Analysis of Network and Non-Network Factors on Traveler Choice Toward Improving Modeling Accuracy for Better Transportation Decisionmaking

PUBLICATION NO. FHWA-HRT-13-097 SEPTEMBER 2014

U.S. Department of Transportation
Federal Highway Administration

Research, Development, and Technology
Turner-Fairbank Highway Research Center
6300 Georgetown Pike
McLean, VA 22101-2296

FOREWORD

Travelers' choices are central to the performance of a transportation system, but little is known about what influences such choices or the impact they have on system performance. When selecting a transportation management strategy, a transportation management center operator must understand and anticipate how travelers will respond (i.e., will they stay on the same routes or divert; will they decide to walk, bike, or take a bus or train instead of driving; will they leave earlier or later, etc.).

The operator must know the potential benefits of alternative overall strategies (e.g., variable pricing or information on dynamic message signs) as well as how to handle day-to-day operations by implementing strategies to provide effective responses to particular events. The operator must also account for non-network, predisposing factors that influence travelers' choices. Such factors, including land use, population density, and walkability, are generally out of the control of the network manager, and their influence may not be intuitively obvious.

This report addresses the current state of the practice, identifies gaps in knowledge regarding traveler choices, and provides six case studies on how to improve current models. This report provides a comprehensive conceptual framework that incorporates traveler behavior and the impact on network performance for demand-side and supply-side measures. This report will be a resource for both traveler choice researchers and organizations considering transportation management strategies that influence traveler choice.

Joseph I. Peters
Director, Office of Operations
Research and Development

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. FHWA-HRT-13-097	2. Government Accession No.	3. Recipient's Catalog No.

4. Title and Subtitle
Analysis of Network and Non-Network Factors on Traveler Choice Toward Improving Modeling Accuracy for Better Transportation Decisionmaking

5. Report Date
September 2014

6. Performing Organization Code

7. Author(s)
Hani S. Mahmassani, Charlotte Frei, Andreas Frei, Joseph Story, Lewison Lem, Alireza Talebpour, Ying Chen, Ali Zockaie, Meead Saberi, Hooram Halat, and Robert Haas

8. Performing Organization Report No.

9. Performing Organization Name and Address
SAIC, M/S E-12-3,
8301 Greensboro Drive, McLean, VA 22102

Northwestern University
The Transportation Center
600 Foster Street, Evanston, IL 60208-4055

10. Work Unit No. (TRAIS)

11. Contract or Grant No.
DTFH61-06-D-00005, Task Order T-11-013

12. Sponsoring Agency Name and Address
U.S. Department of Transportation
Federal Highway Administration
1200 New Jersey Avenue, SE
Washington, DC 20590

13. Type of Report and Period Covered
Final Report; July 2011–April 2013

14. Sponsoring Agency Code

15. Supplementary Notes
The Contracting Officer's Technical Representative (COTR) was Taylor Lochrane, HRDO-20.

16. Abstract
The need to reduce congestion, enhance safety, and make the U.S. transportation system and cities more sustainable has given rise to various programs, technologies, and policies. The effectiveness of these interventions depends on how users eventually respond and, in some instances, modify their travel behavior. While significant advances have taken place over the past 50 years in the field of travel behavior research and travel demand forecasting, the ability to reliably predict the direction and magnitude of behavioral responses to various network and non-network factors and interventions remains limited. Many experts have called for better data collection and analysis methods and better integration of behavior models with supply analysis tools.

This report provides a synthesis of the state of knowledge in travel behavior research and showcases how to improve current models with relevant behavior realism through six case studies. These case studies range from long-term policy interventions (e.g., urban design policy affecting land use and neighborhood walkability), to short-term en-route interventions (e.g., traveler information systems for weather-responsive system management). The case studies also include interventions aimed at environmental as well as congestion avoidance objectives. The applications provide an enhanced capability to capture traveler choices in both the main evaluation tools as well as in supporting the design process actively. This multifaceted research initiative cuts across several Federal Highway Administration (FHWA) programs such as the Office of Planning, Environment, and Realty; Office of Operations; Office of Safety; and Office of Research, Development, and Technology. This study will facilitate implementation of a balanced, cross-cutting effort to better understand the topic of traveler choice, and builds on current activities related to modeling and analysis across FHWA, professional associations, and academia.

17. Key Words
Behavior models, Demand modeling, Weather-responsive traffic management (WRTM), Traffic estimation and prediction, Weather and traffic analysis, Dynamic traffic assignment, Microsimulation

19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 224	22. Price

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

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^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)

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

This study, collaboratively identified and prioritized by Federal Highway Administration (FHWA) Analysis, Modeling, and Simulation (AMS) experts from across the agency during three AMS research symposia, focuses on identifying accurate traveler choice data in network and non-network conditions. It seeks to address the important gap in modeling capability to support initiatives aimed at improving traffic conditions, system safety, and sustainability by targeting user choices before and during travel. The traveler choice focus area targets travelers' higher-level, predictive, strategic choices influenced by a range of variables such as travel time reliability; congestion (recurrent and non-recurrent); environmental factors such as weather that affects both system performance as well as activity engagement opportunities, availability, and accessibility to alternative modes; quality of the walking environment; and measures such as pricing, information supply, and dynamic traffic management.

A comprehensive conceptual framework was articulated to highlight the principal behavior dimensions and how these interrelate with network performance to determine the impact and effectiveness of a wide range of demand-side and supply-side measures. Because no single modeling platform can have the scale, appropriate level of detail, and focus to address all questions and interventions, this study demonstrates improvements in modeling capability through selected case study applications. For each case study, specific modeling tools were elaborated by integrating traveler choice models in system simulation tools and applied to evaluate the effectiveness of the relevant interventions.

The case studies range from long-term policy influences of non-network interventions (namely walkability and crime) on mode choice to short-term en-route behavior of speed compliance as part of intelligent network flow optimization (INFLO) speed harmonization measures. All cases model and treat individual behavior in a completely disaggregated manner. However, depending on the focus of the intervention, scale of application, and resulting size of the problem, the case study models range from macroscopic to microscopic representation of the system. Six case studies were developed: (1) a medium-to-long-term application of urban design policy and non-network interventions, (2) active transportation and demand management (ATDM) with an emphasis on the role of non-network factors and urban policies in promoting active transportation and the use of bicycles as an alternative mode, (3) an exploratory Applications for the Environment: Real-Time Information Synthesis (AERIS)-related agent-based model of social networks and their influence on green attitudes, (4) a second AERIS case study using a microscopic traffic behavior model to evaluate the emissions benefits of an intelligent network flow application of speed harmonization in a connected vehicle environment, (5) weather responsive advanced traffic and demand management, demonstrating integration of traveler choices are integrated in a mesoscopic network wide dynamic traffic assignment (DTA) model using the Chicago, IL, network, and (6) an integrated corridor management (ICM) case study focused on characterizing travel adjustments using loop detector flow data from an integrated corridor managed site in the Seattle, WA, area.

This multifaceted research initiative cuts across several FHWA programs such as the Office of Planning, Environment, and Realty; Office of Operations; Office of Safety; and the Office of Research, Development, and Technology. This study will facilitate the implementation of a balanced, cross-cutting effort to better understand traveler choice and builds on current activities related to modeling and analysis across FHWA, professional associations, and academia.

CHAPTER 1. INTRODUCTION

BACKGROUND

Transportation network flows and the associated performance of these systems are largely the result of choices made by travelers—choices of where to live and work; which activities to engage in and with whom; and where, when, by what mode to get there and along which path. These choices reflect travelers' activity patterns (i.e., work and residence location, mandatory and discretionary activities, etc.) that motivate their desire to travel, situational and environmental variables (e.g., weather), as well as attributes of the transportation system, which determine the users' experienced service levels. In addition to their own experience of the system's attributes, particularly congestion and reliability, travelers are influenced by the information they obtain or otherwise receive about system conditions as well as various controls such as toll prices, access limitations, dynamic control, and other measures.

Researchers' understanding of traveler choice behavior in transportation systems and the approaches used to capture its outcomes has undergone several paradigm shifts over the past 50 years, often through the involvement of different disciplinary perspectives. From aggregate models concerned primarily with total travel between traffic zones, to disaggregate models of household travel decisions, to the current interest in activity-based models that view travel choices in the context of the activity engagement decisions of individuals and households, the field has expanded, evolved, and matured considerably. Yet, while sociologists, geographers, and psychologists have provided valuable insights into many aspects of what people do as well as where and why they do it, the ability to operationally represent traveler choices and use this representation for the purpose of predicting how users will respond to various transportation system interventions remains rather limited.

Tools available to support operational analysis and strategic planning of transportation systems have reached considerable levels of sophistication in the past two decades. On the supply side, microscopic and mesoscopic simulation tools can now be applied to large networks. Most traffic microsimulation tools only consider driving decisions such as car following and gap acceptance but do not include tactical and strategic dimensions. On the demand side, activity-based models for strategic planning purposes are being implemented by several metropolitan planning organizations (MPOs). However, these models have generally lacked sensitivity to network performance attributes, particularly path-level attributes such as time-varying travel times and travel time reliability. As such, they cannot readily be used in the context of operational analysis tools to capture user responses to traveler information and traffic control measures.

Developments in simulation-based network models have provided a suitable platform for integrating user choices in operational analysis tools, especially with regard to incorporating route choice and response to traveler information in modeling traffic flows in highway networks. However, the observational/empirical basis for the behavioral models has been limited, often relying on small-scale laboratory experiments and stated choice methods to calibrate the models.

The needs of transportation agencies for methods to evaluate the relative impact of a growing array of system management measures and policies involving both aspects of the network as a well as non-network elements underscore the need for improved methods that can integrate a richer behavioral basis than is currently available in existing tools. The missing element in many situations tends to be in the representation of traveler choices in a network setting and the influence of both network and non-network variables on these choices.

This project is intended to address this gap in modeling capability to support a variety of initiatives that seek to improve traffic conditions, system safety, and sustainability by targeting user choices before and during travel.

PROBLEM STATEMENT

The main goal of this study is to illustrate the missing gaps in capturing traveler choices in the methods and tools intended for use in operational analysis and planning of a wide range of measures and policies aimed at improving the efficiency, reliability, sustainability, and safety of the transportation system. Another main goal is to present and demonstrate ways to overcome these gaps with available operational tools through case studies. Traveler choice behavior, particularly the dynamics of this behavior in interaction with network and non-network variables, is a challenging domain. Developments regarding various aspects of travel and activity behavior have multiplied over the past few decades, but researchers' ability to predict these responses in conjunction with system planning and evaluation has not improved commensurately. This need is especially critical to the success of emerging program areas such as ATDM, ICM, and AERIS, as well as to much needed enhancements to traffic operations management in connection with adverse weather (weather-responsive traffic management (WRTM)). Similarly, the ability to predict the impact of planning interventions to non-network elements of the urban landscape, such as enhancements targeting walkability, neighborhood safety, and sustainable development density, is of much interest to the professional planning community.

OBJECTIVES AND APPROACH

The main emphasis of this effort is on travelers' higher-level predictive strategic choices that determine when and how they might use the transportation system. These might be influenced by a range of variables, including experienced system performance (i.e., recurrent and non-recurrent congestion and travel time reliability), environmental factors (i.e., weather that affects both system performance and activity engagement opportunities, availability, and accessibility to alternative modes), availability and cost of parking, quality of the walking environment, and measures such as pricing, information supply, dynamic traffic management, etc. A thorough understanding of the determinants of travel choices and behavior and an operational ability to model their dependence on key attributes of the transportation system, network performance, and non-network factors will provide a foundation for designing effective interventions to improve system performance and for evaluating different policies and options by predicting how users will respond to these measures.

The approach adopted in this study is to provide a high-level discussion of all relevant issues in the context of a general, comprehensive framework and then demonstrate the targeted implementations of this overall approach through specific case studies. Each case study addresses one or more of the programs and policy interventions motivating the overall effort. For each case study, the relevant behavioral dimensions were identified, and, when applicable, integrated into a modeling framework that captures the interaction of these dimensions with the relevant supply-side elements. Where available, data were compiled to characterize these behaviors and, in selected cases, to develop and calibrate new models and specifications. For several case studies, the modeling framework developed for that application was applied to predict the effect of selected policy interventions and conduct sensitivity tests to various underlying behavioral parameters. This approach allowed researchers to address the study objectives through specific indepth applications, which, taken collectively, reflect the range of questions and interventions that require prediction of user behavioral responses as well as the range of methodologies and modeling perspectives in addressing these problems. As such, the study contributes to both its methodological and applied objectives.

In addressing the study objectives, the case studies, associated behavioral models, and integration of the models developed in this study are intended to satisfy the following requirements:

- **Responsiveness**: They must be responsive to the policies/actions under consideration and address critical modeling gaps from the standpoint of the success of management programs or policy interventions.
- **Data availability**: There should be data available for calibration or there should be a process for obtaining such data, all the while recognizing the growing array of potential technology-enabled sources of data and identifying and using the most readily available sources.
- **Implementable**: The methods and model inputs discussed are all available and ready to implement.
- **Computationally tractable**: The computational effort required to apply the developed methods in connection with a network analysis methodology is compatible with today's computer capabilities.

The developed models in this study represent a wide a range of analysis tools and demonstrate specific applications of the methods. The developed models also show that there is not one single model or tool capable of addressing all questions that arise in conjunction with management strategies such as ATDM, ICM, AERIS, or WRTM. In other words, the notion of a "one size fits all" condition in terms of modeling capability or resolution is not practical for the range of questions involving behavioral responses of travelers. To address this, the developed case studies use a range of models to achieve the right balance of detail, accuracy, computational tractability, and usefulness for the application under consideration.

REPORT ORGANIZATION AND STRUCTURE

This report begins with an overview and conceptual framework that organizes the wide range of issues and approaches in modeling traveler choices. The framework structures the discussion and leads to identifying the main gaps in terms of current modeling practice versus needs in terms of scope of coverage, usable tools, and relevance to the questions of interest. Based on this gap analysis, the road map is framed to illustrate how these gaps can be addressed at different levels in detailed case studies. Rather than address gaps in a generic fashion, intended for universal applicability but missing some essential aspects of specific applications, the development takes place in specific scenarios where methods and models are used and demonstrated. The different case study scenarios are ordered by decreasing time frame, with longer-term considerations and behavioral adaptations addressed first, progressively leading to short-term, day-to-day, and within-day responses of travelers. Some methodologies overlap. As a result, in order to avoid duplicate discussion, model discussion is organized to best highlight contrasts in advantages and drawbacks. The report organization is as follows:

- **Chapter 1:** Describes the study objectives and approach.

- **Chapter 2:** Presents a review of the main behavioral dimensions and models used to describe and forecast traveler choices in transportation applications.

- **Chapter 3:** Describes the overall conceptual framework. It also structures the different traveler choice dimensions in time (i.e., short-, medium-, and long-term choices) and describes the interface at which different models interact with each other. It also delineates the conceptual horizon that is used in each case study to draw the line between accuracy needed in a certain application and operational usefulness in a practical implementation.

- **Chapter 4:** Presents the first case study, which describes a medium-to-long-term application of urban design policy and non-network interventions.

- **Chapter 5:** Addresses ATDM aspects. Topics include the role of non-network factors and urban policies in promoting active transportation, the use of bicycles as an alternative travel mode, and the implications for modeling tools and data needed to address these questions by planning agencies.

- **Chapter 6:** Describes an AERIS study on how to model social networks and their influence on green attitudes in an agent-based framework. The implications of information diffusion through a social network are discussed.

- **Chapter 7:** Presents a second AERIS case study and describes how an intelligent network flow application of speed harmonization in a connected vehicle environment (part of the INFLO program) can achieve lower emissions.

- **Chapter 8:** Includes two case studies within advanced traveler information systems (ATIS). The first case study concentrates on WRTM and how traveler choices are integrated in mesoscopic network-wide DTA models. It also demonstrates how to achieve network service levels under bad weather that are comparable to those prevailing during clear weather conditions through demand management strategies. The second case study focuses on characterizing travel adjustments using loop detector flow data from an integrated corridor managed site in the Seattle, WA, area.

- **Chapter 9:** Presents the conclusions, including lessons learned and recommendations for next steps needed to advance the state of the art and practice of traveler choice modeling.

CHAPTER 2. TRAVELER BEHAVIOR OVERVIEW

This chapter presents a state-of-the-art overview of previous studies addressing traveler decisionmaking. It organizes travel behavior knowledge by decision horizon. At the within-day and day-to-day levels, route and departure time choices were the primary focus areas. Travelers' experiences from day to day influence their future decisions, and the line between these daily choices and behavioral patterns quickly becomes blurred. For example, a traveler may stop using public transportation after a bad experience even if the utility is otherwise perceived as quite high. Since mode choice is subject to available modes, this tends to be modeled and studied as a behavioral pattern in the time span of weeks or months. Finally, lifestyle and mobility choices reflect the self-imposed or otherwise imposed constraints to which travelers are subjected over longer time frames. Much research has been conducted within each area to understand how various factors influence these choices, but there is less understanding of the mechanisms that operate to define these travel habits, patterns, and long-term constraints. These mechanisms and how they relate to different levels of traveler decisionmaking are also discussed.

LONG-TERM LIFESTYLE AND MOBILITY DECISIONS

This section examines urban form variables and the self-selection phenomenon to understand travelers' lifestyle choices. The influence of added network capacity on travel behavior is briefly discussed as it relates to traveler characteristics.

The effects of price and traveler characteristics on utility are relatively well understood, but existing knowledge on attitudes about mobility and lifestyle and how these attitudes are manifested in behavior is limited. Besides income, psycho-social attributes and their influence on car ownership have been examined.(1) Hiscock et al. and Cullinane found psycho-social benefits in car use, especially for young males.(2,3) In these studies, car owners felt car use improves prestige, protection, autonomy, and self image.

For decades, the supply-oriented approach to transportation planning revealed that network equilibrium often results in increased travel in response to increased capacity, such that adding capacity may only alleviate congestion in the short term. Furthermore, adding freeway capacity is thought to induce additional travel. Fujii and Kitamura explored the relationship between individuals' activities and the travel environment to determine whether this is the case for commuters between the time they leave work and the time they go to sleep.(4) The authors used structural equations to conduct impact analysis of hypothetical freeway lanes in the Osaka-Kobe metropolitan area on residents' time use and travel. The model examined the number of trips during this period, the total out-of-home activity and travel durations, the number of home-based trip chains, and the total amount of time spent at home after arriving for the first time until going to sleep. Their model of travel preferences suggests that older married individuals tend to have a lower preference toward in-home and out-of-home activities, meaning they have lower preferences toward all activity types. People with higher incomes have large preference indicators for both in-home and out-of home activities but more so for out-of-home activities. Time use and travel variables are treated as endogenous in this study; therefore, the impacts of supply changes cannot be thoroughly addressed. However, the results suggest that additional freeway lanes induce little traffic, indicated by only slight increases in number and duration of out-of-home activities. Much of the time savings from added capacity is allocated to in-home activities.

Effect of Transit-Oriented Development (TOD) and Urban Density on Behavior Patterns and Long-Term Choices

Much research on travel behavior and land use interactions consists of aggregate analyses. This focus on the relationship between urban form and aggregated travel patterns provides little insight into the underlying factors and mechanisms by which urban form influences individual choices.[(5)] Disaggregate analysis of household and individual-level behaviors suggests that behavior differences are greater among neighborhoods than among individuals within neighborhoods, and attitudes play an important role in decisionmaking. It is necessary to understand how urban form shapes choice sets since discrete choice theory is only able to illustrate how the factors influence choices within a given choice set.[(5)]

Holtzclaw et al. attempted to determine which factors influence home location selection and associated transit use the most.[(6)] Using odometer readings from emissions systems inspections in San Francisco, CA; Chicago, IL; and Los Angeles, CA, the authors predicted a household's vehicle miles traveled (VMT) as a function of home-zone density, proximity to jobs, transit service and access to jobs by transit, availability of local shopping, and pedestrian and bicycle "friendliness" (i.e., the attractiveness of these options as compared to driving). The elasticities for vehicle ownership with respect to density for the three cities were -0.33, -0.32, and -0.35, respectively. Elasticities for VMT (per capita) with respect to density were -0.35, -0.40, and -0.43, respectively. Since residents in these cities have above average access to transit, while also noting that the model did not control for parking costs, income, and other relevant variables, applying this model across more cities may not yield such results. For example, the model does not control for attitudes toward driving and public transit, differences in living, vehicle ownership cost, or the cost and quality of transit. These variables differ significantly in most major U.S. cities, and attitudes typically exert a strong influence on travel patterns. However, the magnitudes are surprisingly similar for three urban areas that differ significantly in terrain and climate. One should note that density often acts as a proxy for other urban characteristics.

Equally important to the understanding of how these factors may reduce VMT is an understanding of what factors individuals most prefer in "neo-traditional" developments. In Lund's survey where California residents were asked to identify their top three reasons for choosing to live in a TOD, only 33.9 percent cited transit accessibility as a top reason.[(7)] More often, residents preferred type or quality of housing (60.5 percent), cost of housing (54 percent), or quality of neighborhood (51.7 percent). Lund also found that residents who listed transit as one of their top three reasons were 13 to 40 times more likely to use transit than those who did not, suggesting significant effects of self-selection in such developments.[(7)] This endogeneity is discussed further in the next section.

Residential Self-Selection and Vehicle Ownership

Researchers have sought to disentangle the impact of travel preferences and self-selection in home location choice and how this ultimately impacts differences in observed travel patterns across distinct neighborhood designs. Cao et al. suggested that attitudes and socio-demographics are confounding influences in such studies.(8) While definitive conclusions have not emerged, general neighborhood design distinctions (e.g., walk-oriented versus auto-oriented, existence of bicycle lanes, distance to work, and non-work trip purposes) appear responsible for at least half of the observed VMT differences.(8–10)

For example, surveys by Frank et al. in Atlanta reveal that despite driving preferences, residents living in a walkable neighborhood tend to drive far less than those living in auto-oriented neighborhoods.(11) The least walkable neighborhoods generated roughly 45.5 mi of travel per worker per day, while the most walkable neighborhoods generated only 28.3 mi. Furthermore, those who prefer an auto-oriented neighborhood but live in a walkable neighborhood tend to drive significantly less (25.7 mi per worker per day) than their counterparts in auto-oriented neighborhoods (42 mi) despite their stated preference. Of those who prefer walkable neighborhoods, VMT per worker per day average 25.8 and 36.6 mi, respectively, for residents of walkable versus auto-centric. Thus, while someone may prefer to live in a different neighborhood, it appears that he/she will still conform to the travel opportunities of the home neighborhood. It also merits mention that households residing in suburban settings (versus more traditional neighborhoods) tend to be older and have more members. As expected (by VMT patterns), they also own more vehicles per household member.(12) The neighborhoods in Frank et al.'s study had similar densities, though they differed in household size and income.(11)

More recently, Aditjandra et al. applied dynamic (quasi-longitudinal) structural equation models to understand the residential self-selection phenomenon in the United Kingdom.(13) A total of 219 participants who had moved to their current residence in the last 8 years were asked how they drive now compared to before they moved using a five-point scale from "a lot less" to "a lot more." Results suggest that socio-demographic characteristics are the main influence on changes in car ownership, but changes in neighborhood characteristics, in particular, safety factors and shopping accessibility, had an important influence. This method was demonstrated in the United States by Cao et al.(14) The findings from the UK study corroborate with Cao et al.'s study, suggesting that controlling for residential self-selection, neighborhood design impacts on travel behavior may be similar in different geographical settings despite different planning contexts.(13,14) In the United States, car ownership is associated with yard size and availability of off-street parking, whereas in the United Kingdom, shopping/facility accessibility and safety of residential neighborhoods most influences vehicle ownership. Again, one should note that such variables can often proxy for other characteristics. For example, yard size could indicate home lot size or that the residence is a single family dwelling unit.

