.

Some models focusing on analyses of one-hour time periods have also been proposed [Bell *et al.*, 1996; Lam *et al.*, 1999]. These models are generally considered as quasi-dynamic and make some simplifications on the dynamics of the transportation network in order to improve computational efficiency. While they are not true dynamic models, they can be considered as sufficient to assess the long-term impacts of transportation policies [Lam and Yin, 2001]. Dynamic traffic assignment models could also be categorized into models assignment and non-assignment-based approaches [Lin and Chang, 2007]. Assignment approaches rely on assumptions that a reliable prior time-varying O-D set and an accurate dynamic traffic assignment model is available. This approach is used in the research work of Cascetta (1984), Cascetta *et al.* (1993), Ashok and Ben-Akiva (2002), Hazleton (2000), Sherali and Park (2001), and Tsekeris and Stathopoulos (2005). Recognizing the practical difficulty of obtaining reliable prior time-varying O-D information, some researchers developed instead approaches utilizing only the time series of available traffic counts to reduce the dependency on prior O-D matrices and traffic assignment models. This includes research work by Cremer and Keller (1987), Bell (1991) and Lin and Chang (2007).

Another possible classification can be made based on definition of the travel time cost measure used in the development of the equilibrium [Tsekeris and Stathopoulos, 2005]:

- **Dynamic system-optimal assignment**, in which the assignment procedure is based on the minimization of the total travel cost in the network.
- **Reactive dynamic user-optimal assignment**, in which it is assumed that each traveler departing from a particular location at any instant chooses the shortest path to his destination based on the minimization of instantaneous travel time. This is the time perceived according to the currently prevailing traffic conditions. This time is estimated at the time the traveler enters the path.
- **Predictive dynamic user-optimal assignment, in which** the impact of future traffic conditions on route choice behavior is considered. The shortest path is thus determined based on the minimization of the ideal travel time.

In general, predictive traffic assignment problems are much more difficult to solve than the reactive problems due to the restrictive computational needs and the vague properties of actual path travel time in real-life networks. In contrast, the instantaneous path travel time is simpler to elaborate, and it can be derived from the cost experienced in previous time interval. This assumption may be considered reasonable in the view that most users crystallize their decisions to use specific links prior to the current estimation procedure. In most of the current traveler information systems, the information provided to the users is the estimated instantaneous route travel time. This means that assignment methods developed solely on the use of this data may only be reactive in nature, unless some form of data projection is used to make predictive assumptions about future traffic conditions on individual links at the time a vehicle is expected to reach it.

Appendix B - Programmed Paramics Functionalities

To allow experimentations with vehicle navigation applications, several functionalities were added to the Paramics simulator through the software's Application Programming Interface (API). Functionalities added to the model include:

- Ability for all simulated vehicles to keep track of overall travel delays, stopped delay and the number of stops experienced while traveling.
- Output of summary trip statistic for individual vehicles.
- Recording of travel path followed for all simulated vehicles.
- Ability for IntelliDrive vehicles to generate a list of links they project to travel to reach their destination.
- Ability to provide historical travel time and flow inputs for individual links.
- Ability to project future link flows based on the projected paths of individual vehicles.
- Response to incidents.

B.1. Vehicle Performance Measures

To assess the efficiency of routes being taken, functions were first added to allow individual vehicles to keep track of travel delays and the number of stops they made while progressing across a network. This information is compiled both on a link-by-link and an overall trip basis. These added individual statistics are calculated as follows:

- **Overall travel delay:** The overall travel delay is determined by calculating the difference between the actual trip travel time and the time it would have taken the vehicle to travel across each link at the posted speed limit for the link. In many cases, Paramics' stochastic simulation processes will allow individual vehicles to travel at speeds above the posted limit. For these vehicles, no travel delay is counted. There are also no delay credits, in which savings from travel above the speed limit on one link are used to reduce delays incurred on other links. This approach is adopted to avoid masking delays incurred on specific links, which could make it harder to identify locations with potential problems.