These proxy issues indicate the need to better understand human interactions and the mechanisms that drive behavior. After all, if a family moves, their friends may still live in the old neighborhood and exhibit the former travel behavior. As many studies have shown, geography is one of the best indicators of frequency and duration of social contact.

MEDIUM-TERM BEHAVIORAL PATTERNS

Socio-Demographics and Household Composition

The impact of socio-demographic variables on travel behavioral patterns is a well-studied topic. Several studies found significant relationships between travel and variables such as age, gender, household composition, and income. For example, Newbold et al. used the General Social Survey dataset in Canada to determine the travel pattern differences of older (65+) and younger people.[15] The data are available for different time periods and can therefore control for generational differences. The study found significant differences in trip duration and frequency across generations. Employment level and health status were also significant predictors of trip duration and frequency.

Gender differences in trip duration, frequency, and mode choice are significant in many studies, which attest women to be more likely to change their behavior toward more sustainable travel modes.[16,17] Moriarty and Honnery and Best and Lanzendorf found no significant differences between men and women in total number of trips and distance traveled but found differences in activity types.[18,19] Whereas men make more work trips, women make more trips for maintenance activities. Researchers consistently found that household composition influences trip type, duration, and frequency. Key stages in households include the gain or loss of employment, having children, and retirement.[20] Students, unemployed, and part-time employed households with no children are more likely to use non-motorized forms of transportation, and high-income or retiree households are less likely to use non-motorized transportation. Car ownership, also endogenous to some model systems, is found in many studies to be significant with a tendency for people to use cars versus public transit. This trend is significant with high-income groups.[21] Giuliano, Giuliano and Narayan, and Giuliano and Dargay studied differences in travel behavior between different socio-demographic groups in the UK and the United States.[22–24] According to these studies, Americans make 4.4 trips per day with a length of 43 mi compared to 3 trips per day and 16 mi in the UK. In both countries, travelers over age 65 travel roughly half the distance of younger participants. The difference between countries is explained by the lower income and significantly higher transportation costs in the UK compared to the United States.

Bomberg and Kockelman surveyed over 500 commuters in Austin, TX, to gather information on their driving behavior during and after an abrupt increase in fuel prices.[25] For most of summer 2005, price increases were comparable to previous years; however, between August and September 2005, prices increased 36 percent from $2.16 to $2.93/gal. Ordered-probit models to classify the travel behavior change suggest that travelers are most likely to respond by reducing overall driving; this reduction is achieved through increased use of other modes or trip chaining. A traveler's built environment characteristics were more influential in behavior change than even income, education, and average driving. Some drivers even adapted their driving style, suggesting some drivers adopt a series of strategies to cope with system changes. Respondents were surveyed again in 2006 to gather information about response to transportation policy measures. Though there was substantial support for alternative modes and reduced fuel dependency, respondents willingness to pay for driving increased ($1.45/gal as distance from the central business district (CBD) increased by one standard deviation from the mean (3.74 mi).

It is worth noting that some urban form variables were evaluated in addition to the traveler characteristics in these studies. Residents of less dense urban areas tend to travel further. As a result, density influences the price of travel and therefore the travel behavior.[26] In the United States, urban form is thought to reinforce car use and dependency.[23]

Effect of Travel Demand Management Measures and Parking Pricing on Mode Choice

A Transit Cooperative Research Program (TCRP) report found that eliminating minimum parking space requirements and charging market rates for residential parking spaces could reduce vehicle ownership per household enough to reduce household VMT by 30 percent.(27) Additionally, charging employees for parking at work was linked to a 10 to 30 percent decrease in single-occupancy vehicle (SOV) mode share depending on the quality of transit alternatives.(27) In Portland, OR, establishing maximum parking ratios and a parking limit maximum appeared to reduce the downtown parking ratio by half from roughly 3.4 long-term spaces per 1,000 ft^2 of commercial space in 1973 to 1.5 spaces per 1,000 ft^2 in 1990.(27) These parking policies, alongside some transportation demand management (TDM) measures and transit enhancements, are credited with increasing Portland's downtown transit share from 20 to 25 percent in the early 1970s to a downtown commuter transit share of 30 to 35 percent in the 1980s and 1990s.(28) As expected, many urban design variables influence mode share (e.g., cities with few parking spaces per employee tend to have higher transit mode share) since limits on parking are implicitly reflected in the shadow price associated with parking.(28)

Using the 6-week Mobidrive study, Schlich and Axhausen explored repetitious travel behavior.(29) Because people rarely evaluate all their options at each new opportunity and because constraints are relatively similar from day to day, habits are formed but mediated by each day's changing needs. Schlich and Axhausen found that behavior is more variable on weekend days than working days.(29) For each individual in the study, variability was sharply reduced and then constant after 2 weeks (i.e., the respondent looked similar over 3 weeks and over 5 weeks). The authors recommended observing participants over a 2-week period.

Learning, Experience, and Inertia

Inertia, or a traveler's propensity to continue making the same choices based on past experience, is not yet well understood. In 2011, Cherchi and Manca demonstrated that the significance of inertial effect varies substantially with model specification, and this effect is not stable during a stated-preference experiment.(30) Depending on a participant's past experience and exposure to options, the inertial affect also varies, pointing to a need for well-designed and controlled experiments.

Using an agent-based model employing Bayesian perception updating, Chorus et al. determined a perceived value of acquiring travel time information as the difference between expected regret induced by a choice before and after acquiring information.(31) Simulations revealed that this value of information, even for drivers who considered transit as an alternative to driving, is influenced by three factors: information irrelevance, information unreliability, and preference for driving options. These same factors also limit the effect of received information on mode choice when the information is highly favorable toward transit. The authors suggest that only transit information that is freely provided and easily accessible has the potential to be used by drivers. This information should also be reliable and include aspects of comfort, dynamic conditions, convenience, and perhaps even environmental friendliness. Given the difficulty in meeting these conditions of low-cost, high-quality information, Chorus et al. suggested that it may be more efficient to demonstrate the car's limited attractiveness in certain conditions, such as inclement weather or road accidents.(31)

The role of inertia in influencing users' responses to real-time information had previously been captured by Srinivasan and Mahmassani in the context of route switching decisions, as discussed in the next section.[32]

PRE-TRIP, EN-ROUTE, AND DAY-TO-DAY BEHAVIOR

Jan et al. found that travelers habitually follow the same route for the same trip, but route variations increase with longer travel distances.[33] The dominant factors for route choice are travel time and distance.[33–35] Considerable research effort has focused on the effects of route choice behavior under traffic information systems, the dynamic aspects of the route choice behavior, and the relationships among route choice, departure time, and trip-chaining decisions. (See references 32, 36–39.)

Traveler information substantially influences route choice. Abdel-Aty et al. studied route changes in Los Angeles, CA.[35] Only a small percentage of the respondents (15 percent) reported using more than one route on their commute. Of that 15 percent, 34 percent said they changed routes after seeing traffic conditions. Drivers with higher incomes and education levels predicted more route changes, perhaps reflecting schedule flexibility and arrival time expectations.

Mahmassani and Herman performed a survey of commuters in Austin, TX, and yielded a binary logit model that relates route switching propensity to four types of factors: geographic and network condition variables, workplace characteristics, individual attributes, and use of information (radio traffic reports).[40] They found that variables describing the characteristics of the commute itself had a dominant effect relative to workplace rules or individual characteristics. Information in the form of radio traffic reports also appeared to have a strong impact. Regular listeners to traffic are more likely to switch routes. The only socio-demographic attribute significant in the model was age.[41]

In a similar experiment, Avineri and Prashker examined the impact of information on traveler learning, differentiated by travelers' risk aversion.[42,43] The results suggest that when information about travel times is provided, travelers do not always choose the route with the least expected travel time. Giving static information to users serves to increase traveler heterogeneity. In this case, individuals learned more quickly to prefer either routes with less travel time or routes with less variability in travel time. When examined at an aggregate level, this combination could be seen as a "non-learning effect," or no change. Furthermore, higher variation in travel times is associated with lower sensitivity to travel time differences. Avineri and Prashker found in some cases that increasing travel time variability of a less attractive route could increase its perceived attractiveness.[42] This underlines the need for better models of learning and reinforced habits as an alternative to utility maximization.

Beyond these dimensions, only a few studies have addressed destination adjustment in response to real-time information for discretionary (shopping) travel.[44] The remainder of this section discusses the effects of other network and non-network factors.

Effect of Tolling and Other Costs on Mobility Decisions

Travel cost as part of demand management is a powerful tool to influence travel behavior. Hensher and King examined the influence of parking costs in the CBD, a park-and-ride facility with public transit access, and the related mode choice as well as destination choice (including a "forgo the trip" alternative) in Sydney, Australia.(45) Each participant was required to consider six alternatives in a stated preference questionnaire. In 97 percent of the responses, cost was the most significant factor in determining location choice and mode choice. Similar results were found by Handy et al. in a study of whether Americans drive by choice or through necessity.(46)

Congestion pricing of roadways presents a valuable opportunity to rationalize road networks by helping ensure that travelers pay for the delay costs they impose on others. A study of Seattle, WA, travelers with Global Positioning System (GPS) vehicle units estimated that variable network pricing (to reflect the congestion impacts of different demand levels over space and time) would reduce regional VMT by 12 percent and total travel time by 7 percent with a 6-to-1 benefit-cost ratio.(47) Using GPS tolling meters, the study followed participants to establish a baseline tolling routine. Participants were then given a monetary travel budget sufficient to cover the cost of their routine for the duration of the study period, creating an incentive to reduce certain forms of travel to save/make money. This policy approach is very similar to Kockelman and students' credit-based congestion pricing policy proposal, though VMT results differ in their network simulations of the Austin and Dallas-Ft. Worth regions of Texas, where marginal social cost pricing of freeways for all links by time of day is consistently estimated to result in VMT savings of under 10 percent.(48,49)

Saleh and Farrell investigated the influence of congestion pricing on the peak spreading of departure time choice.(50) Taking into account the scheduling flexibility of respondents, results suggest that non-work activities and work schedule flexibility impact departure time choice for the trip to work. Furthermore, respondents were less willing to pay tolls to depart earlier than usual.

Similarly, a TCRP report discusses a number of elements that influence travelers' decisions to use a high-occupancy vehicle (HOV) lane.(51) The report concludes that so many urban, facility, and vehicle characteristics interact with one another that it is difficult to delineate the effect of HOV lanes on travelers. However, the success of HOV lanes, both in terms of drivers served and benefits to the road network, is attributed to combinations of the following characteristics:

- Urbanized population of 1.5 million or more.
- An orientation, preferably radial, to a city center, focusing on major employment centers with preferably more than 100,000 jobs.
- Geographic barriers.
- Congestion in general purpose lanes.
- Realistic potential for 25 to 30 buses per hour.
- Peak hour travel time savings of preferably 1 min/mi or more or at least 5 min of total travel time.

Effect of Walk Quality on Day-to-Day Travel Behavior and Patterns

Beyond information and pricing, the quality of the urban environment can influence route and activity timing decisions. Cervero and Kockelman examined many features of urban form that may reduce auto dependence.[52] Their gravity-based accessibility measure for access to commercial jobs was found to have an elasticity of -0.27, suggesting neighborhood retail shops and pedestrian-oriented design are more significant than residential densities in mode choice selection. Integrating aspects of pedestrian-oriented design, such as four-way intersections and vertical mixing of land uses, may result in significant VMT reductions. For example, a 10 percent increase in the number of four-way intersections in a neighborhood was associated with an average reduction of 5.19 percent of person miles traveled for non-work trips. A doubling of land use mix or variety is associated with a roughly 11 percent increase in modes other than SOV for non-work travel. These effects are discussed in more detail in chapter 4.

Besides urban density, mixed land use and high-quality pedestrian-oriented urban design increase the use of public transit and non-motorized transport modes.[53] Naess and Naess and Jensen found that, in general, car use increases with increasing distance from the city center.[54,55] This could also be an indicator of self-selection or endogeneity. Similarly, Cervero studied the impact of compact, mixed use, and pedestrian-friendly design on mode choice.[56] The study quantified density and diversity and estimated the influence of each on mode choice. The influences were significant but modest. Surprisingly, the most important influence factor for mode choice was the sidewalk ratio. In well-developed pedestrian areas, commuters were more likely to use public transit and join carpooling initiatives.

Information, pricing, and urban form influence day-to-day and within-day behaviors, but they are understood and applied over time such that they also influence travel patterns. These and other influences are discussed in the following subsections.

Behavioral Mechanisms

Besides all the influencing factors and characteristics that help explain travel behavior changes, it is important to understand the underlying process of the perception and manifestation of these characteristics, which then lead to behavior adjustments. That is, how do patterns become lifestyle choices? Even though there are day-to-day travel variations as discussed in the previous sections, it has also been noted that travel patterns repeat themselves, which suggests that parts of travel behavior are habitual and influenced by inertial effects.[57] Furthermore, the effect of information, as discussed in previous sections, depends on whether travelers comply with the prescribed information. Inertia, information compliance, travel experience, and learning determine the system outcomes that feed back into supply and demand models.

Behavior adjustment implies that behavior is an outcome of experience or new information of the current conditions. This can be seen as a learning process, which leads to an adjustment of the behavior. Mahmassani and Chang studied an adjustment and experience-based model of perceived travel time for departure time choice.[58] Under the myopic adjustment rule, the perceived travel time is only a function of the latest day’s outcome. In laboratory experiments conducted to study the effectiveness of different information strategies on user responses to information, Srinivasan and Mahmassani found that route switching model specifications, which predict whether a user will switch paths in a given time interval, consistently outperformed models that view the process as a new choice at every opportunity.[32] These mechanisms are neither mutually exclusive nor collectively exhaustive. As a result, they can operate simultaneously and in conjunction with other mechanisms. The authors designed an experiment whereby virtual commuters were given trip times at three facilities (decision locations), real-time information about congestion on the facilities, a message alerting when they were stuck in a queue, and post-trip feedback consisting of departure time, arrival time, and trip time on the chosen path. Their empirical findings suggest that an individual's negative experience with ATIS information has mixed effects on inertia, but congestion and information quality tend to reduce inertia. Drivers who experience lower switching costs and increased trip time savings tend to comply with information. In the sequential treatment, past negative experience relative to preferred arrival time seemed to increase likelihood of compliance. Inaccurate information decreased drivers' compliance propensity.

Bayarma et al. examined multiday travel behavior as a stochastic process using 6-week travel diary data to explore how travel patterns vary and persist among heterogeneous individuals.[59] The authors classify weekday travel patterns into five representative patterns: public transport commuting; extensive car use involving three or four visits to a location; three to four shopping, leisure, and social trips; high fraction of trips which serve to transport another person; and mostly work visits and time spent on work-related activities. The authors found that transitions from a pattern to itself were frequent, especially for non-workers, but transitions from pattern to pattern varied substantially across individuals. Individuals with a driver's license tended to have a higher level of day-to-day variability in their travel patterns. Residential location type also influenced variability in daily travel, with individuals living in a central area regularly pursuing more shopping and leisure activities. Gender, marital status, and number of household vehicles were insignificant in this study; age, household type, and employment status explained much of the variation.

In a seminal work on attitude-behavior theory, one study examined the interrelationships between attitudes and behavior from multiple modeling perspectives: multi-attribute models, hierarchical models, market segmentation models, and, to a lesser extent, structural equation models.[60] Simple models provide empirical support for behavioral feedback mechanisms, and attitudes and behavior are found to simultaneously influence one another. This concept of simultaneous influence has been explored in greater depth since the study, and market segmentation and structural equations models are still used to explore psycho-social influences on travel behavior. Beyond attitudes, perceptions and intentions also have a substantial influence on behavior. While attitudes and perception have been explored in great depth, less attention has been given to traveler intention until recently. Bamberg found that forming an implementation intention (when, where, and how to perform an action) increases the probability that a goal intention is manifested in behavior.[61] In the study of 90 university students, forming an intent to ride a new bus route was the best predictor of whether the student did in fact ride the new bus route, even more so than current bus and auto use habits. While habit exerted a strong negative effect on whether one would test the route for the control group, this habit strength did not influence the experimental group. Thus, Bamberg points out that influencing behavior involves not only influencing the decisionmaking process but also the formation of implementation intention.[61]

The studies reviewed in this chapter reflect a diverse field of inquiry conducted by researchers in various disciplines. While considerable understanding exists on several aspects of both short- and long-term behaviors of travelers, the level and completeness of that knowledge is highly variable. More importantly, the ability to make operational use through models for the prediction of user responses to contemplated policies and interventions is limited, especially with regard to measures that entail capturing the dynamic aspects of user decisions in transportation systems. The remainder of the report illustrates how different choice dimensions are affected by given policies and programs and how these can be modeled effectively to support design and evaluation of these policy and programs.

CHAPTER 3. SCOPE DELINEATION AND CONCEPTUAL FRAMEWORKS

This chapter discusses the conceptual framework and defines categories to organize operational interventions, traveler choice dimensions, and factors affecting user response. The framework's core components are operational interventions, information dissemination, traveler choice dimensions, and network and non-network influencing factors.

SCOPE DELINEATION

Traveler behavior research is a broad domain. The synthesis presented in this chapter is not intended to be comprehensive over the entire domain. Rather, it focuses on choice dimensions that are influenced by and relevant to operational planning and management interventions. Interventions at this level have a narrower scope than, for example, the strategic level, which involves resource acquisition and network design. Nevertheless, long-term traveler decisions such as mode shifts, auto ownership, or location changes are of interest, as models of activity engagement and related decisions are becoming more realistic in practice. On the intervention side, the focus is mainly on ATDM. ATDM is a strategic approach to apply technology-supported measures in a proactive way to influence behavior and system performance and thus address potential problems before they occur. ATDM covers managing travel demand (MTD) and ICM, including dynamic mobility applications (DMAs). The synthesis also covers active traffic management (ATM) on the supply side since the delineation between supply and demand management is somewhat fuzzy, and some degree of overlap occurs in several areas, such as information supply.

Since most supply management interventions change the level of service of the network, the focus is on network factors influencing traveler behavior. However, demand management interventions may change non-network factors, as well. The range of interest for non-network factors influencing traveler behavior is broad and not rigidly delineated. Non-network factors are numerous, ranging from weather, which is natural and easy to observe, to walkability, which is more subjective and less straightforward to measure. The non-network factors are also important in that they interact with network factors in influencing traveler decisionmaking, as they define the environment (context) and relative attractiveness of choice alternatives. Furthermore, traveler characteristics as well as vehicle characteristics influence traveler choices.

Taken together, these confounding forces and influences become difficult to separate from one another. The comprehensive framework presented in the following sections attempts to conceptualize these person-network interactions over short-, medium-, and long-term time horizons. This framework seeks to capture the anticipated and actual effects of operational interventions on the supply and demand sides.

GENERAL FRAMEWORKS FOR INCORPORATING TRAVELER BEHAVIOR IN SIMULATION MODELS

Conceptual Framework

Transport planning aims to describe, understand, and model the choices households and individuals make during the execution of their daily lives, including the more or less frequent journeys outside their daily activity space.[62,63] The behavioral demand models feed the supply and network models to assign traffic to the infrastructure. These models are in turn used to evaluate and optimize changes to the transport system undertaken by the owners of its various components (e.g., reduction or expansion of road capacity through interventions, including demand management and supply management as well as broader policy changes). Travelers make their decisions based on the characteristics of the system and travelers' perceptions. For example, as new information becomes available, travelers adjust their perception and adapt their travel behavior. Different system factors as well as decisions en-route must be considered. People decide where they want to live, where their workplace is, and whether they will own one or more vehicles, buy monthly transit or toll passes, etc. Travelers must decide how often and where their everyday and less frequent journeys take them, their mode(s) of transport (where multimodal trip alternatives may be available), when to start trips, what destinations to visit along the way and for how long, and what route they want to take. In making decisions, individuals' cognitive abilities and limited information availability play a substantial role, reflecting varying degrees of bounded rationality.[58,64,65] People attempt to make subjectively rational decisions based on a limited amount of knowledge and assessment capacities, not necessarily fully informed or objectively rational choices.

Operational interventions, supply and demand management, traveler choice dimensions, and factors affecting user response, which are considered either endogenous or exogenous, interplay with each other and are summarized in the conceptual framework in figure 1.

Household and individual behavior change dimensions can be categorized according to the time frame over which they might take place. The level of analysis where a particular decision or group of decisions must be considered includes the following:

- **Short-term decisions**: Take place within day as well as from day to day. Short-term decisions can be categorized further as follows:
    - **Strategic pre-trip high-level traveler choices**: Take place before departure (i.e., trip-making decisions).
    - **Tactical en-route high-level traveler choices**: Take place during the trip (i.e., route modification).
- **Medium-term decisions**: Involve behavioral patterns such as activity chain planning and adjustments that take place over a longer period than hours and days.
- **Long-term lifestyle and mobility decisions**: Affect vehicle holdings and location choices and take place over weeks, months, and years.

Operational intervention programs can be categorized by the interventions or controls with which they seek to improve the system operations and performance by influencing the underlying traveler choices.[66] They can target the supply side, (i.e., the network with traffic and infrastructure access controls (e.g., ramp metering)), which in turn affects behavior changes through the level of service as an influence factor. Alternatively, operational interventions may affect the demand directly with pricing (i.e., congestion pricing). Demand and supply management overlap as information supply (i.e., variable message sign (VMSs), earlier traveler time dissemination, etc.) targets both the demand and supply sides indirectly through demand response.

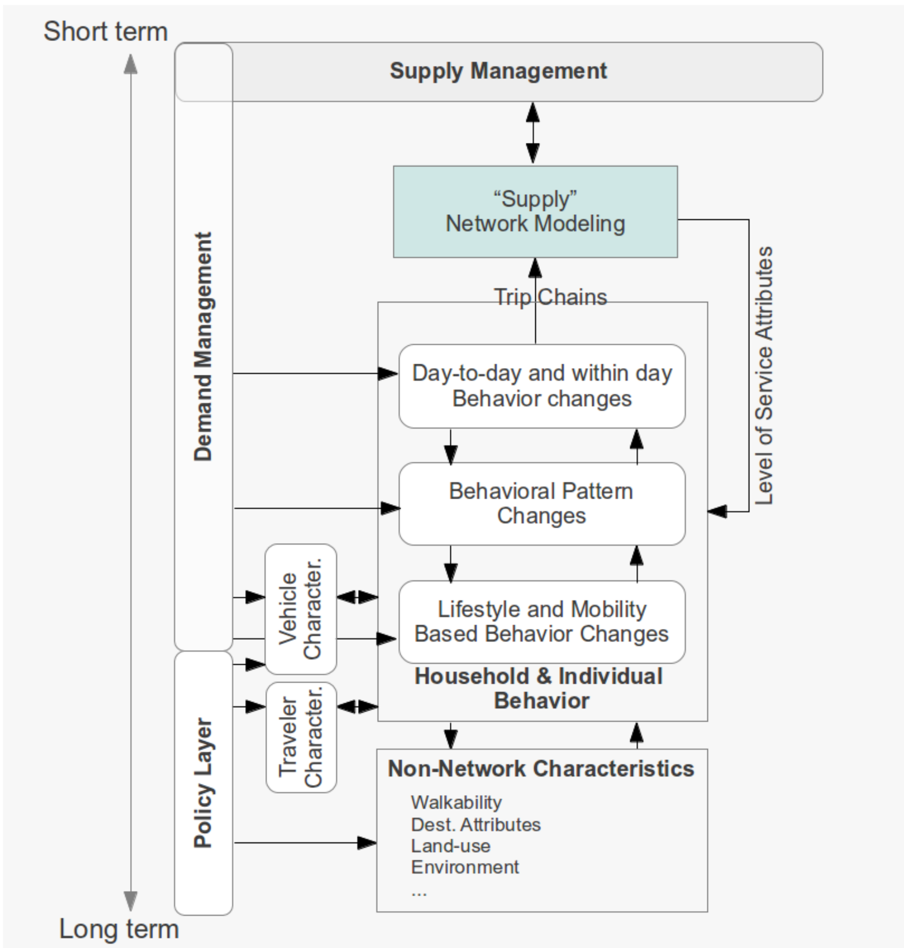


Figure 1. Illustration. High-level conceptual framework.

In addition to demand management, which influences household and individual behavior directly, there are additional influencing factors, which can be divided into two categories: traveler and system factors.

Traveler factors can be further divided into the following categories:

- **Traveler and household characteristics**: Affect traveler behavior.
- **Vehicle characteristics**: Affect traveler behavior (i.e., type, dynamics).

System factors can be further divided into the following categories:

- **Network characteristics (i.e., connectivity, length of route, roadway types) and segment elements**: Define roadway and transit path characteristics (i.e., ride quality, lanes, frequency, etc.).

- **States of or features of the network as well as events that affect traveler behaviors**: Not originating from system control strategies (i.e., weather, walking paths, and other characteristics of transit service besides route configuration, such as headways).

It is important to note that the behavior choices are preferably denoted as behavior changes, as they might often be better represented as the outcome of an adjustment process of a current choice rather than as the outcome of a first-time choice process that does not recognize one's current state. Also, the arrows in figure 1 not only show the possible mappings of an explanatory variable on a possible outcome. Rather, they represent the perception of attributes and characteristics of the user in question.

Modeling and Simulation Frameworks

Three primary categories of modeling tools and simulation frameworks used in transportation studies are adapted in the case studies presented in this report. First, mesoscopic simulation-based DTA tools have become widely accepted platforms for delivering richer behavioral models to network analysis and evaluation applications. Second, microsimulation models for operations analysis are used in applications that involve more geometric detail associated with lane use and other localized interventions. Developments for the former class of tools have been shown to port rather well across software platforms, partly because most have been built on a similar blueprint developed and widely published in the early to mid 1990s. The second category is more challenging to develop generic procedures for, though experience shows that when there are valuable developments coming out of public sector research, vendors tend to adopt and incorporate them in their offerings. Third, rule-based computational process models and agent-based models aim to represent underlying processes directly, similar to a production system model, which contains complex if-then rules. As typically applied in social physics, these models have lacked the ability to statistically capture the significance of the factors embedded in the rules and as such are not always best suited to understand behavior changes, reflect observed behavior empirically or in experiments, or predict future changes for specific actual geographic areas. Conversely, they allow agents not only to interact with their environment, but also to interact with other agents. As a result, they can describe dynamic processes more completely than microsimulation models typically used in practice.

Application-Specific Modeling and Simulation Frameworks by Decreasing Time Frame

Fully configured comprehensive activity-based modeling systems are computationally very demanding, and it takes a long time to execute even a single run. Although figure 1 shows the interrelation of the different user behavior dimensions, which are affected by system or attribute changes, such a modeling system is operationally not practical. Because going through an exercise of updating medium- and long-term choice dimensions with every choice update based on short-term changes is not attractive nor useful, a key question for modelers is which choice dimensions must be treated as endogenous and which choices can be viewed as exogenous. Traditionally, supply and demand management strategies have been used to only update route choices or shortest path calculations in supply tools. However, with additional information provided to travelers, the range of endogenous choices included in the model can and should be expanded. This concept is illustrated in figure 2 where long-term changes are outside the modeling realm, and information blurs the boundary between day-to-day behaviors, behavioral patterns, and medium-term changes. As travelers gain more information, the inner sphere expands to include these behavioral patterns, which may be adjusting more dynamically than has been recognized in existing models.

The different case studies presented in the following chapters follow their time horizon from long-term policy interventions to short-term interventions. Each case study includes a general framework that points to the relevant choice dimensions to be included into the modeling tools. This framework discussion within subsequent chapters focuses on specific interventions and the associated data and modeling requirements. Within each of the following intervention areas, the following case studies are presented:

- Policy and non-network interventions.
- AERIS.
- ATDM and MTD.
- ATIS:
    - ICM.
    - WRTM.

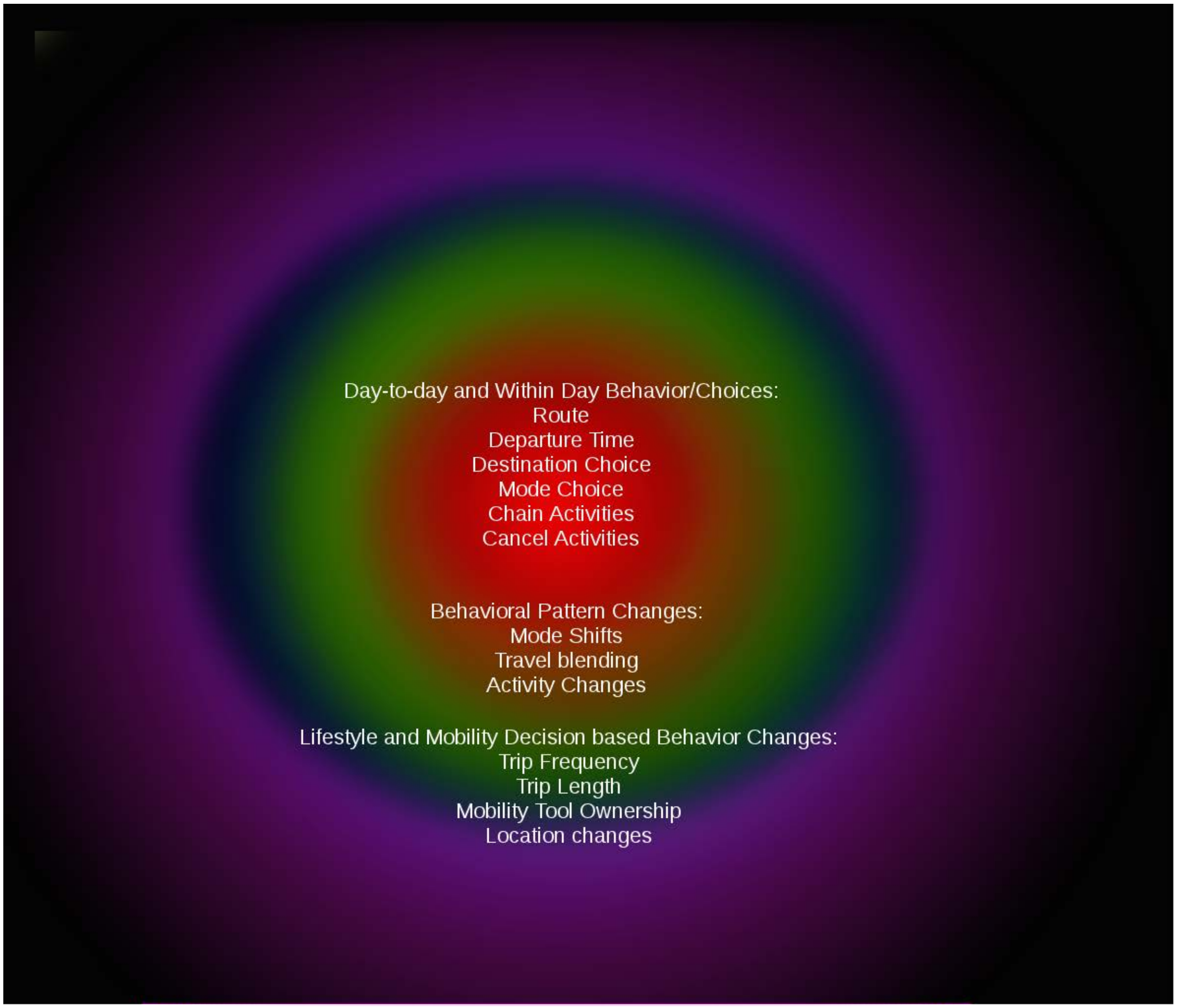


Figure 2. Illustration. Expanding sphere with fuzzy boundaries.

CHAPTER 4. URBAN POLICY AND NON-NETWORK INTERVENTIONS CASE STUDY

PROGRAM INTERVENTIONS: URBAN DESIGN POLICY

Built Environment

The potential influence of the built environment on travel behavior has been widely studied in the literature.[56,67,68] Early studies of land use and travel behavior focused more on hypothesis testing regarding the correlation between built environment and travel, but the debate about causality of observed correlations is ongoing. Despite the large number of existing studies, the magnitude of the effects of built environment on travel behavior, specifically mode choice, is unclear. Self-selection/endogeneity and serial and spatial correlation among individuals and environments surveyed are difficult to measure and evaluate, and the relationships between built environment and travel behavior cut across levels of time and space.

Cao et al. and Mokhtarian and Cao provide an extensive discussion on how to robustly infer causality in this regard.[8,9] To do so, four types of evidence are required: correlation, non-spuriousness, time precedence, and causal mechanism.[9] Correlation refers to a significant association between the considered variables and travel behavior. Non-spuriousness refers to a relationship that cannot be attributed to another variable. Time precedence requires causes to precede effects, and causal mechanism is a logical explanation for why a cause should produce the observed effect. Many studies in the past have carefully controlled for the statistically significant correlations and causal mechanism in which a logical explanation of the cause and effect exists. However, few studies have been able to meet the non-spuriousness and time precedence criteria.[69] Mokhtarian and Cao suggested that a model that explicitly includes attitudinal and socio-demographic variables could perform well on the non-spuriousness criterion, specifically with regard to residential self-selection.[9] "Residential self-selection" refers to the tendency of people to choose locations based on their travel abilities, needs and preferences.[69] Therefore, an observed correlation between land use and travel behavior can be ensured to be the non-spurious result of the unmeasured variables. Performing temporal analyses and involving measurement at multiple points in time can help to meet the time precedence criterion.[9,70] While these considerations would help strengthen a planner's argument, they still fall short of accepted standards for scientific evidence.

Most of the land use-travel behavior studies are regression-based, in which socio-demographic characteristics and measures of land use are treated as independent variables.[69] Suggesting that the underlying behavioral structure of how land use influences travel is missing in regression-based analyses, Boarnet provided a review of methodologies to overcome this limitation.[71] Land use can influence the cost to travel by changing travel time. Boarnet and Crane suggested that travel speed and trip distance are functions of land use and proposed using a composite travel price variable representing the impact of land use on travel cost.[26] Cervero also uncovered the possible impacts of residential self-selection on travel behavior.[72] A quantitative approach suggested by some researchers to deal with this problem is to develop joint discrete choice models of residential location and travel behavior.[73–75] The endogeneity of policies, plans, and urban development patterns is another limitation which has been virtually neglected in the literature.[71,76] This endogeneity results in serial and spatial correlation, which affects how individuals make decisions over time, affecting network accessibility and location choices.

A recent study by Zhang analyzed the influence of land use on travel mode choice using data from Boston, MA, and Hong Kong for work and non-work travel.[68] Under the assumption that attitudes affect both travel behavior and land use through residential self-selection, this study did not properly detect the true effect of land use on mode choice because the model did not consider self-selection bias. Improvement in a model's goodness-of-fit after the inclusion of land use variables does not necessarily imply that land use has an independent influence on mode choice.[68]

Crime

While transit agencies can control many aspects of their service, the public nature of transit means that passengers' experienced quality of service is subject to environmental factors often outside of the agency's control. Concern for personal safety/security is a primary concern of transit riders and non-riders, and studies suggest that fear of crime acts as a deterrent to transit ridership. (See references 77–80.) Needle and Cobb presented case studies that indicated that crime and peoples' perception of it reduces transit ridership and revenues.[81]

Loukaitou-Sideris et al. studied 10 bus stations with the highest crime rates in Los Angeles, CA, and found that physical environment and the occurrence of crime are correlated.[79] Most of the 10 high-crime bus stops in the study were located in parts of the city that lack proper lighting, good police deployment, or public phones (the study precedes the widespread availability of mobile phones). Painter studied the effects of street lighting on crime, fear of crime, and pedestrian street use and also concluded that lighting improvements can reduce street crimes to a large extent.[82] Painter also found that street lighting could increase pedestrians' propensities to use the streets after dark in urban streets and residential settings.[82] One approach to reduce crime at transit stations is to follow recommendations of a program called Crime Prevention Through Environmental Design (CPTED).[83,84] The CPTED concept is based on the defensible space concept in which people need to see and be seen in order to protect themselves and avoid crime, and people need to report crimes when they occur.

Some studies have suggested counterintuitive results (i.e., higher crime attracts transit use). This may be because crime influences market segments differently. Transit captives by definition do not have much choice in mode, so the interaction of crime and income and their effects on transit use is still unclear. Ferrell and others have argued that these contradictory results of effects of crime on women and adolescents' physical activities could be related to the differences in actual/reported crimes and individual perceptions of neighborhood crime.[85,86] Less serious crimes such as intimidation, public indecency, obscenities, vagrancy, and vandalism affect the transit environment but may go unreported if riders choose to ignore them. While in these studies the relationship between reported crimes and physical activity engagement is unclear, the perceptions of crime and safety are related to the physical activity engagement.[87] Kim et al. found that women's access mode to transit is influenced by crime. Women are more likely to be dropped off at the station at night than drive, use transit, or walk.[88] Employing CPTED concepts to enhance defensibility, awareness, and surveillance could influence these choices over time.

Behavioral Dimensions—Mode Choice

Cervero and Kockelman suggested that land use characteristics can be categorized in "three D's:" density, diversity, and design.[52] *Density* refers to the variable of interest divided by area (e.g., population density, job density, etc.). *Diversity* refers to the different land uses in a given area (e.g., entropy index, diversity index, mixed use development, etc.). *Design* refers to the properties of the network such as connectivity, grid, or cul-de-sac, etc. Zhang summarized the direction of effects of land use on travel behavior (see table 1).[68] An increase in density often decreases the likelihood of driving, driving length, and trip chaining while having mixed effects on driving frequency, route choice, and telecommuting. Increases in diversity measures reduces driving choice while increasing driving frequency and trip chaining. Diversity has mixed effects on driving length and route choice. Network design with more connectivity also decreases the likelihood of driving while it may increase driving frequency. The effects of land use on departure time choice and telecommuting are mostly unknown.

Table 1. Summary of the effects of land use on travel behavior.[68]

Travel Behavior	Dimensions of Land Use			Travel Patterns
	Density	Diversity	Design	
Driving choice	−	−	−	Modal split
Driving frequency	±	+	+	Total trips
Driving length and duration	−	±	?	VMT/vehicle hours traveled
Departure time	?	?	?	Peaking
Route choice	±	±	±	Road congestion
Trip chaining	−	+	±	Trip rate and distance
Tele-travel	±	?	?	All

Note: The symbols +, -, and ? indicate positive, negative, and unknown effects, respectively.

The research has grown from the "three D's" to include detail, destination, and a dozen others. This requires new ways of thinking and additional data to understand a suite of trips and socialization. There are strong attitudinal elements and a wide variation of elasticity of attitudes with respect to different interventions; this requires capturing heterogeneity among travelers. The understanding of interactions between modes is growing, and often a number of modes are competing for the same space. There are also interactions between network and non-network characteristics of modes. For example, walkability requires that sidewalks exist and be in good condition. There is a demand for different products, so researchers need to think of a synergistic suite of options or a mobility bundle.

The FHWA Complete Streets program is intended to examine such mobility bundles and provide viable alternatives to auto travel via infrastructure that accommodates all types of users. The program suggests improving land use and design measures that enhance accessibility and walk quality, such as sidewalks, bicycle lanes, safe and accessible transit stops, and frequent and safe crossings for pedestrians.[89] Regarding transit accessibility, several studies have found a positive impact on transit choice with elasticities between 0.02 and 1. (See references 90−94.) Others have looked at the effect of transit accessibility on VMT. (See references 90, 92, and 95–99.) They all found a significant negative impact with elasticities between -0.01 to -0.19. Mixed use development has been found to have a positive impact on transit choice. Studies by Zhang and

Frank et al. suggest that the effect of land use mix on transit choice is larger for non-work trips than work trips.(92) Table 2 presents point elasticities of different land use variables reported by Cervero.(56) Sidewalk ratio, as a walk quality measure, has a negative impact on driving regardless of trip purpose and positive impact on transit use.

Table 2. Point elasticity estimates imputed from mode choice models: percentage change in probability of choosing mode with a 1 percent increase in built environment factor.(56)

	Home-Based Work Trips	All Trip Purposes		
Built-Environment	Drive Alone	Drive Alone	Group Ride	Transit
Gross density[1], origin	-0.151	-0.163	-0.124	+0.511
Gross density, destination	-0.259	-0.137	-0.096	+0.268
Land use diversity[2], origin	-0.141	-0.340	-0.361	+0.615
Land-use diversity, destination	-0.197	-0.291	-0.165	+0.452
Sidewalk ratio[3], origin	-0.390			
Sidewalk ratio, destination	-0.448	-0.366	-0.062	+0.327
Transit-oriented multi-family housing, origin		-0.052	-0.066	+0.195
Job accessibility[4], origin	+0.141			
Labor force accessibility[5], destination	+0.290			

Note: Blank cells indicate instances that were not measured.
[1]Gross density = (population + employment)/gross square miles (in thousands).
[2]Land use diversity = Retail employment and population relative to countywide ratio.
[3]Sidewalk ratio = Ratio of sidewalk miles to road miles.
[4]Job accessibility = Number of jobs (in thousands) within 45-min highway network travel time.
[5]Labor force accessibility = Number of households (in thousands) within 45-min highway network travel time.

Framework for Evaluation

The interest in analyzing transport policies in terms of their impacts has led to the use of disaggregate demand models, which seek to understand short-term effects of such policies as congestion pricing. The limitation of traditional trip-based travel models to capture the complex ways travelers respond to such policies has led to the development of behavior-oriented activity-based models and the introduction of traveler response to current cost, travel time, reliability, and other service information.

The advantages of activity-based models are diverse and include the following:

- They can identify the influence of trip attributes on time, destination, and mode.
- They capture longer-term behavior, overcoming the limitations of tour-based models by including activity patterns outside the daily schedule in addition to time dependency, destination, and mode.
- They better capture certain characteristics of individual based decisions beyond aggregate traffic analysis zones (TAZs).

- They capture short-term decision shifts which may have substantial impacts at the network level.

- Linkage of interpersonal decisions, which are crucial to policies such as HOV or high-occupancy toll lanes, can be taken into account. Traditional models cannot account for the coordination of activities between different individuals (e.g., individuals carpooling together), yet this is a characteristic of activity and travel patterns.

These are also the main reasons to incorporate an activity-based framework over a trip- or tour-based framework into the analysis of pricing policies.

Within activity-based models, the modeled behavior choices for households and individuals are normally organized sequentially on the basis of the timeframe over which they might take place. Long-term decisions are modeled first, followed by medium- and short-term decisions. Each of the models imposes certain restrictions on the subsequential decisions on a shorter time horizon. The same conceptual framework is kept in place for integrating activity-based models with the network assignment procedure to analyze pricing strategies, which is discussed later in this report regarding traveler response to network information.

In the short term, it is expected that travelers' safety/security perception and built environment factors influence mode choice. However, in the medium-to-long-term horizons where policy influences the environment and crime rates, policy will indirectly influence further user decisions. This is illustrated in figure 3 by taking accessibility measurement calculations into account, which in return have effects on upper-level choices of car ownership, daily activity patterns, as well as longer-term higher order choices of home, workplace, and school locations.

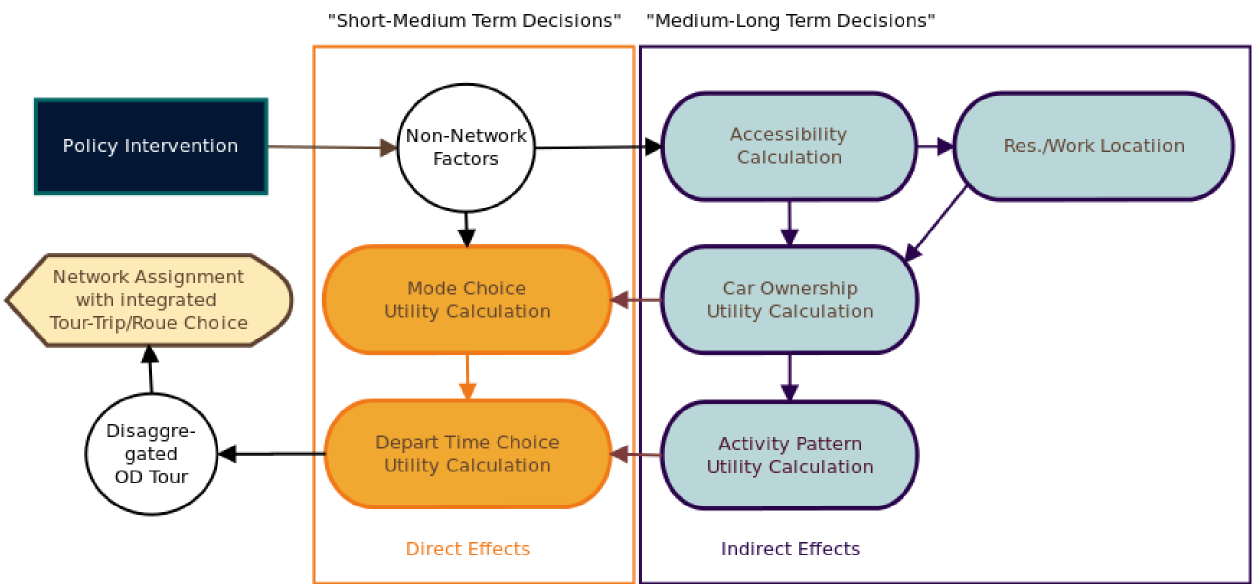


Figure 3. Illustration. Direct and indirect influences of non-network factors over time.