- **Stopped delay:** The stopped delay is calculated as the amount of time a vehicle spends immobilized.

- **Number of stops:** The number of stops is calculated as the number of instances in which the speed of a vehicle drops to a speed below 5 mph (8 km/h) from one simulation time step to the next. This definition is adopted to avoid counting multiple stops while vehicles are adjusting their position in a queue. For instance, it prevents the counting of multiple stops when vehicles move up a queue after a vehicle in front makes a right turn on red. The selection of a 5 mph threshold is consistent with various other studies focusing on the number of stops.

B.2. Travel Path Record

Paramics does not normally retain detailed trip information from individual vehicles. . However, as IntelliDrive is concerned with the travel time and routes of individual vehicles, the path individual vehicles take from an origin to a destination is of interest. To enable the retrieval of this information, each simulated vehicle is then instructed to keep a list of links on which they have traveled from their origin zone. This list is updated each time a vehicle transfers from one link to the next. Each time a vehicle exit a link, the following information is recorded:

- Link name.
- Turning movement at downstream end of link: Name of next link entered by the vehicle.
- Link entry time: Simulation time at which the vehicle entered the link.
- Link travel distance: Length of the link being traveled.
- Link travel time: Time to travel across the length of the link.
- Link total delay: Difference between the actual link travel time and the travel time that would have been observed if the vehicle had traveled at the specific link speed limit.
- Link stopped delay: Time the vehicle spent traveling at a speed of less than 5 mph (8 km/h) on the link.
- Link stops: Number of stops made on the link by the vehicle.
- Link travel cost: Travel cost returned by Paramics, or from any custom cost function supplied with an application.
- Link cost factor: Multiplicative factor from Paramics modeling that can be used to increase or decrease the weight of the travel cost associated with the link.
- Link distance factor**:** Multiplicative factor used to indicate whether a vehicle has traveled the full length of a link or only a portion of it (such as for vehicles inserted midblock onto a freeway link in the merge section of a freeway on-ramp).

B.3. Vehicle Trip Summary Output

If requested, a trip summary can be produced for each vehicle. This summary is produced when a vehicle reaches its intended destination and records the following information:

- Vehicle identification number.
- Vehicle type.
- Number of passenger car units (PCUs) associated with the vehicle type.
- Is the vehicle a truck?
- Is the vehicle a bus?
- Origin zone.
- Destination zone.
- Trip start time (seconds).
- Trip end time (seconds).
- Is the vehicle an IntelliDrive vehicle?
- Is vehicle navigation on?
- Trip cost estimated when vehicle was generated.
- Estimated number of links to travel through when vehicle was generated.
- Actual number of links traveled through.
- Trip distance (feet or meters).
- Trip time (seconds).
- Average trip speed (mph or km/h).
- Total incurred delay.
- Total incurred stopped delay.
- Total number of stops incurred.
- Trip final cost.

B.4. Projected Travel Path Search

In addition to knowing where a vehicle has been, there is significant interest in knowing where a vehicle will be traveling. In a basic simulation, vehicles are routed through a network according to route trees that are built by considering the costs and restrictions of traveling on individual links from a given origin to a specific destination. In a basic Paramics simulation, a vehicle only retains information about the current link it is traveling on and about the next two links it intends to travel on. While a table of minimum cost paths from each node to each destination is periodically built by Paramics for routing purposes, the information defining these trips is not stored within each vehicle. Vehicles only retain information about the current and next two look to help them make appropriate lane-choice selections.

In reality, vehicles equipped with GPS-based navigation systems have a more extensive knowledge of their projected path than what is currently modeled in Paramics. In most cases, a path is known for the entire length of a projected trip. This path is then automatically recalculated if the vehicle makes a "wrong turn" or if path updates are requested when there are significant changes in reported traffic conditions (for instance, occurrence of an incident).