BEHAVIORAL MODELS

In order to detect the true effect of land use, Mokhtarian and Cao proposed different approaches including direct questioning, statistical control, instrumental variables modeling, sample selection modeling, joint models, and longitudinal designs.(9) *Direct questioning* refers to asking people in focus groups and personal interviews whether land use affects their travel behavior. The statistical method estimates the proportion of total effect of land use on travel behavior which is due to land use alone rather than due to the effect of attitudes on land use (via residential self-selection) by inclusion of a rich set of attitudinal and socio-demographic variables in the model. In instrumental variable models, land use is first modeled as a function of relevant instrumental variables and then replaced in the choice model. The sample selection modeling technique explicitly models the prior selection into different residential location types and then models the outcome as conditional on that prior selection. The joint modeling approach considers endogenous variables of residential location and travel behavior jointly and models the joint probability bundled. Finally, longitudinal design refers to before-after measurements. Referring back to the study by Zhang, although a significant correlation between land use and travel behavior was observed, the magnitudes of the elasticity estimates for mode choice with respect to the land use variables were relatively small, with an absolute value no greater than 0.3.(68) Therefore, Zhang properly concluded that land use is necessary but not sufficient to influence travel.(68)

Ewing and Cervero used a meta-analysis to make a similar conclusion that the relationships between travel variables and built environmental variables are inelastic, with the greatest absolute magnitude of 0.39.(67) Nevertheless, both Zhang and Ewing and Cervero highlighted that the combined effect of land use variables could be large.(68,67) Moreover, a study by Chatman showed that self-selection is more likely to increase the influence of land use.(100)

Assuming that residential self-selection is generally a result of attitudes and socio-demographic traits, Mokhtarian and Cao suggest that inclusion of a rich set of attitudinal and socio-demographic variables in a model could offer insightful evidence whether the influence of land use is entirely due to predisposed attitudes (self-selection) or not.(9) Mokhtarian and Cao proposed a statistical method to estimate the proportion of total effect of land use on travel behavior which is due to land use alone rather than due to the effect of attitudes on land use (via residential self-selection).(9) To do so, the ratio of the incremental change can be computed in the model log-likelihood measure when land use variables are added to a model containing all other variables including attitudinal and socio-demographic variables, to the incremental change when attitudinal and socio-demographic variables and land use variables are added together (see figure 4).(9)

$$\xi = \frac{L_3 - L_2}{L_3 - L_1}$$

Figure 4. Equation. Land use effect.

Where:

ξ = True effect of land use.
L_1 = Log-likelihood of the base model.

L_2 = Log-likelihood of the model when attitudinal and socio-demographic variables are added.
L_3 = Log-likelihood of the model when attitudinal and socio-demographic variables and land use variables are added together to the base model.

For this analysis, mixed logit models were used to evaluate the influence of non-network factors on mode choices. To realistically capture the impact of non-network impacts on different user groups, it is essential to represent users' preferences in response to crime, accessibility, walkability, and travel time in the choice models. To capture the differences between heterogeneous users, mixed logit models with random parameters were estimated to model the response on mode choices based on the travel time and cost skims. In the mixed logit model framework, the utility of each alternative *j* to each individual *i* can be represented by the equation shown in figure 5 as follows:

$$U_{ij} = x_{ij}b_j + (z_{ij}n_i + e_{ij})$$

Figure 5. Equation. Utility function (mixed logit).

Where:

u_{ij} = The utility of alternative *j* for individual *i*.
$x_{ij}b_j$= The systematic part of the utility for alternative *j* and individual *i* where b_j is a vector of parameters to be estimated for each alternative *j*.
x_{ij} = The vector of characteristics unique to alternative *j* relative to individual *i*, unique to individual *i*, or both.
$z_{ij}n_i + e_{ij}$ = The stochastic component of the utility, where z_{ij} is the cost vector that varies over individuals, n_i are individual-specific parameters to be estimated by a distribution with fixed parameters, and e_{ij} is an independent and identically distributed error term across individuals and alternatives.

For each individual, the choice probabilities will depend on b_j and η. Conditional on η, the probability that individual *i* selects alternative *j* is simply multinomial logit as shown in figure 6 as follows:

$$P(j \mid \eta) = \frac{e^{X_j\beta_j + Z_j\eta}}{\sum_{k\in J} e^{X_k\beta_k + Z_k\eta}}$$

Figure 6. Equation. Choice probability (multinomial logit).

Where:

η = Model parameter for the cost vector.
$P(j|\eta)$ = The probability that individual *i* selects alternative *j* conditional on η.

If the value of *n* were known for each individual, the solution to figure 4 would be straightforward. However, *n* is unobserved, although it is drawn from a known joint density function *g*. Thus, to obtain the unconditional choice probability for each individual, the logit probability must be integrated over all values of *n* weighted by the density of *n* using figure 7.

$$P(j) = \int_{\eta} \left[\frac{e^{X_j \beta_j + Z_j \eta}}{\sum_{k \in J} e^{X_k \beta_k + Z_k \eta}} \right] g(\eta \mid \Omega) \partial \eta$$

Figure 7. Equation. Choice probability (mixed logit).

Where:

Ω = Fixed parameters of the distribution of g.
$P(j)$ = The probability that individual *i* selects alternative *j*.

The parameters in the mixed logit probability formulation in figure 5 are estimated by maximizing the following log likelihood function shown in figure 8 as follows:

$$L(\beta, \Omega) = \sum \sum y_{ij} \log \left[\int_{\eta_i} \left\{ \frac{e^{X_{ij} \beta_j + Z_{ij} \eta_i}}{\sum_{k \in J} e^{X_{ik} \beta_k + Z_{ik} \eta_i}} \right\} g(\eta_i \mid \Omega) \partial \eta_i \right]$$

Figure 8. Equation. Log-likelihood function (mixed logit).

Where:

y_{ij} = An indicator of whether individual *i* chooses alternative *j*, can be solved as follows:

$$y_{ij} = \begin{cases} 1 & \textit{if i chooses j} \\ 0 & \textit{otherwise} \end{cases}$$

Figure 9. Equation. Choice indicator.

Ideally, latent class models with random parameters would be well suited to capture endogeneity, built environment effects, and the (perhaps counterintuitive) influence of crime on transit. Actual crime and crime perception may be related to trip purpose, accessibility, and transit captivity, but such perceptions are typically unobserved by transport analysts. Using the general method described by Ben-Akiva et al., walkability and safety perception would be treated as latent variables, and Walk Score™ or another built environment indicator could be used to measure walk quality.[101] Figure 10 illustrates the model concept.

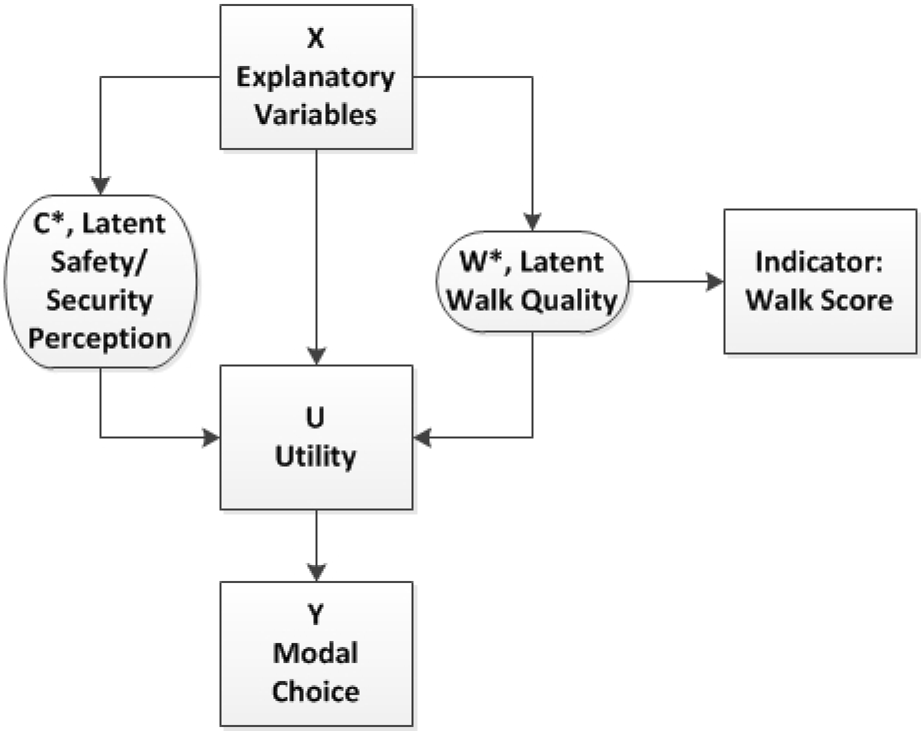


Figure 10. Illustration. Hybrid choice model with latent variables.

DATA AVAILABLE AND USED IN CASE STUDY

The case study presented in this chapter highlights and leverages new data sources that are publically available and ready to be integrated in tools and models at very low cost which would allow improving current models and improving the accuracy of predictions without costly survey work. Accordingly, multiple data sources are combined to capture network and non-network impacts on travel choice. This section provides a detailed description of the datasets that are used to estimate the mode choice model. Figure 11 illustrates the variety of information used for modeling.

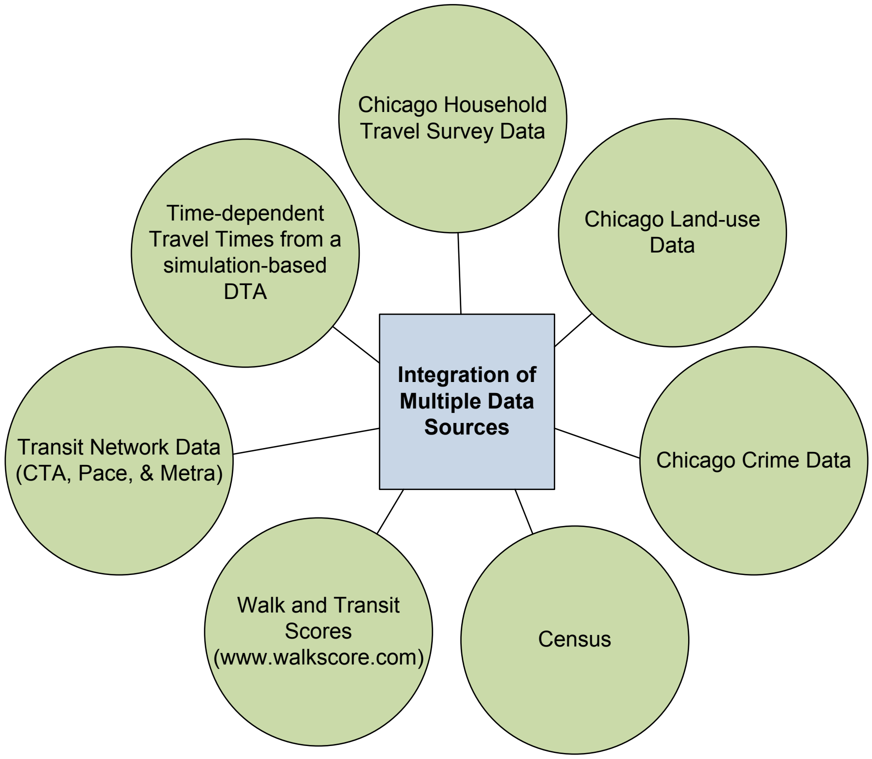


Figure 11. Illustration. Integration of multiple data sources.

Spatially Disaggregated Information About Walk Quality and Safety in Chicago, IL

Walk and Transit Scores

Walk Score™ is an increasingly popular measure of a location's walkability.[(101)] Using the free walk score Application Programming Interface (API) and the longitude and latitude of Chicago Transit Authority (CTA) bus stops, each stop was assigned a walk score between 1 and 100 as defined by the Walk Score™ creators:

- **0–24**: Car-dependent, almost all errands require a car.
- **25–49**: Car-dependent, a few amenities within walking distance.
- **50–69**: Somewhat walkable, some amenities within walking distance.
- **70–89**: Very walkable, most errands can be accomplished on foot.
- **90–100**: Walker's paradise, daily errands do not require a car.

To compute a walk score, points are awarded based on the distance to amenities by categories, where amenities within 0.25 mi receive maximum points, and no points are awarded for amenities further than 1 mi.[(102)]

Similarly, a transit score is a measure of transit accessibility computed using General Transit Feed Specification data. As with the other transit network accessibility measures, since household travel information was available for a single point in each TAZ, the transit score for this particular point (not the exact location of a trip start or end), is not particularly meaningful. It was included for completeness, but not as significant as the developed measure of transit accessibility for estimating mode choice. The definition for transit score is as follows:

- **0–24**: Minimal transit, it is possible to get on a bus.
- **25–49**: Some transit, a few nearby public transportation options.
- **50–69**: Good transit, many nearby public transportation options.
- **70–89**: Excellent transit, transit is convenient for most trips.
- **90–100**: Rider's paradise, world-class public transportation.

Crime Data

The Chicago Police Department's crime dataset reflects reported incidents of crime (with the exception of murders where data exists for each victim) that occurred in Chicago, IL, from 2001 to the present. In order to protect the privacy of crime victims, addresses are shown at the block level only, and specific locations are not identified. Since crime rates vary by season and year, this analysis combines crime data from 2005–2008 to represent what may be travelers' overall perceptions of crime in different areas. Crimes were categorized and aggregated for each origin and destination TAZ in the Chicago Metropolitan Agency for Planning (CMAP) household travel tracker survey (see figure 12). The crimes were categorized according to the Federal Bureau of Investigation's crime classification codes (see table 3). Because it is anticipated that crime will be higher where there are more people, total TAZ crimes by category are divided by TAZ population to obtain a density as opposed to a count.

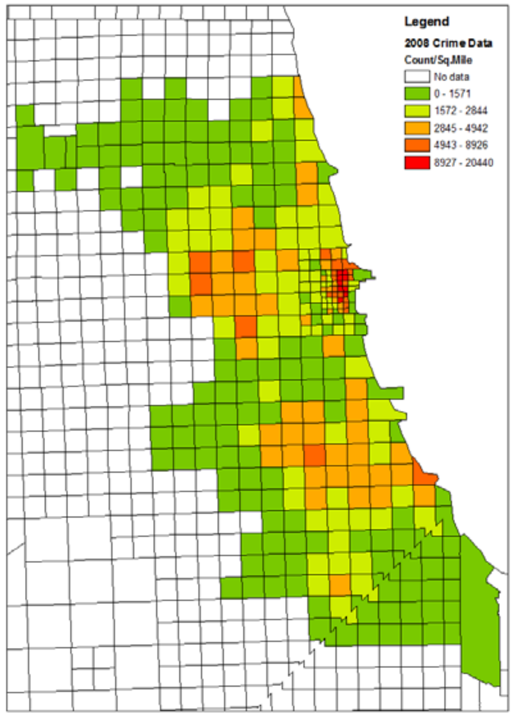


Figure 12. Illustration. Chicago, IL, crime count at the TAZ level in 2008.

Table 3. Crime categories tested in model.

Category	Definition
Index	More serious offenses. Homicide first and second degree, criminal sexual assault, robbery, aggravated assault, aggravated battery, burglary, larceny, motor vehicle theft, and arson.
Non-index	Less serious offenses. Involuntary manslaughter, simple assault, simple battery, forgery and counterfeiting, fraud, embezzlement, stolen property, vandalism, weapons violation, prostitution, drug abuse, gambling, offenses against family, liquor license, disorderly conduct, and miscellaneous non-index offense.
Property	Burglary, larceny, motor vehicle theft, and arson.
Violent	Homicide first and second degree, criminal sexual assault, robbery, aggravated assault, and aggravated battery.
Aggravated assault	An unlawful attack by one person upon another wherein the offender displays a weapon in a threatening manner. Placing someone in reasonable apprehension of receiving a battery.
Aggravated battery	An unlawful attack by one person upon another wherein the offender uses a weapon or the victim suffers obvious severe or aggravated bodily injury involving apparent broken bones, loss of teeth, possible internal injury, severe laceration, or loss of consciousness.
Drug abuse	The violation of laws prohibiting the production, distribution, and/or use of certain controlled substances and the equipment or devices utilized in their preparation and/or use.
Index transit	Index crimes occurring in/on transit vehicles, stations, platforms, or facilities.

Time-Dependent Travel Times

Data on the comparative travel times and travel costs of competing modes (CTA bus and rail and Metra rail) for each trip are obtained from network databases. Auto travel times are estimated based on time-dependent origin-destination travel times obtained from a simulation-based DTA model, Dynamic Network Assignment-Simulation Model for Advanced Roadway Telematics (DYNASMART).(102) When skimmed travel times were not available, mode-specific average speeds were used to estimate travel times. Table 4 shows the average speeds obtained from the reported travel times of the chosen alternatives in the survey data.

Table 4. Mode-specific average speeds from Chicago, IL, Household Travel Survey data.(103)

Mode	Average Speed (mi/h)
Auto	14.4
Bus	5.9
CTA rail	8.5
Metra rail	17.7

Chicago Household Travel Survey

The main source of data was the 2008 Travel Tracker Household Survey conducted in the northeastern Illinois region during 2007 and 2008 by CMAP.(104) Travel diary information with origin and destination information reported trips (figure 13) was collected from 14,390 households in the Chicago, IL, region, including some households in western Indiana and southern Wisconsin.

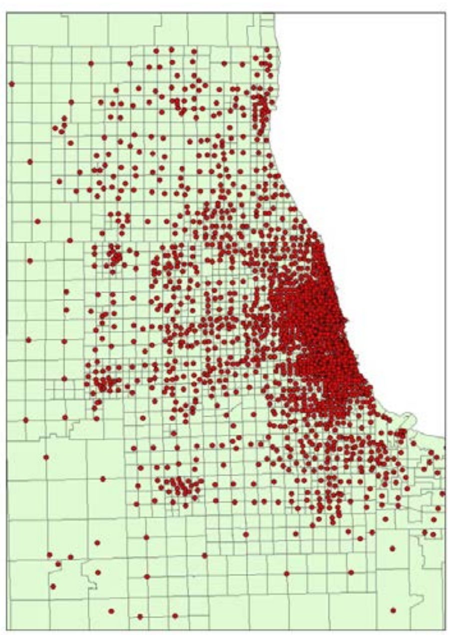


Figure 13. Illustration. Map of approximate locations of all origins and destinations recorded in the CMAP Household Travel Survey data.

The dataset includes a total of 78,681 recorded trips with the four following trip purposes:

- **Home-based to work (HBW)**: 14,895 trips.
- **Home-based to school (HBSch)**: 5,640 trips.
- **Home-based to other (HBO)**: 36,888 trips.
- **Non-home based (NHB)**: 21,258 trips.

Travel costs for auto and CTA bus/train were estimated using figure 14 through figure 16 based on the Federal rates for privately own vehicle mileage reimbursement:

$$\text{Auto cost} = 0.505 \times \text{distance} + \text{toll(s)} + \text{parking fee}$$

Figure 14. Equation. Auto cost estimation.

$$\text{CTA bus/train cost} = 1.75 + 0.25 \times \text{number of transfers} + \text{parking fee}$$

Figure 15. Equation. CTA bus/train cost estimation.

$$\text{Metra train cost} = \text{fare} + \text{parking fee}$$

Figure 16. Equation. Metra train cost estimation.

Fares for Metra rail are estimated based on a distance-based zonal system, as shown in table 5.

Table 5. Distance-based Metra fares.[105]

Zone	Distance (mi)	Fare ($)
A	0–5	1.95
B	5–10	2.14
C	10–15	3.05
D	15–20	3.45
E	20–25	3.91
F	25–30	4.32
G	30–35	4.68
H	35–40	5.14
I	40–45	5.55
J	45–50	6.00
K	50–55	6.41
M	> 55	7.32

Chicago, IL, Land Use Data

Land uses were obtained from CMAP's 2005 land use inventory. The inventory was created using digital aerial photography supplemented with data from numerous Government and private-sector sources. The land use data identify areas as small as 1 acre using a 49-category classification scheme. The following list presents main classes included in the database:

- Residential.
- Commercial and services.
- Institutional.
- Industrial, warehousing, and wholesale trade.
- Transportation, communication, and utilities.
- Agricultural land.
- Open space.
- Vacant, wetlands, or under construction.
- Water.

For this analysis, the list was reduced to five classes: residential, commercial, institutional, industrial, and other. In order to examine the effect of mixed use development on traveler behavior, several dummy variables at different spatial scales (with a radius of 0.25, 0.5, and 1 mi) were created for trip origin and trip destination, separately. These dummies were not significant in the model, and ultimately a measure of land use mix was most significant. Land use mix diversity index was estimated at different spatial scales (with radius of 0.25, 0.5, and 1 mi). The land use mix diversity index is computed as proposed by Bhat and Gossen and Rajamani et al. using figure 17.[106,94]

$$\text{Diversity index} = 1 - \frac{\left|\frac{Res}{T} - \frac{1}{5}\right| + \left|\frac{Com}{T} - \frac{1}{5}\right| + \left|\frac{Ind}{T} - \frac{1}{5}\right| + \left|\frac{Ins}{T} - \frac{1}{5}\right| + \left|\frac{O}{T} - \frac{1}{5}\right|}{\frac{8}{5}}$$

Figure 17. Equation. Land use mix diversity index.

Where:

Res = The area of residential land.
Com = The area of commercial and services land.
Ind = The area of industrial land.
Ins = The area of institutional land.
O = The area of all other classes.
T = The total area around the desired location.

The mix diversity index is zero if land use is completely homogenous with only one class. The mix diversity index is equal to 1 if land use is fully mixed with equal proportion of all included land use classes.

Census Data

Census data include housing, population, and employment information at the smallest possible spatial aggregation (tract level). Population, housing, and employment densities were calculated for each trip origin and destination recorded in the Chicago Household Travel Survey data. Figure 18 shows a map of the population density in the Chicago, IL, metro region at the TAZ level.

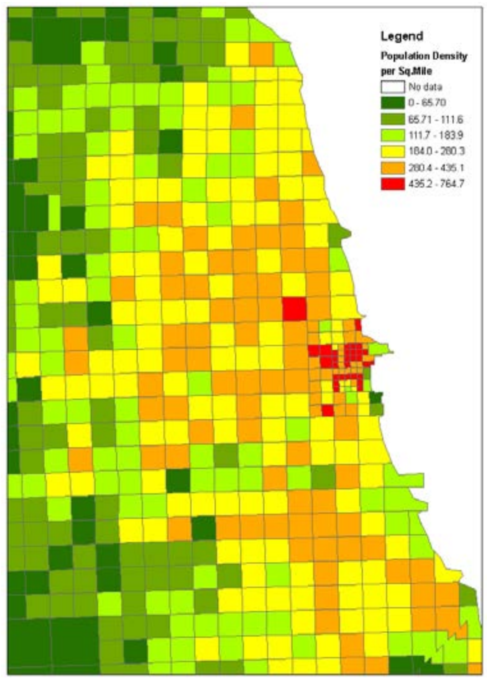


Figure 18. Illustration. Population density in the Chicago, IL, metro region at the TAZ level from Census data.

Transit Network Data

Added to the land data are information from CTA, Pace (the premier suburban transit provider in Chicago's suburbs), and Metra. The transit network in Chicago covers many suburbs and is strongly oriented toward the CBD.

For each trip origin and destination separately, several dummy variables at different spatial scales (with radius of 0.25, 0.5, 0.75, and 1 mi) were created to reflect the following transit accessibilities:

- Dummy variable for accessibility to CTA bus stop.
- Dummy variable for accessibility to Pace bus stop.

- Dummy variable for accessibility to CTA train stop.
- Dummy variable for accessibility to Metra train stop.

Ultimately, due to the precision of origins and destinations for each observation, these accessibilities were also reduced to a simple indicator of whether there was transit within a 0.25-mi radius of the origin or destination. This loss of resolution is due to insufficient observations of individuals over the course of a typical week and the aggregation of origins and destinations to a zonal centroid. Without knowing the precise origin and destination point of each traveler, it is difficult to determine exactly how accessible transit is for a given trip. Figure 19 through figure 22 provide the geo-coded location of the CTA bus stops, Pace bus stops, CTA train stops, and Metra train stops, respectively.

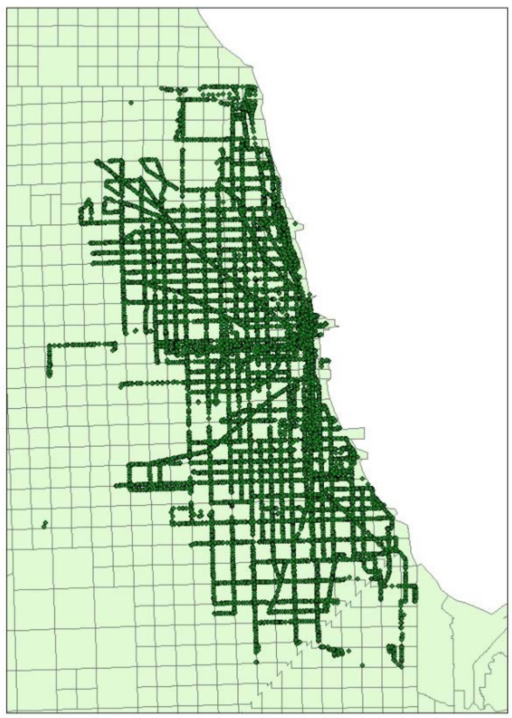


Figure 19. Illustration. Geo-coded locations of CTA bus stops.

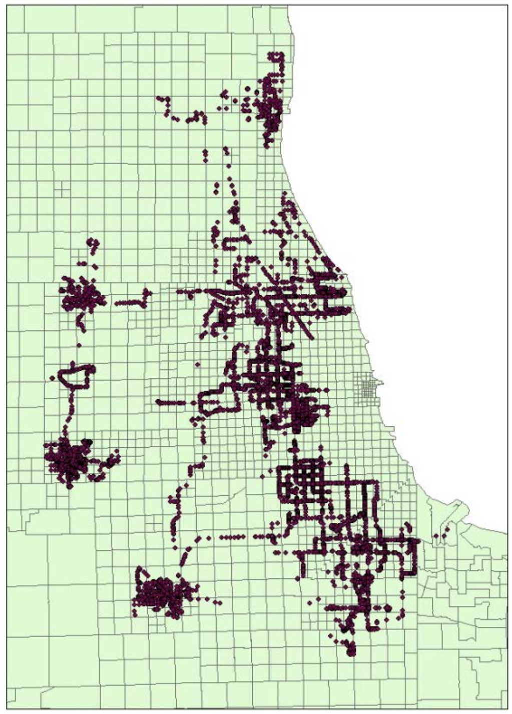


Figure 20. Illustration. Geo-coded locations of Pace bus stops.

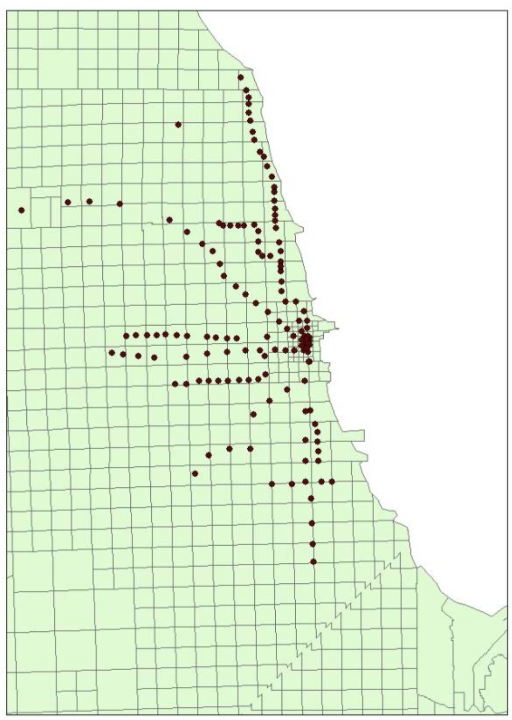


Figure 21. Illustration. Geo-coded locations of CTA train stops.

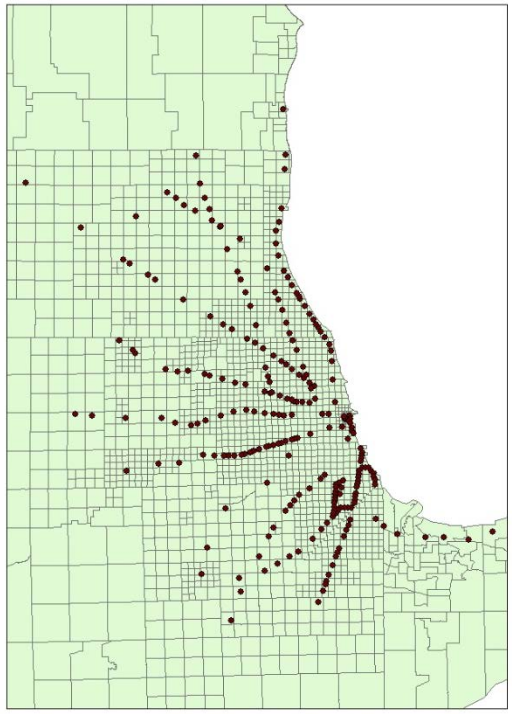


Figure 22. Illustration. Geo-coded locations of Metra train stops.

MODEL DEVELOPMENT AND CALIBRATION

Mixed logit models were estimated to test combinations of variables until a satisfactory exploratory model was found. The final model is described in table 6. The most significant crime category influencing mode choice was drug use, though it was only significant in explaining urban transit mode choice, not suburban rail.

Travel time and travel cost divided by income had a negative impact on mode choice as expected. Since theory and common sense suggest that the importance of cost should decrease with income, cost was divided by the income. The values of time had to be adjusted to reflect the income units. As the travel costs are in dollars, travel time in minutes and income in dollars per year, the value of time spent in travel to the value of time spent working can be calculated by multiplying the ratio of the parameters by 12. That is, the estimated parameters, which are used to generate a distribution, from which the mean can be simulated. This gives a mean ratio of value of time spent in travel to value of time spent working of 0.23. This is in line with obtained values from other studies, which suggest a value of time in Chicago for traveling of around $10/h, which is smaller than the mean income.

The travel time index, a measure of congestion, is the ratio of reported travel time to free-flow travel time. The negative sign on this variable may indicate the self-selection of auto users versus choice transit users. Travelers are more likely to use transit for work trips and much more likely to use transit if the trips start and/or end in CBD due to the downtown-oriented transit systems.

The effects of land use diversity and density on urban transit use (i.e., CTA) corroborate the findings of Cervero.[56] Origin population and destination job densities increase transit use but tend to decrease suburban rail (Metra) use. This negative effect could be due to the relatively large catchment areas for suburban rail. The number of park and ride spaces was not a significant variable for either mode, which is probably due to the practice of parking on neighborhood streets to access transit. Similarly, origin land use mix is not a significant variable for predicting suburban rail, probably because of the nature of the suburban areas served. Land use mix was significant and positive at the destination end for both urban and suburban rail.

In exploring model specifications, it was found that crime types were highly correlated. Detailed factor analysis of crime and how it influences transit use is a topic left for further research. Incidences of reported drug abuse tend to decrease transit use, but this is only significant for urban transit. The lack of significance for urban rail may be due to the differences in nature of the stations or opportunities for crime between these mode types.

Table 6. Mixed logit mode choice model.

Variable	Estimate	Standard Error	*t*-Value
Intercept			
CTA	-3.350	0.268	-12.518
Metra	-6.440	0.434	-14.854
Dynamic travel time	-0.014	0.001	-14.452
Standard deviation of travel time	0.031	0.012	8.213
Travel Time Index			
CTA	-0.091	0.012	-7.447
Metra	-0.086	0.021	-4.094
Cost/Income	-1.191	0.348	-3.419
Ratio of Vehicles to Household Members			
CTA	-3.361	0.148	-22.743
Metra	-0.735	0.176	-4.180
Trip Purpose is Work			
CTA	1.149	0.094	12.196
Metra	1.570	0.178	8.831
Start and/or end in CBD			
CTA	2.308	0.130	17.788
Metra	4.356	0.243	17.889
Transit Accessibility of Destination			
CTA	0.544	0.134	4.062
Metra	0.104	0.173	0.597
Walk Score of Origin			
CTA	-0.007	0.004	-1.983
Metra	0.007	0.005	1.539
Walk Score of Destination			
CTA	0.011	0.003	3.608
Metra	0.016	0.006	2.915

Origin End Population Density (1,000/1 mi)			
CTA	0.051	0.000	5.851
Metra	-0.097	0.000	-6.261
Destination End Job Density (1,000/1 mi)			
CTA	0.080	0.000	5.490
Metra	-0.029	0.000	-1.030
Origin Land Use Mix (0.25)			
CTA	1.713	0.306	5.604
Metra	-0.741	0.453	-1.635
Destination Land Use Mix (0.25)			
CTA	0.842	0.307	2.743
Metra	1.484	0.602	2.467
Drug Abuse Crimes/1,000 Population (0.25 mi)			
CTA	-6.807	0.003	-2.262
Metra	-0.200	0.002	-0.100

Based on the results presented in the table, the log likelihood is -2784.4, and the McFadden R^2 value is 0.484.

LIMITATIONS

The Household Travel Survey data used in this analysis were aggregated by zone, and origin and destination points were designated to protect the privacy of survey respondents. This kind of aggregation results in a loss of specificity, and measures such as land use diversity and transit accessibility are not exact for each individual.

Another limitation of the data and model is the inability to capture longer-term higher order decisions that may be influenced by policy. For instance, a number of attributes were not significant at the origin but were significant at the destination. This may reflect self-selection of respondents in that their origins were fixed whereas the destinations (at least for non-work trips) were somewhat more flexible. The opposite could be said for work trips: employees are not always able to select their work location. The selection of residential and work locations should be understood in the context of shorter-term decisions.

Recommended Next Steps and Research

There has been relatively little comprehensive cross-disciplinary exploration of the quality of life implications of travel. The physical activity afforded by walk trips—for whatever purpose—is of considerable interest to the public health community.[107,108] Research and implementation of environments that promote physical activity exist in Atlanta (e.g., strategies for metropolitan) and Seattle (e.g., land use, transportation, air quality, and health), and the recent panel studies of these travelers could be of great value for future research in non-network factors and active transportation. Crime is difficult to measure and even harder to predict, so the studies discussed here offer only snapshots of elements of the relationship between crime and transit mode choice. Capturing data on public health and safety in conjunction with travel behavior studies could illuminate these relationships. As in this study, such data may be combined from multiple sources, but the quality and level of capture of each data element cannot be overlooked. Open data may be the key to effectively integrating behavioral methods and concepts from psychology, sociology, geography, and transportation.

Such analyses require not only better measures of the walking environment and safety statistics, but also capturing trips by alternative modes. Passive data collection methods such as GPS and accelerometers on cell phones could be used to capture these trips without burdening the study subjects.[(109)] Longitudinal data collection is especially needed to capture self-selection and strategic behavior on the part of travelers, which influences the magnitude and significance of non-network effects at both origin and destination, and changing attitudes of travelers over time.

The case studies presented in chapters 5 through 8 represent advances in the state of the art and a significant step toward advancing the state of the practice in capturing user behavioral responses to operational and management interventions in assessment and simulation models. However, they are limited by the lack of sufficient data to calibrate all parts of the behavioral models. Conversely, the case study presented in this chapter highlights and leverages new data sources that are publically available and ready to be integrated in tools and models at very low cost which would allow improving current models as well as the accuracy of predictions without costly survey work.

Going beyond the immediate application presented in this chapter, the Internet has profoundly transformed activity engagement by creating virtual worlds or environments for activities, such as work and shopping, commonly pursued in the physical world. For travel behavior and time use analysts, virtual environments provide new opportunities for investigating decisions within a potentially experimental setting but also new opportunities to obtain rich data sources to integrate within models. Given the increasing engagement in online activities, such as social networking or games, understanding time use and travel decisions within these virtual environments may lead to an improved understanding of time use and travel in the physical environment. Individuals are increasingly engaging in virtual world activities, sometimes simultaneously or in conjunction with physical world activities.[(110,111)] Considering a set of activities that are engaged in the physical and a set in the virtual world, the set of activities that occur in both worlds can be conceptualized as the intersection of these two sets. As the opportunities for activity engagement in the virtual world continue to grow, a gradual eclipsing between these two worlds occurs.

Travel behavior and time use analysts have shed some light on this eclipsing by examining the role of information and communication technologies for work-related activities, from both a work management perspective and a travel/spatial location perspective. (See references 112–116.) For future research, such data from virtual worlds could be utilized and integrated further. Areas that come to mind include the following:

- Quality indicators from social networking sites such as Foursquare® or Yelp® could be used to build additional attributes for location choice models and/or location choice set generation.

- Real estate Web sites with an API, such as Trulia or DreamTown, can be used for residential location choice models.

- Data from online travel portals can be used to generate long-distance location choice sets.
- Activity patterns could be studied through social rating sites by looking at similarity patterns between locations that are visited by the same users.

CHAPTER 5. ATDM CASE STUDY

INTRODUCTION

The traveler choice focus area targets a traveler's higher-level predictive strategic choices influenced by a range of variables such as travel time reliability, congestion (recurrent and non-recurrent), weather, pricing, availability of transit services and parking, and sidewalks. Traveler choices in network and non-network conditions can be influenced by dynamic factors (e.g., travel time, level of congestion, and weather that travelers will encounter on trips) and static factors (e.g., availability of transit services, parking, sidewalks, and bike routes). The capability of existing transportation analysis tools to accurately model and simulate traveler choices is limited due to the lack of adequate methodologies and reliable data. Consequently, it is critical to understand choices made by travelers under various circumstances and the impact of these choices on the transportation system.

Within the area of ATDM, the study focused on identifying information and data that can inform the development of factors that are critical to bicycle riders' travel decisionmaking. The examination included a review of information and data collected by local areas in regional case studies on active transportation demand and supply travel information and identify available data and information that may inform the choices that travelers make about under what circumstances bicycle trips occur. This work builds on previous efforts related to bicycle travel data in the Metropolitan Washington region conducted by the Metropolitan Washington Council of Governments (MWCOG) as well as the Southern California region.

CURRENT AGENCY PRACTICES

The study reviewed the current practice and availability of active transportation planning data by region by conducting a literature search of publicly available documents, reports, and data. The Web sites of the significant transportation planning agencies within each region, including the MPO, large cities, and urban counties were reviewed. The study included telephone interviews with appropriate transportation planning staff of local and regional transportation planning agencies. The goal of the interview was to collect information on current practices in planning for active transportation and identify available data that the agencies have collected or used for this purpose. Some local bicycle travel data were requested and collected from government transportation planning agencies as examples of the state of the professional practice and the state of the art are for bicycle planning data collection efforts.

The following four urban metropolitan regions in the United States were examined for this effort:

- Washington, DC, metropolitan region.
- Southern California metropolitan region (Southern California Association of Governments (SCAG) region).
- San Francisco Bay area region.
- Cleveland region.

The initial review of existing local and regional transportation planning agency reports found that bicycle travel data were being collected and used to some degree for descriptive purposes. Data collected from the four metropolitan regions confirm that bicycle travel is increasing both as an active transportation mode and as a means of travel demand management. Bicycle travel supply and demand variables collected from local agencies varied in quality and robustness. Some agencies are beginning to integrate bicycle use data into travel forecasting, but simple trend extrapolation is the most common use. Changes in road capacity usage, particularly in larger urban areas, has the potential to impact automobile travel capacity and travel speeds along key urban street corridors.

The use of bicycle travel data for travel demand forecasting purposes was more limited. Leading edge travel demand modeling agencies are incorporating bicycle travel into overall regional travel forecasting, but significant data gaps limit the completeness and robustness of locally collected bicycle data for these purposes.

Information about data collection efforts in the San Francisco Bay Area Rapid Transit (BART) Agency includes the following:

- Station profile studies.
- Customer surveys.
- Passenger online surveys.
- Bike station surveys.
- Bicycle parking inventories.

Regional household travel surveys, such as the one conducted by MWCOG in 2007–2008, included data collection on the bicycle mode of travel. Some examples of data that were collected or estimated based upon the household travel surveys include the following:

- Number of bike trips.
- Bike trip distance.
- Percentage of population for whom biking is the primary travel mode.
- Percentage of daily trips by biking.
- Percentage of work trips by biking.
- Percentage of school trips by biking.
- Percentage of employers providing bike/pedestrian facilities or services.

- Type of bikeway mostly used (off-road bike trails versus on-road lanes).
- Percentage of daily trips by walking.

Other more specialized regional transportation planning studies collected data on bicycle modes as part of examinations of accessibility of neighborhoods and of transit stations. For example, in the Washington, DC, region, an internal study of the transportation and land use interaction included consideration of access to the bicycle mode and the potential use of the bicycle mode under different scenarios for transportation and land use in the region. Another internal study in the Washington, DC, region for the regional rail transit agency (Metrorail) collected and estimated data on the following:

- Bicycle infrastructure availability.
- Mode share of biking for Metrorail access by station type.
- Mode share of walking for Metrorail access by station type.

FRAMEWORK FOR EVALUATION

As discussed in chapter 4, the policies of interest in the realm of ATDM call for a deeper understanding of mode use in the context of individuals and household activity engagement decisions and behaviors. As a result, some of the same factors discussed in chapter 4 in relation to transit mode use and the influence of network and non-network factors, particularly land use, urban design, and safety/security perceptions are applicable in this case study, as well. Some of the main differences arise from the particular characteristics of active modes, especially bicycles, including their perceived (and actual) safety when running unprotected along with vehicular traffic, the physical effort that needs to be exerted in connection with frequent stop-start patterns, and the relative lack of protection vis-à-vis inclement weather. However, the basic structure of the modeling frameworks remains the same, with activity-based models providing an appropriate construct and tools to examine bicycle mode use as part of auto demand management strategies.

In the short term, it is expected that travelers' perceptions, prior experience, and built environment factors will influence mode choice in general and bicycle use in particular. However, in the medium- to long-term horizons, policy will indirectly influence further user decisions. This is illustrated in figure 23.

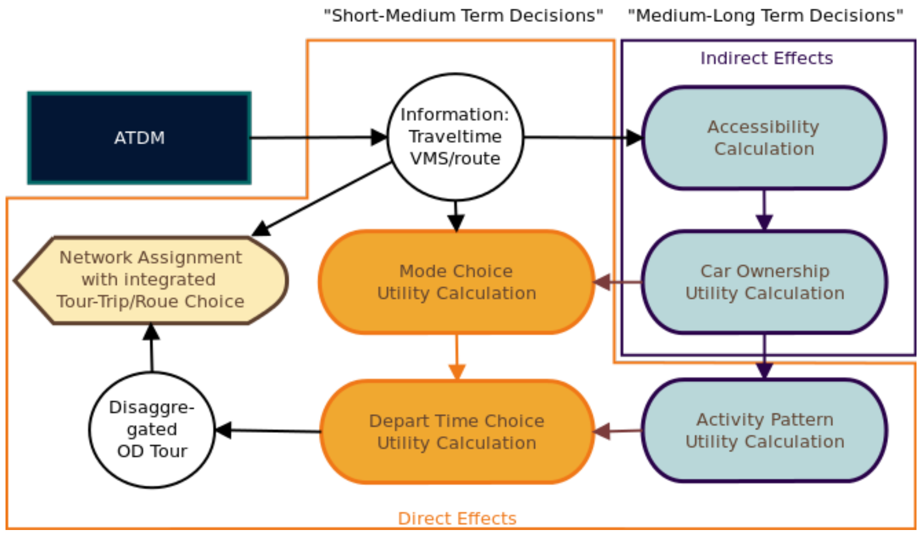


Figure 23. Illustration. Modeling framework for analyzing ATDM policies.

BEHAVIORAL DIMENSIONS AND IDEAL DATA

Relevant Bicycle Use Patterns

There is a considerable need for additional data to be collected within individual metropolitan regions regarding patterns of bicycle travel in order to increase the understanding and modeling of bicycle travel behavior. The overall sense obtained from the review of existing data, studies, and current planning practices is that within the past decade, cities and regions around the United States have begun collecting some bicycle data that are locally specific but are constrained by funding, resource, and expertise limitations. One example of this is in the San Francisco Bay area, where data on bicycle travel speeds were not available for modeling purposes. As a result, the staff from the county planning agency reported that individual staff members would spend time on weekends and other non-work hours riding their own bicycles on different streets in order to estimate bicycle travel speeds for these links that could then be used in a travel demand modeling framework.