To add similar functionality in Paramics, vehicles identified as IntelliDrive vehicles are provided with the ability to generate and store a list of links onto which they intend to travel. The following describe the link search process, the functions use for estimating travel cost, the process by which routes can be updated, and some validation results.

B.4.1. Route Search Algorithm

The minimum cost route between a given location and given destination is generated by using a routing algorithm based on the traditional Dikstra's algorithm:

- Starting from a vehicle's current location, the algorithm first calculates the cost of travel to the node at the end of the link onto which the vehicle is located
- From the identified node, the algorithm calculates the cost of travel to all neighboring nodes. At each node reached, the minimum cost path between the trip origin zone and the node being considered is stored within the node's data structure.
- The node with the lowest travel cost is then selected as the next node from which travel is to be considered.
- If travel to a specific node results in a lower travel cost from the trip origin than the currently stored path, the path with the lowest cost is always retained.
- The above process is repeated until the intended destination node is reached or until all nodes have been visited at least once.
- If all nodes are visited before the destination is reached, an invalid path search is then declared and no path is returned by the algorithm. Such cases may occur due to some complex network geometry requiring drivers to visit some nodes multiple times from different directions.

At the end of a route search, the produced path is stored within the vehicle that has requested its generation as a list of projected travel links. For each link along a given path, the following information is retained:

- Link traveled.
- Link projected turn movement (next link to take).
- Link projected entry time.

- Link projected travel time.
- Link projected travel distance.
- Link projected travel cost.
- Link cost factor.
- Link distance factor.

In addition to individual link data, the following overall trip statistics are also produced:

- Number of links along projected path.
- Projected total trip time.
- Projected trip distance.
- Projected trip cost.
- Flag indicating whether the intended destination has been successfully reached.

B.4.2. Travel Cost Estimation Function

By default, the search for a minimum cost route is done using Paramics' cost function. This function estimates travel costs using a weighted combination of travel time, travel distance, and out-of-pocket costs, as shown in the equation below:

$$Travel\ Cost = \sum_{link\ i} \left[f_{cost\ i} \times \left(\alpha\, TT_i + \beta\, Dist_i + \gamma\, Toll_i \right) \right] \qquad \text{[B-1]}$$

where: *Travel Cost* = Network travel cost
TT_i = Travel time on link *i* (seconds)
$Dist_i$ = Travel distance on link *i* (meters)
$Toll_i$ = Toll to travel on link *i*
α, β, γ = Network-wide weight cost element parameters
$f_{cost\ i}$ = Cost multiplication factor for link *i*

The parameters α, β and γ are uniformly applied to all vehicles in a network. They specify the relative importance that travelers put on each cost element. Default values assume $\alpha = 1$, $\beta = 0$, and $\gamma = 0$, i.e., routing considering only travel time. Link cost factors, $f_{cost\ I}$, are further used to provide higher or lower weights to the travel costs associated with specific link. For instance, a link factor greater than 1 can be used to increase the perceived cost of traveling on links with construction activities to emulate the desire of travelers to avoid such links if alternatives exist. A link factors lower than 1 could also be used to reduce the perceived impacts of traveling on freeway links and create a bias in route choice towards using freeways.

Within Paramics, routing decisions are based on the latest available estimates of link travel times and prevailing toll rates. The degree to which this information represents current conditions is determined by the frequency of information feedback defined in the network configuration file. If no feedback is defined, then all routing will be based on observed traffic conditions at the beginning of the simulation. If a 5-minute is instead provided, then all link travel times will be reassessed every 5 minutes based on the observed travel times of vehicles that have go across each link during the interval. The result of this reassessment will depend on a series of smoothing factors defined by the user.

In addition to travel costs based on the equation shown above, options have been built to allow routes to be built only speed-limit travel times or a user-defined table of historical travel times for each link.

Plans are also being drafted to develop functions assessing travel times according to projected traffic conditions.