In addition, bicycle trips may constitute only one segment or link of a longer multimodal trip. As a result, there is a need for more data and understanding about metropolitan travel (e.g., commuting) where a bicycle may provide one trip segment of a multimodal trip.

Previous work has identified that bicycle travel includes different types of trips with different characteristics. Good active transportation data should include robust and reliable information on different types of bicycle trips, including the following:

- Commuting trips that are completely on bicycle mode.
- Non-commuting bicycle use for short trips.
- Longer distance bicycle on public transportation trips.

Examples of the travel data that this project sought to identify and analyze included the following:

- Commuter trips bike mode share.
- All trips bike mode share.
- Bike trips for the region disaggregated on a county by county basis.
- Trip distances, including access segment, bicycle segment, and linked line-haul public transportation segments.
- Mode shift from pedestrian and automobile to bicycle mode.
- Baseline mode splits for active transportation modes and induced (new trips) on bicycle mode.
- Bicycle trip counts at specific locations, station areas, and cordons.
- Trip purposes for different bicycle trips.
- Bicycle travelers access to motor vehicles.

The findings of this study are that while basic bicycle use data elements are being collected to an increasing degree by local transportation planning agencies, these data are of limited use for travel demand forecasting. Since mode shift data and data on other traveler attributes are usually not collected, it is difficult to measure and model a trend in mode shift or forecast forward in time based on historical trends. As a result, to the degree that travel demand forecasting is occurring for the bicycle mode, they are often being forecasted or modeled using assumptions about future mode shares and based on simple trend extension.

Since most local governments around the United States rely on federally designated and federally funded MPOs for travel demand forecasting, it is often the case that mode-based travel forecasts are not available at a city or county level unless they are obtained from regional MPO forecasts. Local governments appear to be focused on developing plans for infrastructure improvements related to bicycle travel but do not always link them to the travel demand forecasting and data. This appears to be somewhat different for cities and counties that have greater in-house travel demand analysis and forecasting capabilities. San Francisco is an example of this, where the central city and county maintains its own advanced travel demand forecasting capabilities.

This review of existing practice suggests that even amongst the more progressive MPOs, inclusion of bicycling and active transportation options as integral parts of activity-based model systems remains in the very early stages.

Data Needs for Incorporating Bicycle Use into Travel Demand Forecasting

Some counties and metropolitan regions that conduct travel forecasting and modeling incorporate limited bicycle capacity and bicycle travel usage data into their forecasting on a limited basis (e.g., general mode shares). Without sufficient data to calibrate or corroborate the forecasting or modeling data, these travel forecasts may be limited in usefulness.

The study identified one example by an MPO where bicycle travel was attempted to be forecast forward in time. Discussion of this example highlights the data needs and the data collection gaps that exist in order for more robust travel demand forecasting to occur with respect to bicycle travel. The Washington, DC, MPO MWCOG staff developed a spreadsheet model to estimate the benefits and costs of bicycle travel using a planned bikeshare system. The model was developed and used as part of a process to apply for Federal grant support for the system.

Bicycle sharing systems are increasingly popular and diverse. A number of bicycles are made available for shared use by individuals who do not own bicycles. Public bicycles are a mobility service, mainly useful in urban environments for proximity travels.

It has been estimated that as of 2010, there were more than 200 such schemes operating worldwide. The early attempts at unregulated bikeshare programs encountered numerous problems such as theft and vandalism. In 1993 in Cambridge, UK, the majority of the fleet of 300 bicycles was stolen in one program, and the program was abandoned.

The latest generation of this program includes bicycles that are kept at self-service terminals throughout the city. Individuals registered with the program identify themselves with their membership card (or a smart card, cell phone, etc.) at any of the hubs to check out a bicycle for a short period of time, usually less than 2 h. In many schemes, the first half hour is free, such as the Capital Bikeshare program in Washington, DC.(117) Additionally, many of the membership programs are being operated through public-private partnerships. Several European cities, including the French cities of Lyon and Paris as well as London, Barcelona, Stockholm and Oslo, have signed contracts with private advertising agencies that supply the city with thousands of bicycles free of charge (or for a minor fee). In return, the agencies are allowed to advertise both on the bikes themselves and in other select locations in the city.

The spreadsheet model estimates the regional bikeshare use on the then planned (now active) bikeshare system in the Washington, DC, metro region. Some examples of basic data elements that were estimated or assumed in the spreadsheet model include the following:(117)

- Number of bikes.
- Number of bikes added each year.
- Number of riders per bike.
- Daily bicycle riders.
- Number of trips per day.

- Average bike trip length (miles).
- Bicycle miles traveled per day.

It is evident by comparing the data from the spreadsheet analysis tool with the actual data that are being collected in the Washington, DC, region that there is a significant gap between the bicycle travel data that has been found to be collected and the data needs for even a relatively simplified spreadsheet estimation tool for bicycle travel.

The review of existing data and studies found some promising data sources that potentially could be adapted to be incorporated into a more robust travel demand forecasting framework. Two examples of this are specialized travel surveys and specialized service operator data from both public transportation agencies and bicycle service providers (e.g., bikesharing operators). Specialized travel surveys ask respondents a set of standardized questions and collect detailed data (e.g., time of day, location, etc.) that could be used to develop and calibrate models on general relationships between bicycle travel and other variables (e.g., demographic, trip purpose, time of day, etc.). Specialized service operator data (e.g., Capital Bikeshare and Cleveland Transit) incorporate origins and destinations and, as a result, can be linked with geographic and other datasets (e.g., weather) and used to estimate travel speeds. In the absence of such specialized data, travel speeds for bicycle travel must be collected on a link-by-link basis and is extremely time intensive (e.g., Santa Clara County in the San Francisco Bay area). Discussion and examples of the different data types and elements found are presented in the following section.

CHARACTERIZATION OF BICYCLE USE PATTERNS BASED ON AVAILABLE DATA

Data Sources and Elements

Some local governments collect bicycle count data for intersections and corridors of interest. The bicycle count data are often limited in usefulness since they are not linked to mode shift and other data attributes of travelers. In addition to a review of regional transportation planning data and studies, local government data collection and studies were also reviewed. Many local governments have been developing a bicycle master plan that focuses on the development of additional bicycle infrastructure. However, these plans are not strongly linked with historical bicycle use data and bicycle travel forecasting. For example, in Southern California, all six counties in the MPO region either have bicycle master plans or non-motorized transportation plans that include the bicycle mode.(118) Transportation planning for the bicycle mode has often been incorporated into broader studies by local governments related to TDM, in which bicycle use is included as one element of a larger portfolio of TDM strategies and efforts. In these cases, since the bicycle mode is only one element of a larger set of topics, specific detailed historical data on bicycle travel were not usually collected, nor were specific travel demand forecasts made for the bicycle mode.

In spite of the limited amount of data collection and robust travel forecasting with respect to bicycle traveling, local and regional transportation planning agencies often incorporate planning processes and committees with respect to bicycle, and increasingly, pedestrian travel. As a result, while the political and organizational will to conduct bicycle planning appears to exist at the local and regional level, a commensurate degree of data collection and data analysis does not seem to be arising, perhaps due to limited resources for these efforts.

Selected niche data collection is occurring for specific segments of bicycle travel of key interest to organizations. Examples of this include bikesharing system usage data collected by the operating agency, bicycle on rail system data collected by the public transportation agency in specialized studies, and bicycle on bus data collected as part of normal bus transit operations.(119) Some examples of promising and successful local and regional bicycle travel data collections efforts identified include the following:

- Los Angeles County Metropolitan Transportation Authority (LAC MTA) study collected data of last mile bicycle trips that are linked with transit trips.(120) This focused study collected data from intercept surveys of bicyclists at a subset of Metrorail stations. Counts and surveys were conducted during weekday morning commute and weekday evening commute periods. Volunteers collected 605 usable surveys and counted 2,305 bicyclists at the 19 transit stations that were part of the study.

- Data on bicycle sharing in the Washington, DC, region, which is one of the first regions of the country to have an operational bicycle sharing system.(117) Capital Bikeshare in Washington, DC, began operations in 2010 with 1,100 bicycles at 114 stations throughout Arlington, VA, and Washington, DC. The system has expanded to 1,670 bicycles at 175 stations. Membership has reached 19,000 persons, making it the largest bikesharing organization in the United States as measured by membership.

Since bikesharing relies to a large degree on technology, there is potential for significant data to be available for planning purposes based on the actual database of use by members. In addition, if confidentiality issues can be overcome, the trip patterns of individual members may also be linked with other attributes of the bikeshare users. Capital Bikeshare makes data about usage patterns available on its Web site and also conducts regular surveys of its members.

Bikesharing is expanding rapidly across the United States. Plans are being implemented for operation of bikesharing systems in both the San Francisco Bay area and over a larger portion of Los Angeles, as well as other parts of the United States.

Data collected by the San Francisco County Transportation Authority (SFCTA) and the San Francisco Bicycle Coalition on the GPS-data related to routes taken for bicycle commuter trips. With funding from a California Department of Transportation (Caltrans) planning grant, SFCTA was able to work with San Francisco Bicycle Coalition member volunteers who agreed to travel on their regular bicycle commuting routes with a GPS device. With the information from these GPS tracking of bicycle commuters, SFCTA was able to obtain and incorporate more and better information on bicycle commuting route choice and time of day patterns than they had available before the study.

The ideal robust data collection for bicycle travel for a regional or local transportation planning effort is one where at least three types of data elements could be identified and collected. The following data needs to be local and specific in order to be incorporated into travel demand forecasting methods:

- Bicycle use basic data elements.
- Bicycle mode shift table data elements.
- Bicycle travel linked to other traveler attributes.

The first type, count and overall usage, is discussed in the following subsection using counts in the Washington, DC, metropolitan area, including Arlington, VA, as well as counts in the Los Angeles, CA, area. The second type, data that could support mode shift analyses, is discussed in connection with survey data of bike on rail users in both the Los Angeles and San Francisco, CA, areas. The third type, explicitly linking traveler and service attributes to the likelihood of bicycle rail usage, is illustrated using data from Cleveland, OH.

Bicycle Use Count Data: Washington, DC, and Southern California

The bicycle mode still contributes a relatively small share of overall trips and travel distances at a national scale and also at smaller geographies within the four individual metropolitan regions examined. There are some cities that have relatively higher mode shares for bicycle commuting, but bicycle use is small overall. At the same time, bicycle use has been growing in many cities in recent years, and cities have been planning and implementing dedicated bicycle infrastructure.

Local governments, including both cities and counties, are increasingly collecting basic bicycle travel use data. One example of basic bicycle use data are intersection bicycle count data from Arlington County, an inner-ring suburb in the Washington, DC, metropolitan region. Another example is corridor-based bicycle counts relative to time of day in Washington, DC.

In Arlington County, the local government operates 10 counter locations for bicycle lanes and 14 counter locations on highly used trail locations. The basic bicycle use data collected include the number of bicycles and the direction of travel. The data are used for general trend analysis as a justification for future investments in bicycle infrastructure. The data collected are not currently used for travel demand modeling purposes. There has been an increasing interest in collecting and using bicycle travel data within the county government.

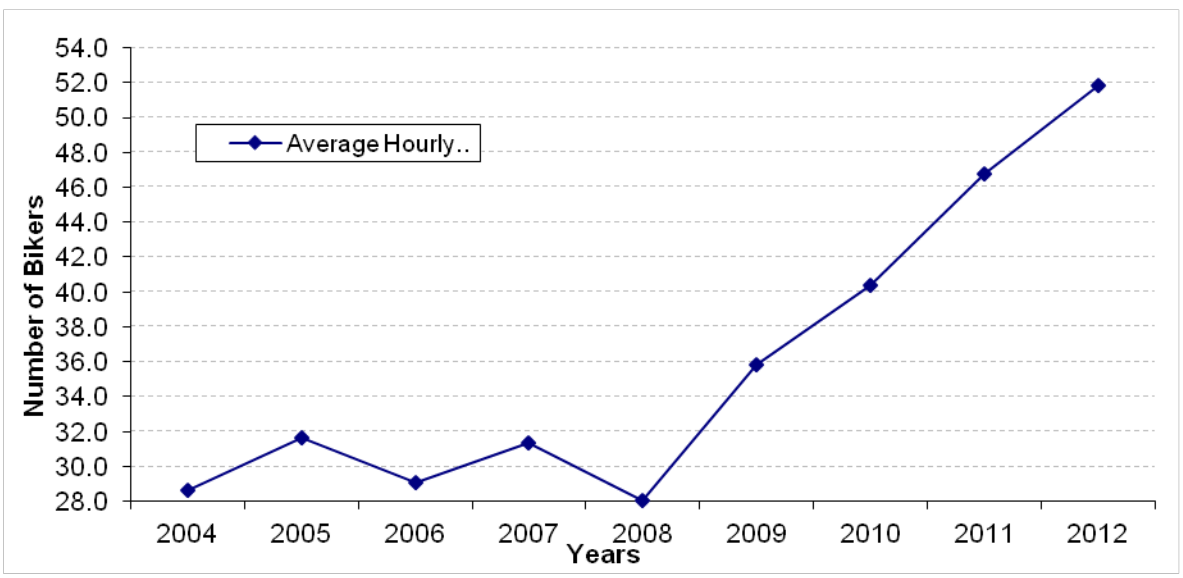
Within Washington, DC, the local council government approved a complete streets policy in October 2010. There are 40 locations where bicycle counts are collected by the Washington, DC, Department of Transportation, including 9 or so bridge locations and other strategic locations. The data are used to assess general trends and to help increase understanding of usage of the bicycle and road facilities. The data are not yet incorporated into travel demand forecasting. Some specific corridor studies have included bicycle use data. The bicycle counts program has been funded through technical assistance funding from MWCOG, the regional MPO. MWCOG also keeps the regional travel demand model that is the general forecasting model for the region. Table 7 shows an example of some of the results of basic bicycle and pedestrian use data collected within Arlington County at a specific intersection during a morning peak hour period.

Table 7. Basic non-motorized use data element: intersection non-motorized counts in Arlington County, VA.

Date/Time	Bicycle Counts by Location: Custis Rosslyn	Custis Rosslyn Pedestrians	Custis Rosslyn Bikes
Mon, Jan 3, 2011, 06:00 a.m.	6	0	6
Mon, Jan 3, 2011, 06:15 a.m.	8	3	5
Mon, Jan 3, 2011, 06:30 a.m.	13	2	11
Mon, Jan 3, 2011, 06:45 a.m.	18	3	15
Mon, Jan 3, 2011, 07:00 a.m.	23	2	21
Mon, Jan 3, 2011, 07:15 a.m.	19	4	15
Mon, Jan 3, 2011, 07:30 a.m.	27	3	24
Mon, Jan 3, 2011, 07:45 a.m.	39	4	35
Mon, Jan 3, 2011, 08:00 a.m.	36	6	30
Mon, Jan 3, 2011, 08:15 a.m.	40	6	34
Mon, Jan 3, 2011, 08:30 a.m.	43	9	34
Mon, Jan 3, 2011, 08:45 a.m.	35	6	29
Mon, Jan 3, 2011, 09:00 a.m.	32	8	24
Mon, Jan 3, 2011, 09:15 a.m.	23	8	15
Mon, Jan 3, 2011, 09:30 a.m.	18	7	11

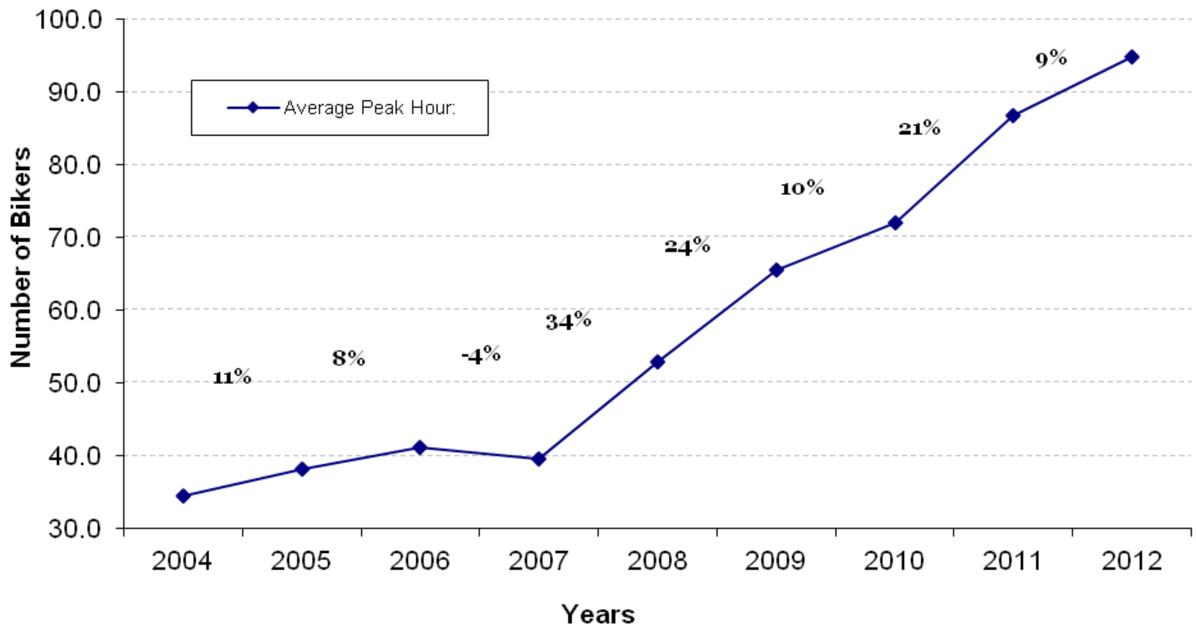
Data for this table were provided by Arlington county staff and is available to the public (public domain).

Selected summary results and data from Washington, DC, bicycle counts data collection are shown in figure 24 through figure 26. These graphs generally reveal the increasing trends in bicycle use and trips.



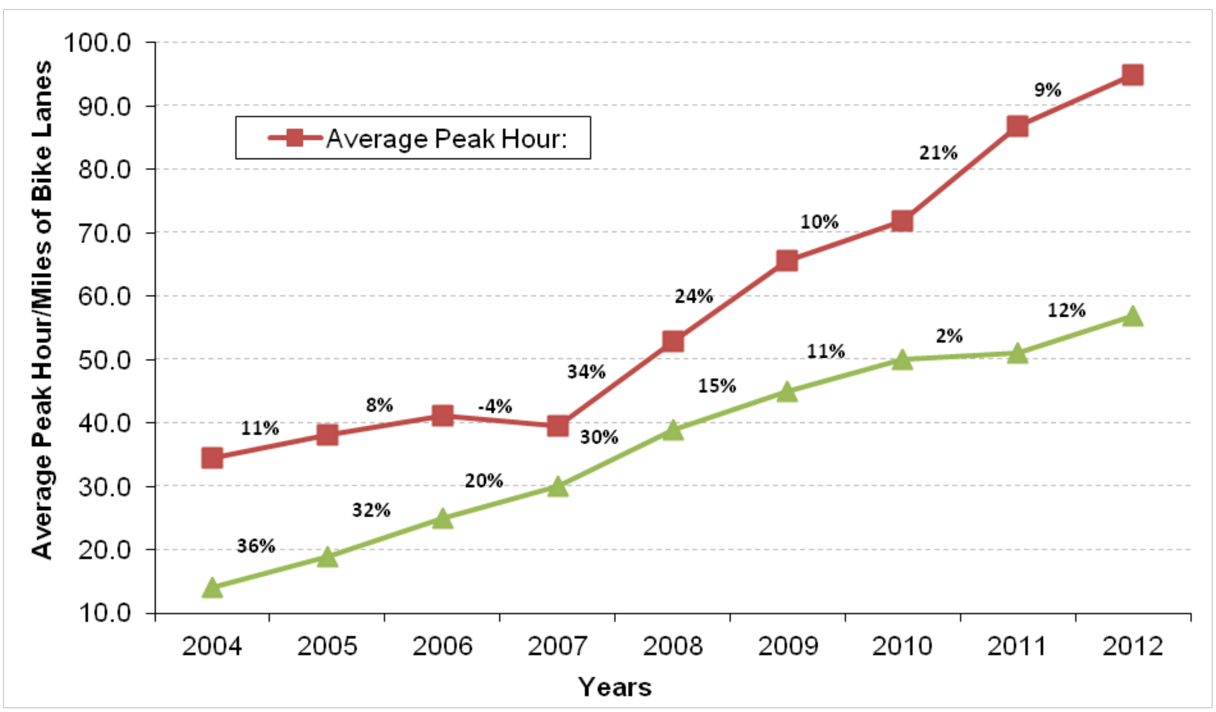
Data for this figure were provided by DDOT staff and is available to the public (public domain).

Figure 24. Graph. Increase in hourly bicycle counts on specific street corridor from 2004–2012 in Washington, DC.



Data for this figure were provided by DDOT staff and is available to the public (public domain).

Figure 25. Graph. Increase in peak hour bicycle counts on specific street corridor from 2004–2012 in Washington, DC.



Data for this figure were provided by DDOT staff and is available to the public (public domain).

Figure 26. Graph. Average peak hour bicycle counts on specific street corridor per mile of bicycle lanes from 2004–2012 in Washington, DC.

Another example of data being collected for bicycle travel consists of specialized trip data collected by major public transportation agencies in both northern and southern California.

The data examples show data collection from a LAC MTA study of last mile bicycle trips that are linked with transit trips.[121] These data provide a good example of the existing data that have been collected at a local level within one region of the country.

Table 8 shows data collected from LAC MTA of the number of Metrorail stations where bicyclists boarded or alighted.

Table 8. Number of Metrorail stations where bicyclists boarded or alighted, by rail line; LAC MTA.

Bicyclist Boardings and Alightings by Line	Number of Stations on Line	Number of Stations Where Bicyclists Boarded or Alighted	Percent of Stations Represented
Red line/purple line	16	16	100
Blue line	22	22	100
Green line	14	14	100
Gold line	21	19	90
Total	**73**	**71**	**97**

Data for this table were provided by LAC MTA staff and is available to the public (public domain).

The unpublished study estimated that bicyclists made up 1.3 percent of all annual Metrorail trips. In terms of mode shift, the study found that 27 percent of bicycle-rail trips replaced a motor vehicle trip. Additionally, 13 percent of bicyclists report that they would not take the trip if they did not have the option of making the combined bicycle-rail trip. On average, bicyclists traveled 2.2 mi to access the Metrorail stations. As a result, LAC MTA was able to obtain more information on the bikeshed of Metrorail stations.

Only to a limited degree was bicycle use data collected by local governments linked with other traveler attributes. In specialized cases of public transportation agencies, some effort has been made in leading practice examples to collect additional traveler attribute data to link to bicycle mode use. For example, in the case of the Los Angeles County Bicycle Transit study, the trip purposes of bicycle mode users were included as part of the survey data collected.