B.4.3. Route Update Mechanisms

To allow projected paths to adjust to changes in network traffic conditions or to respond to unexpected turn decisions made by individual drivers, the following events are programmed as triggers for the regeneration of a vehicle's projected path:

- Vehicle entering a different link than the one stored within its projected path.
- Vehicle entering a link more than *n* second before or after the expected link entry time (user-defined parameter).
- Execution of a link travel cost feedback loop by Paramics. This event results in vehicles reassigning their projected path the next time they transfer from one link to the next. Any change in projected path then takes effect at the downstream end of the link just entered.

The user is provided with the option to turn off both the link entry time adjustment and path re-generation following a link travel time feedback loop by Paramics.

To reduce the computational burden, constraints have also been defined to reduce the number of path re-generations. Currently, path re-generation can be blocked when a vehicle:

- Has had a path generated within the past *n* seconds (user-definable parameter).
- Is within *n* feet of its destination (user-definable parameter).
- Is currently on a link connected to its destination zone.

In addition to the above elements, a repeat mechanism has been built to allow vehicle to bypass some of the above constraints in cases in which the search algorithm fails to determine a valid path. In such a case, a flag is turned on when an invalid search is obtain to indicate that the vehicle attempting to obtain a path was unable to do so. This flag will allow the vehicle to ignore time and distance constraints between path regeneration until a valid path is obtained. When this occurs, the flag is then turned off to resume normal path search activities.

Finally, an option has been built to allow a specific path to be imposed to a vehicle. Each time a vehicles enters a link, it will assess whether the next and second next intended links returned by the Paramics default routing algorithm corresponds to the first and second next links in the vehicle's stored path. If a difference exists, vehicles then have the option to either follow the routing decision determined by Paramics or to stick with the path stored in their memory. Which approach is taken will entirely depend on how the user sets up a specific routing application.

B.4.4. Search Algorithm Validation

Validation of the search algorithm has been conducted by comparing vehicle behavior under identical cost weight assumptions in scenarios using the default Paramics routing and scenarios using the developed search algorithm. Simulation results have indicated that the developed routing algorithm generally produces identical travel paths as Paramics' internal routing functions. Differences were observed in a very small number of cases (less than 3 percent for the test network used and described later in this report). In most cases, these differences could be attributed to network geometrical constructs that make it difficult to correctly process a specific sequence of nodes that a driver would take to cross an intersection. Particularly difficult intersections to process are those with “Michigan Left-Turns.” At these intersections, vehicles have to turn right and use a median U-turn to make a left turn.

B.5. Provision of Historical Link Flows and Link Travel Times

Another programmed addition to Paramics is the ability to provide the model with a table of projected link travel times. This feature was implemented to enable the evaluation of applications seeking to do routing according to historical traffic conditions. Currently, Paramics route vehicles according to current traffic conditions. At the beginning of a simulation, average link travel times are simply the link travel times at speed limit, without consideration of delays associated to traffic control devices or traffic flow interactions. These elements can be considered by specifying an information feedback loop in which average link travel times are recalculated every n minutes. However, this approach will not allow calculating projected path according to the conditions that a vehicle may truly experience. If a vehicle takes 30 minutes to travel across a network, its entire route will be planned according to the existing traffic conditions at the time of origin.

In many urban areas, historical traffic flow and travel time information may be compiled from existing traffic detectors and other surveillance equipment. In such cases, it is possible to consider typical traffic conditions that may be expected on each link along a given route at the time a vehicle is expected to reach the particular link. This can be done by simply matching the projected link entry time with the travel time that is typically observed at that time. Consideration of projected travel conditions rather than existing conduction may lead to different routing decisions for trips of sufficient length, particularly when trips occur at a time when traffic conditions are changing.

To provide a similar capability in Paramics, functionalities have been programmed to allow model users to enter for each link a list of historical link travel times and link entry flows. For each link, this information can be provided for a sequence of intervals, such as for every 5, 10 or 15 minutes. The length of this interval is user-definable.

For many networks, the information characterizing historical average link flow and link travel time could be developed based on data from traffic surveillance systems. If such data is not available, model users are provided with the option to have Paramics automatically generate “historical” link travel time and link entry flow data based on simulated data. In such a case, the user would run a simulation while indicating that observed link travel times and flows should be outputted at the end of the run. Following a simple change of file extension, the resulting output files could then be used as input file for other simulations using the same network.

In the input file, travel time and flow projections are provided for individual link exit movements. For instance, at an intersection where vehicles could turn left, go straight or turn right, travel time and flow projections would be provided for each of the three movements. This is to allow evaluations or applications considering specific movements. In this context, flow statistics for the link as a whole are estimated by summing the flows associated with each exit movement, while average link travel times are determined by calculating a weighted average of the travel times associated with each movement.

B.6. Routing Link Flow Projections

In addition to the route generation functions, functions have been programmed to allow Paramics to keep track of the projected link flows on individual links that may result from the routing decisions being made. This functionality uses the expected link entry time attached to individual link record within a vehicle's projected path to compile future demand for each link. To account for potential time-based fluctuations, this demand is compiled in intervals with duration specified by the model user. If the user specifies the use of 5-minute intervals, projected link entry flows will then be compiled for each successive 5-minute interval.

Updates in the link flow projections are made in the following three cases:

- Each time a new route is generated upon the release of a vehicle from an origin zone.
- When an existing route is updated.
- When a vehicle transfers from one link to the next.

In the first case, the projected link entry times of the newly released vehicle are used to increment the number of vehicles expected to enter each link along its path in the corresponding time interval. In the second case, projected flows on individual links within a specific interval are adjusted to account for changes in the time at which a vehicle is projected to enter a link. This adjustment only has an impact if it results in a vehicle entering a link in a different time interval. Adjustments are also made to account for path changes. For instance, projected flows would be decremented on links that are removed from the projected path of a vehicle and increased on links that are part of any new projected route. In the last case, addition and subtraction to projected flows are carried out to account for vehicles entering and leaving links.

Flow projections are made both for the link as a whole and for individual exit movements. This enables evaluations or applications focusing either on the entire traffic traveling on a link or on issues related to specific turning or through movements.

B.7. Response to Incidents

Paramics allows model users to simulate incidents that disrupt network operations, for example, the impacts of a vehicle breakdown on a traffic lane or vehicles stopping on a traffic lane to drop off or pick up passengers near a bus terminal or other point of interest. Incidents are defined by coding in an input file labeled "incidents" the location of the incident, its duration, the speed at which vehicles pass the blockage on adjacent lanes, and, to simulate rubbernecking, the speed of vehicles traveling on the opposing lane.

Under normal Paramics operations, vehicles would only adjust their routing decision in response to an incident if a dynamic information feedback loop is used. These loops are used to update at regular intervals the cost of traveling on individual links. These cost updates are executed by factoring in actual link travel times from vehicles that have completed travel on each link since the execution of the last feedback loop. Following an incident, queue buildup on links leading to the incident would result in increasingly longer travel times. As these increases in travel times get incorporated into the average travel cost estimates of individual links, alternate routes could then be produced if these changes lead to the identification of new shorter travel paths to a vehicle's intended destination.

The rate at which Paramics updates link travel costs depends on the frequency of the feedback loop set up by the model users. If a 5-minute frequency is used, a 5-minute delay could then occur before the congestion created by an incident starts to affect routing decisions. In such a case, the response may be further dampened by the use of moving averages and other smoothing parameters. This may result in a system that reacts too slowly to an incident.