Table 9. Bicycle boardings data at transit stations: LAC MTA blue line.

Row Labels	Count of Boarding
Blue	180
103d Street	3
1st Street	1
7th/Metro	30
Anaheim	5
Artesia	1
Compton	3
Del Amo	25
Firestone	3

Data for this table were provided by LAC MTA staff and is available to the public (public domain).

Mode Shift Analysis: Los Angeles and San Francisco Bike-on-Rail User Surveys

The unpublished LAC MTA study is a good example of more robust data collection, since some information was collected that could be used for mode shift analysis. Table 10 and table 11 show to what degree bicyclists had access to motor vehicles and the results of a question that asks bicycle riders what mode they might have used if not for the availability of the bicycle-rail trip, respectively.

There is a need to examine actual mode shift to bicycle from other modes to ascertain changes over time in order to accurately estimate, model, and better forecast future travel. Without a good basis for estimating mode shift to the bicycle mode, it is clear that the future estimates would be limited in value and robustness.

Table 10. LAC MTA bicycle transit survey responses to motor vehicle access question, "How often do you have access to a motor vehicle?"

Response	Number	Percent
Always	161	29.76
Sometimes	121	22.37
Rarely	60	11.09
Never	199	36.78
Total	**541**	**100**

Data for this table were provided by LAC MTA staff and is available to the public (public domain).

Table 11. LAC MTA bicycle transit survey responses to motor vehicle access question, "If you did not have your bike, how would you get from your origin to the first station?"

Response	Number	Percent
Walk	300	42
Bus	258	35
Drive alone	55	8
Train/subway/light rail	32	4
Carpool	19	3
Drop off	18	3
Other (please specify)	13	2
Would not make the trip	24	3
Total	**719**	**100**

Data for this table were provided by LAC MTA staff and is available to the public (public domain).

Some of the data elements related to mode shift that were assumed or estimated by MWCOG include the following:(122)

- Percentage of riders shifted from auto to bike.
- Percentage of riders shifted from bus/rail to bike.
- Percentage of riders who also use transit.

- Percentage of riders with increased access to transit.
- Percentage of bike riders as new transit riders.
- Percentage of new transit trips coming from auto.
- Average transit trip length.
- Percentage of trips not made before.
- Percentage of riders shifted from walk to bike.
- Percentage of riders shifted from taxi to bike.

Data are available from an MWCOG analysis of BikePODs, and the following mode shift percentages off of baseline were assumed for one bikeshare system similar in size to that in Montreal, which contains roughly 5,000 bicycles and 400 stations:[(122)]

- 8 percent of bike riders shifted from SOV to bike.
- 3 percent of riders shifted from taxi to bike.
- 8 percent of bike riders as new transit riders.
- 10 percent of new transit trips shifted from SOV to transit.

In 2010, MWCOG proposed to develop a regional bikesharing system for the Washington, DC, area. MWCOG conducted a benefit-cost analysis for the proposed system in application for funding from the Transportation Investment Generating Economic Recovery II Grants Program.

In developing the Washington, DC, Bicycle Sharing Spreadsheet Tool, it became clear that no applicable data would be available from cities in the United States, since the Washington, DC, region was one of the first regions in North America and the United States to implement bikesharing. As a result, the estimation process relied on adapting data from European cities' experience with bikesharing. Example mode shift values for Paris, France, and London, United Kingdom, are presented in table 12. It is clear that the validity of this data for estimating future bikesharing in a U.S. city like Washington, DC, would be limited and that a preferable situation would be data collection of actual bikesharing use from U.S. cities.

Table 12. Example of comparison data from other cities: mode shift to bikeshare.[122]

Mode of Transportation	Paris (percent)	London (percent)	Average (percent)
Transit	65.0	34.0	50.0
Walk	20.0	21.0	26.0
Car/motorcycle	8.0	6.0	7.8
Personal bike	N/A	6.0	5.0
Taxi	5.0	N/A	2.5
No travel	0.0	23.0	8.3
Total	**98.0**	**90.0**	**99.6**

N/A = Not applicable.

Table 13 provides an example of bicycle use data linked to other traveler attributes, namely the trip purpose for which the bicycle is used in connection with an intermodal metro rail trip in the Los Angeles, CA, metropolitan region.

Table 13. Example of bicycle use data linked to other traveler attributes: bicycle trip purpose data from Los Angeles County.

Bicyclist Entering Station After Traveling From…	AM Weekday (percent)	PM Weekday (percent)	Total (percent)
Doctor, dentist, or other personal business	0	3	1
Family or friend’s house	1	6	5
Home	90	22	58
Store, restaurant, movies, or other shopping and entertainment	1	5	4
Work	5	54	27
School	1	7	4
Other	0	2	2
Total	100	100	100

Data for this table were provided by LAC MTA staff and is available to the public (public domain).

Another example of the specialized data collected by a public transportation agency is a study by the BART Agency entitled, *BART Bicycle Plan: Modeling Access to Transit*. Like the SFCTA study, the study was funded by a Caltrans planning grant.[123]

An example of mode share information that is collected by a public transportation agency is data from the BART Agency related to mode shares for specific rail stations on the system.[121] Based on data collected from two station profile studies with a 10-year interval between the data collection, BART has been able to document bicycle mode shares for individual stations for the two study years as well as interpolate a growth rate in bicycle mode access to the stations. Data collection from these studies is a promising approach to obtaining data for travel demand forecasting for bicycle-rail transit trips.

As part of a larger study, BART developed a bicycle investment tool, which is intended to help BART and other rail transit operators in the San Francisco Bay Area with estimating the effects of bicycle-related investments on bicycle access rates at individual rail stations in order to compare costs of bicycle-related investments with the cost of providing more automobile parking.[124] The BART system overall has established a goal of doubling the bicycle access for regional trips from approximately 4 to 8 percent by 2022, and the analysis tool is intended to aid in this effort.

Cleveland Bicycle on Bus Boardings

One of the more promising examples of modeling a subset of bicycle trips is in the Cleveland metropolitan region. An academic study conducted by researchers at Temple University estimated a regression model to identify what factors predicted bicycle-bus trips.[125]

The Greater Cleveland Regional Transit Authority (GCRTA) through its operations had a 3-year dataset of over 160,000 trips with bicycle on bus boardings (BoBBs) between 2008 and 2011. The research study sought to answer the following two questions:

- On a typical day in the operations of a large public transit system, what determines the number of bus riders who decide to travel with their bicycles?
- What factors influence the highly variable number of BoBBs observed on GCRTA's motor bus network in recent years?

Similar to the case of bicycle-rail transit travelers in Los Angeles County, the bicycle on bus travelers in the Cleveland, OH, region represent a subset of overall bicycle trips within a region. At the same time, since the public transportation operator has a means and desire to collect data in the course of operations, this example is unusual in that it includes a 100 percent sample of all bicycle trips within the subset of trips in question. For those buses with bicycle racks installed, it was possible for GCRTA to collect and maintain data on the BoBB trips. A summary of the key data obtained is shown in table 14.

Table 14. Summary of Cleveland, OH, BoBB data.[124]

Year	Daily BoBBs	Daily Unlinked Passenger Trips (UPTs)	BoBBs/ 1,000 UPTs
Non-Work Days			
2008	9,185	5,880,700	1.56
2009	8,621	5,675,931	1.52
2010	7,803	4,735,601	1.65
2011	8,755	4,794,631	1.83
Percent change 2008–2011	-4.7	-18.5	16.9
Work Days			
2008	36,170	43,167,714	0.84
2009	30,385	32,520,479	0.93
2010	30,298	31,580,559	0.96
2011	31,858	32,404,132	0.98
Percent change 2008–2011	-11.9	-24.9	17.3
All Days			
2008	45,355	49,048,414	0.92
2009	39,006	38,196,410	1.02
2010	38,101	36,316,160	1.05
2011	40,613	37,198,763	1.09
Percent change 2008–2011	-10.5	-24.2	18.1

The study found that the number of BoBB travelers showed seasonal variation, with the lowest levels in the winter and highest levels in the summer. Use also varied by bus route.

While data on individual traveler attributes were not part of the dataset, the researchers were able to develop a model predicting what external factors had a significant influence on bicycle on bus trips. A summary of the major determining factors is shown in table 15.

The researchers concluded that weather was the most important variable in predicting the number of daily BoBBs. For every increase of one degree Fahrenheit in the mean daily temperature, there was an average of 2.21 more BoBBs. In addition, the occurrence of significant levels of precipitation was associated with an average of 22.06 fewer BoBBs.

Table 15. Example of bicycle use data linked to other traveler attributes: bicycle trip purpose data from Los Angeles County.

	BoBBs	UPTs
Mean temperature (degrees Fahrenheit)	(–) Large positive	(–) Very small negative
Precipitation (dummy variable, 1 ≥ 0.10 inch)	(–) Small negative	(+) Very small positive
Standard bus fare (cents)	(+) Small positive	(+) Small positive
Price of gallon of gasoline (in cents)	(+) Small positive	(+) Small positive
Vehicle revenue miles of service (hundreds of miles)	(+) Medium positive	(+) Large positive
Percentage of outcome variable variation explained by model	67.4 percent	88.5 percent

Data for this table were provided by LAC MTA staff and is available to the public (public domain).

SUMMARY AND CONCLUSIONS

This case study focused on identifying information and data to help understand the factors underlying traveler choices to use bicycling as an active transportation mode as well as the development of models of bicycle mode shift and usage patterns that may be incorporated in regional and operational travel demand forecasting frameworks. The examination included review of information and data collected by local areas in regional case studies consisting of the following urban metropolitan regions: Washington, DC, region, Southern California metropolitan region (SCAG region), San Francisco Bay Area, and the Cleveland, OH, region.

Data collected from four metropolitan regions confirm that bicycle travel is increasing both as an active transportation mode and as a means of travel demand management. However, bicycle travel supply and demand variables collected by local agencies vary considerably in quality and robustness. While leading edge travel demand modeling agencies are beginning to integrate bicycle use data into travel forecasting, simple trend extrapolation remains the primary approach. Significant data gaps limit the ability to fully incorporate bicycling choice and use in activity-based models of travel demand.

Examples from the four metropolitan study areas were presented, focusing on overall bicycle use and limited evidence for potential modal shift in connection with bike on transit service options and bikesharing plans. The importance of factors such as weather in bicycle use decisions is strongly evident through the available data. Recommended data needed to advance the state of the art and the practice were identified and presented.

CHAPTER 6. AERIS CASE STUDY I: SOCIAL NETWORKS AND GREEN BEHAVIORS

ROLE OF ATTITUDES IN BEHAVIORAL DECISIONMAKING

The objective of this chapter is to present a social network-based attitude diffusion system model in the context of activity and travel choice behavior, especially in response to a new green transportation alternative. The model framework could be extended and modified to include attitudes toward other choice dimensions (e.g., mode choice, departure time choice, etc.).

Most choice behavior dimensions are explained by the individual decisionmaking entity's socio-economic characteristics and attributes of the different alternatives to choose from. However, these are not the only variables that explain heterogeneity in the mode preferences. Following the pioneering work of Koppelman and Pas and McFadden, it has become well accepted that attitudes and perceptions play an important role in the decisionmaking process.(126,127) Attitudes and perceptions cannot be directly observed from the data and are as a result considered latent variables.

The structural equation models of attitudinal variables are integrated into choice models in order to make use of simultaneous estimation of choice and attitudinal variables.(128) These integrated models, which have been in use since the early 1980s in travel behavior studies, were later generalized into so-called hybrid choice models and popularized by Ben-Akiva et al.(129,130) They provide a general framework where attitudinal variables are considered as latent variables.

In transport research, a large literature base exists on the use of attitudinal latent variables to explain traveler behavior and choices. Golob presents a good overview of these studies.(128) Scheiner and Holz-Rau analyze the interrelation between socioeconomic characteristics, lifestyle, residential choice, and travel behavior of individuals.(131) They confirmed that lifestyle preferences play a key role in the residential choice of individuals, which in turn has an important impact on the travel mode choice. Similarly, Van Acker et al. studied how residential and travel attitudes affect residential location and travel behavior decisions using data from an Internet survey in Flanders, Belgium.(132) The study provides confirmatory evidence that car ownership is significantly affected by residential attitudes. Van Acker et al. extended the model by including interrelations between residential and travel mode choices for leisure trips.(133) The study points out that the strength of interrelation depends on the mode as well as the activity performed. It also identifies different lifestyle characteristics that result in different travel mode decisions. By comparing the models with and without lifestyle characteristics, the authors conclude that inclusion of these subjective variables results in improvement in terms of the explained variance in mode choice.

In integrated choice and latent variable models, the attitudinal variables are included as explanatory variables of the choice. Johansson et al. analyzed the effect of the latent variables of environmental preferences, safety, comfort, convenience, and flexibility on mode choice using a sample of Swedish commuters.(134) They provide insights for policymakers so as to improve the transport systems through the use of the attitudinal variables. Espino et al. studied the mode choice behavior for suburban trips by including the latent variable of comfort.(135)

Abou-Zeid et al. explained the variability in individuals' willingness to pay using individuals' attitudes toward travel through a latent variable model.[136] They introduce a car-loving attitude and show that individuals who dislike public transport are more sensitive to the time and cost changes of public transport compared to others.

While conceptually appealing and empirically significant, incorporating attitudes in forecasting model systems has always been somewhat problematic when the target population of interest is large. Unlike measurable attributes, the latency of attitudes has made forecasting their future values especially challenging. For this reason, when applying travel choice models to predict demand in practice, it is generally assumed that the attitudes are stable and that travelers are aware of the attributes of the available alternatives. However, when new services are introduced or some attributes of the transport system are changed, not all travelers will be aware of the change to adjust their attitudes accordingly. Rather, they will learn about those changes through various information sources, including social interaction. In these cases, consideration of the new opinion generation process and the role of information diffusion in social interaction becomes an important element in the attitude updating process that determines the eventual demand for the service. Furthermore, several new policy interventions aimed at changing the habitual behaviors of tripmakers and overcoming the associated inertia associated with established routines, especially towards more sustainable (greener) alternatives, require targeting the underlying attitudes. Hence, it is important to understand the mechanisms by which attitudes are formed, updated, and transformed, in addition to their impact on individual decisionmaking processes.

FRAMEWORK FOR EVALUATION

Attitudes can influence individual choices on many different levels, as discussed in the brief literature review in the previous section. However, most studies using latent variables in the context of travel behavior include lifestyle attitude variables toward or against more environmentally friendly modes in mode choice models or in longer-term decision models toward the ownership of certain transportation tools.

This section discusses the sequence of models used to disseminate information to form and influence attitudes as well as the influence of attitudes on choice models and how these choice models interrelate with other choice models.

The integration of these different models has several parts. First, information about greener or more environmentally friendly modes/travel opportunities is available and is disseminated across individuals. Second, based on this new information, a certain portion of the public can be influenced. As a result, people change their attitudes. These first and second steps heavily depend on interactions between individuals and their environment. Third, the attitude updates are used together with socio demographic variables and attributes that describe the different options in a choice set for a given decision. The decisions that are primarily and directly affected are the short- and medium-term traveler decisions shown in figure 27. This includes direct impacts of attitudes on mode choice and car ownership through the utility expressions for each choice alternative.

However, in the short, medium, and long term, attitudes can also further indirectly affect user decisions, such as activity pattern changes and accessibility as well as departure time choices and location choices. They may also affect even longer-term choices of home, workplace, and school location (not illustrated in the figure).

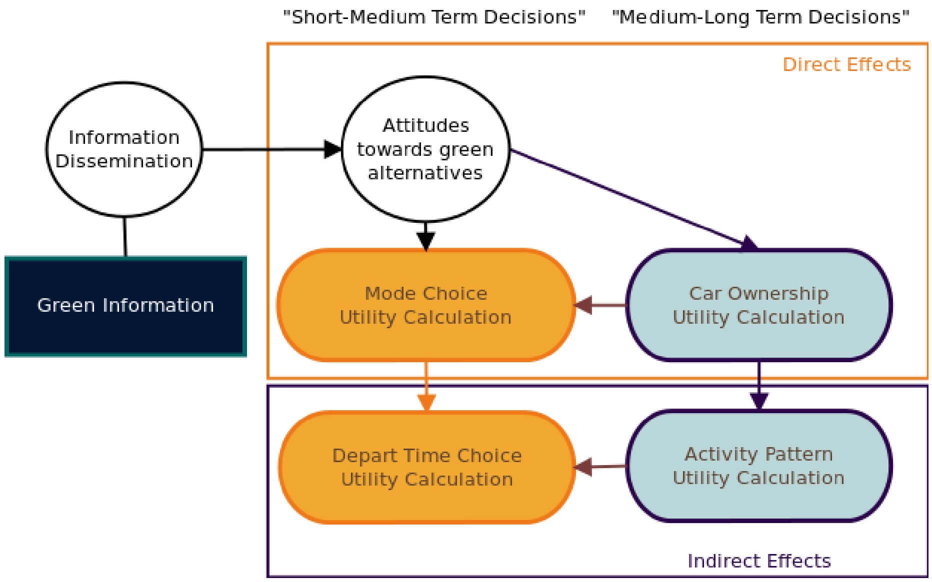


Figure 27. Illustration. Attitudes and information dissemination impact modeling framework.

Though some studies have shown the potential of growing green transport market share and highlighted the importance of information diffusion in market adoption, there is lack of knowledge on how and to what extent that information will affect the mode choice behavior of users. When some acquaintances of an individual become commute greener fans, will he/she modify his/her own attitude or not? When a friend selects public transit or a new mobility alternative as her/his transportation mode, will that individual consider this new alternative, and will his/her mode choice change accordingly?

In this case study, the word-of-mouth mechanism was mainly used, which is modeled for large populations where people meet in small groups (e.g., pairs) with two agents to discuss their attitudes on a particular product, service, or topic. Mathematical models are developed to capture this information diffusion process.

AGENT-BASED MODELS AND MACROSIMULATION/MICROSIMULATION

In transportation models, it is most common to represent individual-level decisions with given attributes. These attributes determine individuals' behaviors (e.g., choices or decisions given the characteristics of alternatives), often modeled within the random utility framework. These models are intended to provide a statistical representation of the target population. The individual behavior affected by environment attributes is calibrated at the micro level using actual data, and validation of aggregate properties in distribution against actual data. The interaction with the environment affects the decisions through many different attributes of the environment and the individual itself. Most common in transportation models is the interaction of individuals with the transportation system itself and the representation of the system through level of service attributes, which are affected by the choices of each individual and in turn affect the choices the individual makes. This iterative loop of interaction between the demand and supply models is commonly used for forecasting purposes and the evaluation of projects.

For the dissemination of information and attitudes, these kinds of models are less common and useful, as the processes rely heavily on interaction of individuals with each other. Such an interaction model is a typical feature of agent-based models, which can be described as a computational method that relies on models composed of agents that interact within an environment and with each other. Agent-based models rely on behavior rules in the form of computational models explicit about inter-agent communication and interaction, explicitly capturing processes such as learning. However, these models do not rely on statistical theories and have no such basis for prediction.

In the case of information and attitude update processes, such agent-based models are ideal, as they allow including such processes through information and interaction with other agents.

Two different kind of models, microsimulation/macrosimulation and agent-based models, can be integrated with each other by allowing the output of the agent-based models, which in this case determine the updated attitudes to be used as an input variable in utility-based choice models, as illustrated in figure 28.

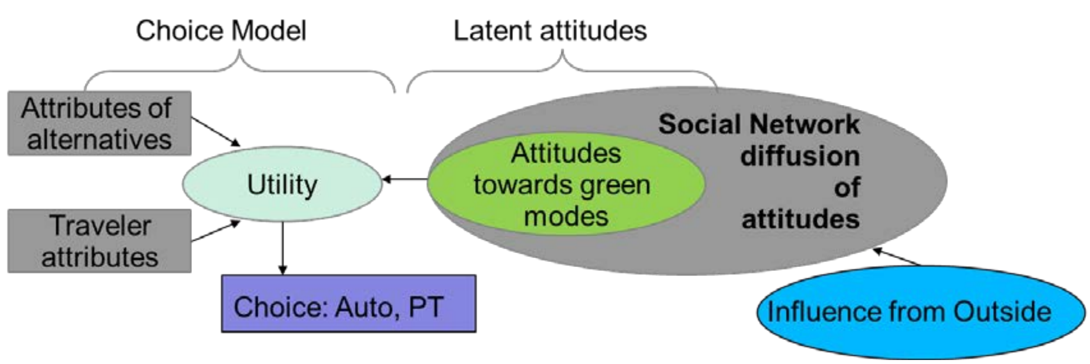


Figure 28. Illusttration. Social network attitude diffusion influence process integrated into utility-based choice models.

In the following sections, the development of an agent-based model to capture attitudes is described and then applied in a hypothetical scenario.

MODEL DEVELOPMENT

The agent-based model developed and described in this chapter assumes a neighborhood-based environment, within which agents interact with each other. Such an environment can be thought of as being important in influencing longer-term decisions such as mobility tool ownership. The interrelation between socioeconomic characteristics, lifestyle, residential choice, and travel behavior of the individuals has been studied by Scheiner and Holz-Rau and Van Acker et al. (See references 130–133.) Both find that residential location, lifestyles, attitudes, and travel behavior are strongly interrelated. Such an environment is created by letting agents communicate with their neighbors and influence each other (lattice social network), which then results in dynamically updating their attitudes. In such a case, the probability of communicating with a neighbor and adjusting attitudes is based on a word-of-mouth mechanism, described in the following section. The attitude adjustment calculation for each interacting pair of individuals is described in the section, "Opinion Change Model."

Other environments to disseminate different kinds of information could be built (e.g., influences on short-term behavior could be represented within a scale-free or small world network where communication takes place trough social networking tools).

Communication Model

A basic idea of the word-of-mouth mechanism is that information is diffused from an individual to a friend or to somebody in that individual's social network. For this reason, it is unusual that people communicate with a stranger. Thus, this mechanism implies that a threshold of selectivity exists. In reality, rich people usually have the resources to convince others regarding the merit of certain services or products. Thus, this research considers one aspect of social status, referred to as social class, as a factor in opinion formation and propagation. Following the suggestions of many sociologists, five classes were adopted: elite, upper middle, lower middle, working, and poor. Besides, the personality or charisma of people also attracts others to believe them and accept their choices in some ways. Therefore, social type, which is another social parameter, is involved. Social type characterizes an individual as an opinion leader or an opinion follower by an individual's personality.