To model the potential capability to quickly inform IntelliDrive vehicles of an incident, functionalities have been added to allow IntelliDrive vehicles to respond more quickly to the occurrence of incidents. These functionalities are programmed through the provision of information characterizing the duration and magnitude of incident in the "*DSRCSetup.dat*" input file used to model the operational parameters of an IntelliDrive system being simulated. Figure 1 presents the format of the information being provided. Parameters between brackets are those that must be provided by the user.

```
Number of Incidents <n>
1  <Link Name>   <Start Time> <End Time>   <Cost Factor>
2  <Link Name>   <Start Time> <End Time>   <Cost Factor>
…  …          …             …              …
n  <Link Name>   <Start Time> <End Time>   <Cost Factor>
```

Figure A.34 – Incident Setup in Paramics IntelliDrive setup file

The first element of the incident response modeling adds an incident multiplication cost factor in the function used by Paramics to estimate link travel costs. The resulting function takes the following form:

$$Travel\ Cost = \sum_{link\ i} \left[f_{cost\ i} \times f_{incident\ i} \times \left(\alpha\, TT_i + \beta\, Dist_i + \gamma\, Toll_i \right) \right] \qquad \text{[B-2]}$$

with:

$$f_{incident\, i} = \begin{cases} user-defined\, value & if\ T \geq I_{start}\ and\ T < I_{end} \\ 1.000 & ortherwise \end{cases} \qquad \text{[B-3]}$$

where:
- *Travel Cost* = Network travel cost
- T = Simulation time (seconds)
- TT_i = Travel time on link *i* (seconds)
- $Dist_i$ = Travel distance on link *i* (meters)
- $Toll_i$ = Toll to travel on link *i*
- α, β, γ = Network-wide weight parameters
- $f_{cost\ i}$ = Cost multiplication factor for link *i*
- $f_{incident\ i}$ = Incident cost multiplication factor for link *i*
- I_{start} = Start time of incident (seconds)
- I_{end} = End time of incident (seconds)

The multiplication factor is only applied when an incident is assumed to be affecting traffic. Both the parameters defining start time (I_{start}) and end time (I_{end}) of an incident are user-defined. Any vehicle intending to travel on the link affected by the incident between the defined start and end times will then have its travel cost on the affected link adjusted by the defined factor. Use of a multiplication factor of 1.0 would result here in the incident being effectively ignored. Factors greater than 1.0 would then result in a proportionally higher additional cost for traveling along the link. To effectively prevent a vehicle from traveling on the link, a very large factor, such as 1000 or 10,000 could be used to generate a large cost increase that would make any other potential route more attractive.

Vehicle re-routing following an incident is set to only affect vehicles defined as IntelliDrive-equipped. When the simulation reaches the start time of an incident (I_{start}), a flag is activated to instruct all IntelliDrive vehicles to start assessing whether they are projecting to travel on a link affected by an incident. Any vehicle projected to enter the link with the incident while it is still active (i.e., while the vehicle's link entry time based on its projected travel path is less than I_{end}) is then instructed to re-evaluate its intended route.

Route reassessment typically happens the next time a vehicle transfers from one link to another. This modeling approach was adopted for computational efficiency reasons. Since road networks are typically modeled in Paramics using short links, this typically results in delays of only a few seconds between the start of an incident and the moment vehicles start to respond to the incident. This delay can be assumed to be part of the time that would normally be needed for receiving the incident notification information or for a navigation system to generate a new route. The only vehicles for which this approach may negatively restrict routing options are those that are currently traveling on the link immediately upstream of the last potential re-route decision point. Because routing is reassessed after the vehicle has transferred to the downstream link, these vehicles will effectively be prevented from seeking an alternate route. However, because of the use of short links, such a treatment should only affect a very small number of vehicles.

Depending on the scenario being considered, the incident's start and end times set up in the "DSRCSetup.dat" input parameter file may not correspond to the actual incident's start and end times. Paramics is left in charge of simulating the actual incident. The incident start time provided in the DSRCSetup.dat input file can be the time at which IntelliDrive vehicles are notified of the incident. Similarly, the incident end time could be the time at which the incident notification is removed and vehicles are again allowed to normally route through the affected link. The incident end time could for instance be the time at which a queue that has built up being the incident is assumed to have sufficiently dissipated.