For this model, it was hypothesized that the role of the word-of-mouth mechanism changes by social type first and by social class second. When an information source is questionable, an individual may be less likely to revise his/her opinion during the interaction with other individuals in the future. The confidence of that individual in his/her opinion will have the same influence on opinions regardless of social class and social type. Since personalities are important in the adoption of an innovation in a community, social type has the most impact on the role mechanism.[137]

This model explains similarity concept by incorporating dissimilarity parameter and threshold parameter. The word-of-mouth dissimilarity between two communicating individuals is represented in figure 29, which is used in measuring the difference of two individuals who are trying to communicate.

$$\text{Dissimilarity}_{ij} = \beta_1|SC_i - SC_j| + \beta_2|ST_i - ST_j| + \beta_3|A_i - A_j|$$

Figure 29. Equation. Dissimilarity function.

Where:

i = The target individual.
j = The interacting individual.
β_1, β_2, and β_3 = Model parameters.
SC_i = Social class of individual i.
SC_j = Social class of individual j.
ST_i = social type of individual i.
ST_j = social type of individual j.

A_i = Attitude strength of individual i.
Aj = Attitude strength of individual j.

The more similar two individuals are, the higher the likelihood of tending to interact or revise opinions. In this model, the researcher considers $SC = \{1,2,3,4,5\}$, $ST = \{1,2\}$, $\beta_1 = 0.2$ for the difference of social class, $\beta_2 = 0.5$ for the difference of social type, and $\beta_3 = 0.3$ for the difference of opinion. These parameters are not calibrated but are used for illustration purposes. Data collection needs are described in the section, "Recommended next steps and research."

The interaction threshold is speciafied in figure 30. The social type-related component follows the distribution of the diffusion of innovation theory (see figure 31) for opinion followers and increase the tolerance for opinion leaders. The social class dependent component implies the lower the social class of an individual, the larger the threshold parameter. Thus, an individual is more likely to revise his/her opinion according to the opinion of those who are more rich and powerful. When the target individual encounters other individuals and more interaction takes place, the interaction efficiency increases so that the target individual has more confidence in his/her opinion, resulting in the decrease of the threshold to interact with others.

$$TH_i = TT_i \cdot ST_i(C - SC_i)(1 - E_i)$$

Figure 30. Equation. Interaction threshold function.

Where:

THi = Interaction threshold for individual i.
TTi = Type-dependent tolerance of individual i.
C = Largest social class index plus 1.
Ei = Communication confidence of invididual i.

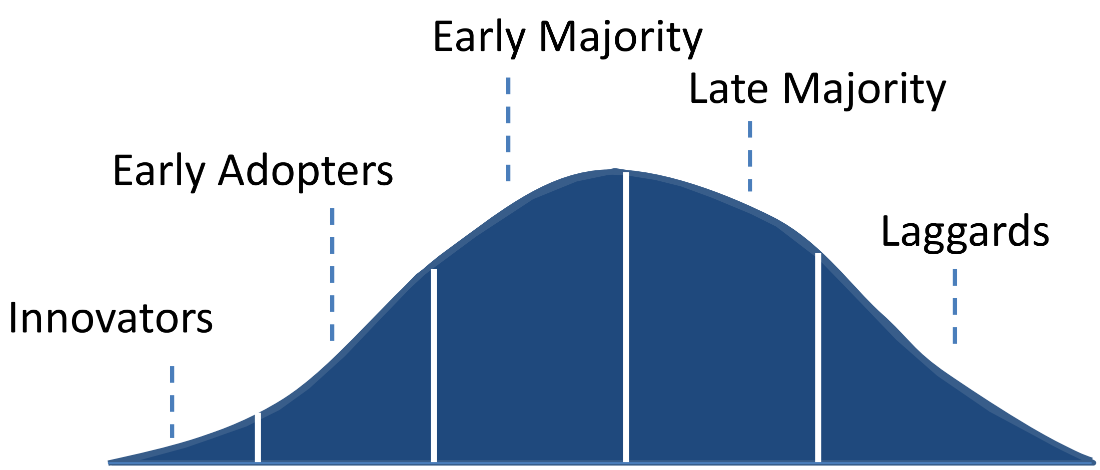


Figure 31. Illustration. Rogers' bell curve of the innovation adoption life-cycle distribution.

The communication confidence parameter can be expressed using the following equation:

$$E_i = \begin{cases} \sum_{k=t-L}^{t} \left(\frac{N_{ik}}{J \times k} \times M_{ik} \right) \times \frac{1}{\sum_{k=t-L}^{t} M_{ik}} & \text{if } T - \mathrm{L} \geq 0 \\ \sum_{k=1}^{L} \left(\frac{N_{ik}}{J \times k} \times M_{ik} \right) \times \frac{1}{\sum_{k=1}^{L} M_{ik}} & \text{if } T - L < 0 \end{cases}, \forall t \in [1, T], E_i \in [0,1]$$

Figure 32. Equation. Communication confidence parameter.

Where:

k = Current simulation step.
J = Number of encounters in each simulation step.
L = Number of last simulation step.
t, T = Total simulation step.
N_{ik} = Number of interactions at simulation step k.
M_{ik} = the type-dependent memory coefficient of individual i at simulation step k.

The memory coefficient captures psychological phenomena such as the availability heuristic, whereby individuals tend to recall recent events.(138) If it is assumed that one simulation step is 1 day, memory decays in a matter of days unless individuals purposely review what they had learned. According to it, the type-dependent memory coefficient is specified as follows:

$$M_{ik} = \mathrm{e}^{-\frac{t+1-k}{S}}, k = 1, \ldots t, M_{ik} \in [0,1]$$

Figure 33. Equation. Type-dependent memory coefficient.

Where:

S = Relative strength of memory.
t = Total simulation step.

In figure 34, a typical exponential forgetting curve shows how information is lost over time.(139)

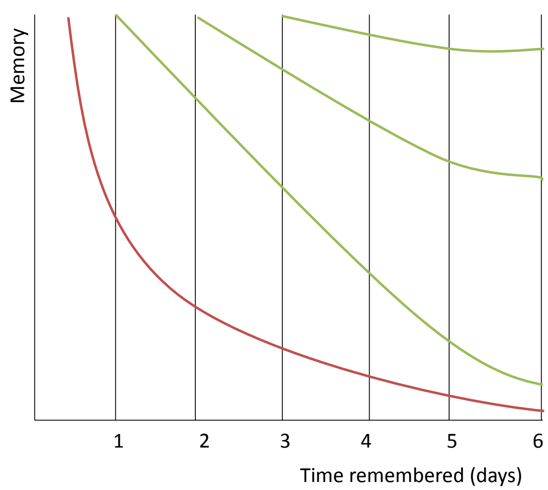


Figure 34. Graph. Forgetting curve.

When the dissimilarity is smaller than the threshold of the target individual, two individuals communicate, and the target invididual considers updating its opinion value. This situation can be discribed by the inequality in figure 35.

$$|\text{Dissimilarity}_{ij}| < TH_i,\ i \neq j$$

Figure 35. Equation. Dissimilarity inequality.

Table 16 presents the variables and their coresponding values used in the simulation experiment presented in the following sections.

Table 16. Variables and values used in the simulation experiment.

Variable	Value
TT_i	Inventor = 0.9; early adopters = 0.7, early majority = 0.5, late majority = 0.3, and Laggards = 0.1
C	6
SC_i	Social class
S	Opinion seeks = 0.5; opinion leaders = 1
ST	1, 2

For each individual, TH_i and ST_i are calculated using the value in table 16.

Opinion Change Model

When an individual decides to revise an opinion value, the opinion change model is triggered. This model utilizes an opinion-following mechanism, shown in figure 36, which is adapted by Kozuki from the car-following mechanism.(77,140)

$$\dot{A}_i(t+T) = \lambda(ST, SC)(A_j - A_i)$$

Figure 36. Equation. Opinion change function.

Where:

$\dot{A}_i\ (t + T)$ = Change in opinion value for the target individual at time $t + T$.
A_j and A_i = Current opinion values of the target individual and interacting individual, respectively.
$\lambda\ (ST, SC)$ = Impedance function that depends on social type and social class.

The new opinion value of the target individual is displayed in figure 37.

$$A_i(t+T) = A_i(t) + \dot{A}_i(t+T)$$

Figure 37. Equation. Opinion value function.

Where $Ai\ (t + T)$ is the new opinion value and $Ai(t)$ is the previous value.

The impedance function is composed of four mechanisms with binary variable: class-type similarity, opinion leader, opinion follower and status quo. It is represented by figure 38.

$$\lambda(ST,SC)=(1-\delta_i)\left[0.5\eta_i+\tau_i\left(\frac{1}{\rho SC_i}\right)^{\alpha Z}+\omega_i\left(\frac{\varkappa}{Y|SC_i-SC_j|}\right)^{\beta}\right]$$

Figure 38. Equation. Impendance function.

Where:

λ = Impedance.
δ_i = Opinion leader status-quo bias indicator.
τ_i = Opinion leader indicator for individual i.
η_i = Class-type similarity for individual i.
ρ = A User-defined constant.
Y= A user-specified constant.

Class-Type Similarity Mechanism

For the class-type simiilarity mechanism to be triggered, two interacting individuals must be similar either in social class or social type. This is described as a binary variable in figure 39.

$$\eta_i=\begin{cases}1 \text{ if } SC_i-SC_j\leq 0 \text{ or } ST_i=ST_j\\ 0 \text{ otherwise}\end{cases}$$

Figure 39. Equation. Class type similarity indicator.

If the individuals are similar in social class or social type, they simply average their opinions since they carry the same social resources.

Opinion Leader Mechanism

For an opinion leader, the opinion exchanged between the leader and the other individual does not depend on the other individual's social class. If the interacting individual is another opinion leader in a different class, the individual becomes aware of social class differences only. The following function displays these behaviors:

$$\tau_i\left(\frac{1}{\rho SC_i}\right)^{\alpha Z},\ C_i\geq 1$$

Figure 40. Equation. Opinion leader mechanism.

Where:

$$\tau_i=\begin{cases}1 & \text{if } ST_i=1\\ 0 & \text{otherwise}.\end{cases}$$

ρ = A user-specified constant.

Where τ_i specifies if the opinion leader mechanism is triggered by a binary value and ST is a binary value equal to 1 if an individual is an opinon leader, and 0 if the individual is an opinion follower. In this model example, the researcher sets α = 2 for the opinion follower and α = 0.8 for the opinion leader and Z = 2 when the interacting opinion leader is in the lower social class.

Opinion Follower Mechanism

For an opinion follower, the opinion exchanged between the follower and the other individual does not depend on the other individual's social class. The following function displays these behaviors:

$$\omega_i \left(\frac{\varkappa}{Y|SC_i - SC_j|} \right)^{\beta}$$

Figure 41. Equation. Opinion follower mechanism.

Where ω_i specifies if the opinion follower mechanism is triggered by a binary value. In this model example, the researcher sets $\varsigma = 2$ if the interacting individual is an opinion leader and the target individual is an opinion follower and $\beta = 2$ when the interacting individual is in the lower social class.

Status Quo Mechanism

Figure 42 shows the status quo mechanism as a binary variable. This states that opinion leaders do not update their opinion based on opinion followers.

$$\delta_i = \begin{cases} 1 & \text{if } ST_i = 1 \text{ and } ST_j = 0 \\ 0 & \text{otherwise} \end{cases}$$

Figure 42. Equation. Status quo mechanism.

Attitude Update Model

For a new opinion, five attitudes, strongly disagree, disagree, no opinion, agree and strongly agree are considered. Attitude update thresholds are are follows:

- Strongly disagree: [-2,-1.5).
- Disagree: [-1.5, -0.5).
- No opinion: [-0.5, 0.5).
- Agree: [0.5, 1.5).
- Strongly agree: [1.5, 2].

SIMULATION OF ATTITUDE DIFFUSION THROUGH SOCIAL NETWORK

The simulation experiment is based on a Netlogo modeling platform.(141) Netlogo was developed by the Northwestern University Center for Connected Learning and Computer-Based Modeling. The simulation experiment illustrates the information diffusion process through a social network in different situations. The experiment is proposed to provide a reference for the diffusion of information regarding green travel modes in a lattice neighorhood network and the possible implications of this information diffusion process on attitudes.

Design of the Experiment and Network Initialization

Based on the social class of the household, a lattice neighborhood network with four blocks is created in the Netlogo platform. Each block represents a neighborhood in the real world. Each agent in the experiment represents a family. The total number of agents in the whole network is 22,500, and each neighborhood has 5,625 families/agents. Each color represents the attitude of each agent towards green transportation modes. Violet is strongly agree, blue is agree, green is no opinion, yellow is disagree, and red is strongly disagree.

According to the distribution of the five social classes in each neighborhood (see figure 43 through figure 46), their correlation with attitude distribution (see table 17) and the distribution of social type (see table 18), the network is initialized where neighborhood 1 is a hypothetical high-income homogenous neighborhood. Neighborhood 2 is composed of middle upper income agents that are heterogeneous. Many low-income agents live in neighborhood 3, which represents a rather homogenous neighborhood. Neighborhood 4 is composed of middle lower income agents, which is heterogeneous.

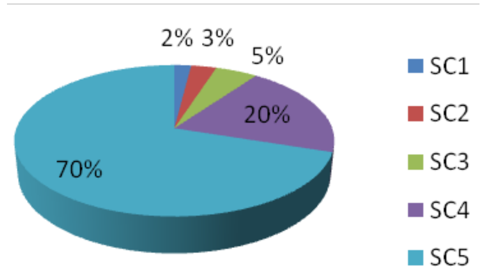


Figure 43. Graph. Social class distribution in neighborhood 1.

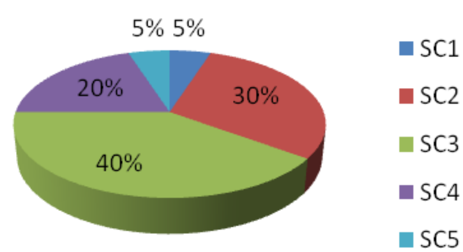


Figure 44. Graph. Social class distribution in neighborhood 2.

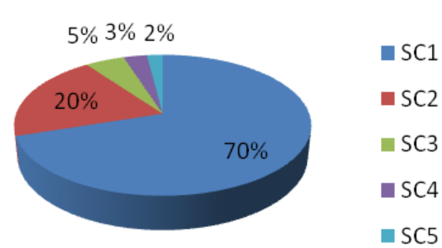


Figure 45. Graph. Social class distribution in neighborhood 3.

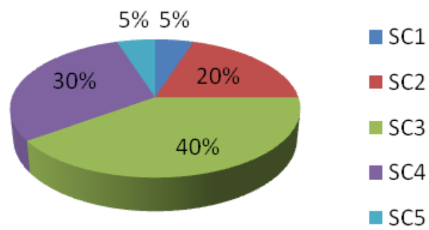


Figure 46. Graph. Social class distribution in neighborhood 4.

Table 17. Neigborhood description with social class (household income) related to attitude.

Neighborhood	Social Class Value	Social Class Number (agents)	Distribution (percent)
1	1	113	2
	2	169	3
	3	281	5
	4	1,125	20
	5	3,938	70
2	1	281	5
	2	1,688	30
	3	2,250	40
	4	1,125	20
	5	281	5
3	1	3,938	70
	2	1,125	20
	3	281	5
	4	169	3
	5	113	2
4	1	281	5
	2	1,125	20
	3	2,250	40
	4	1,688	30
	5	281	5

Note: Social class: 1= Poor; 2 = Working class; 3 = Lower middle class; 4 = Upper middle class; and 5 = Elite.

Table 18. Social type distribution in all neighborhoods.

Social Type	Follower Type	Distribution (percent)
Opinion leader	Leader	50
Opinion follower	Innovator	1. 25
	Early adopters	6.75
	Early majority	17
	Late majority	17
	Laggards	8

For the neighborhood representation of the experimental scenarios in figure 47 and figure 48, there are two main assumptions in this model as follows:

- All agents in a given neighorhood only communicate with others in that same community.
- Individuals in the lattice network are able to communicate with their eight immediate neighbors and do not interact with other agents in the same neighborhood.

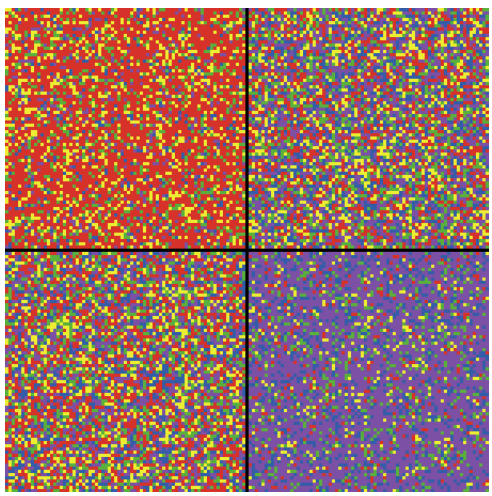


Figure 47. Illustration. Agent locations and social classes for a network before simulation stabilization.

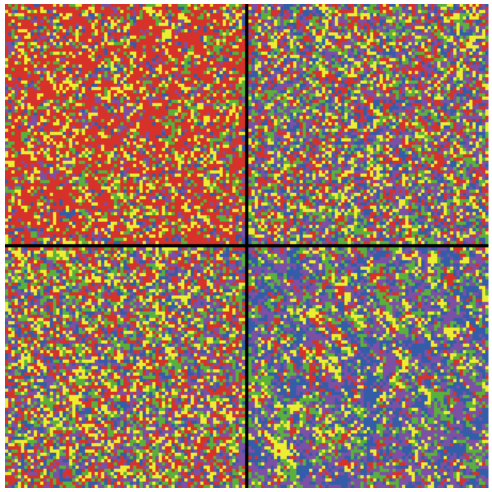


Figure 48. Illustration. Agent locations and social classes for a network after simulation stabilization.

Basic Scenario

After the initialization of the lattice neighborhood network, the model is built on the Netlogo platform, where figure 49 shows the model interface. After the initialization, the simulation is run in Netlogo untill a stable state is reached, whereby the attitude shares among the five classes do not change anymore.

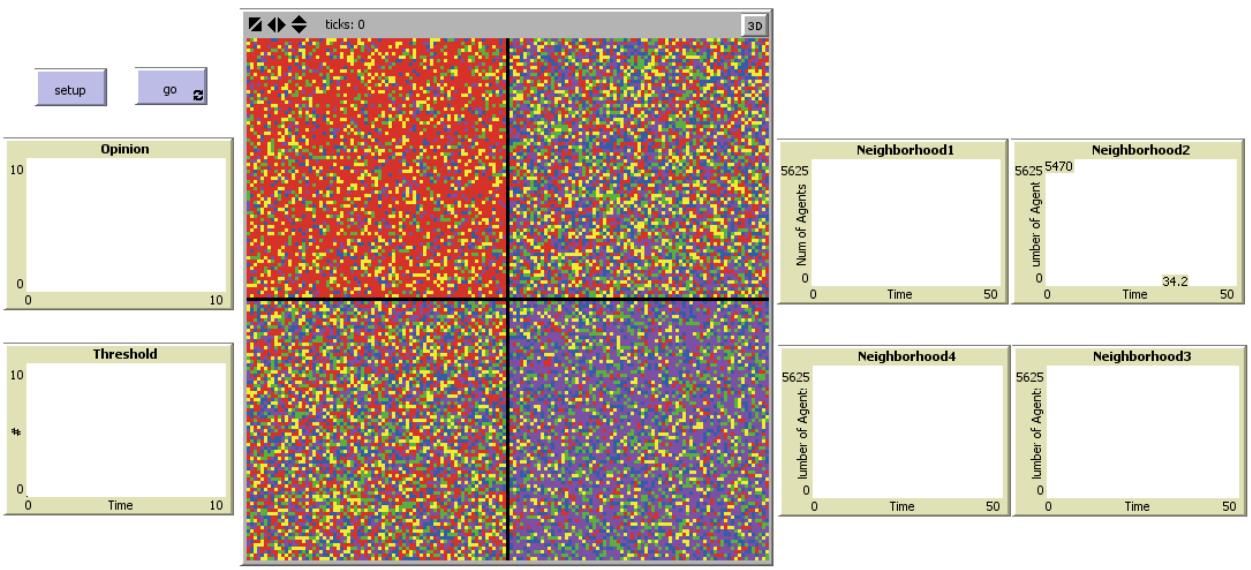


Figure 49. Screenshot. Netlogo model interface.

The attitude share distribution stabilizes with time, and its steady state is shown in figure 50 through figure 53. Each diagram describes the relationship between the number of agents and simulation time. The different colors represent the different attitudes. The statistical distribution of attitudes in each neighborhood after the simulation (base scenario) is shown in figure 54.

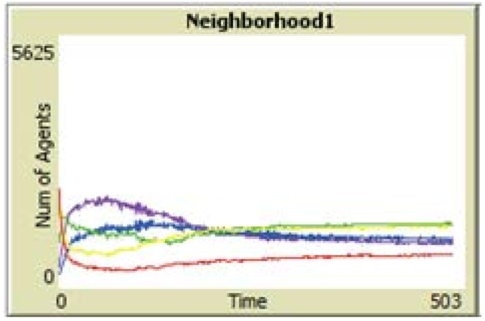


Figure 50. Graph. Number of agents with different attitudes in neighborhood 1.

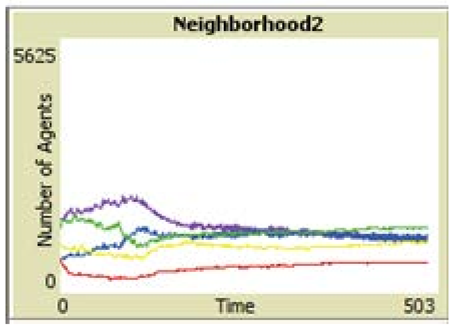


Figure 51. Graph. Number of agents with different attitudes in neighborhood 2.

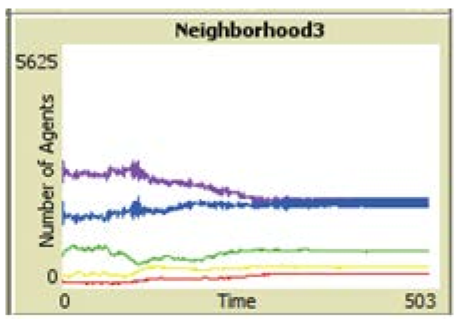


Figure 52. Graph. Number of agents with different attitudes in neighborhood 3.

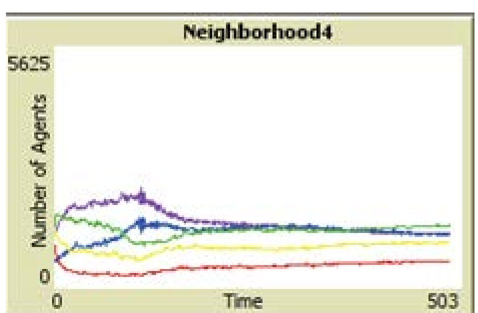
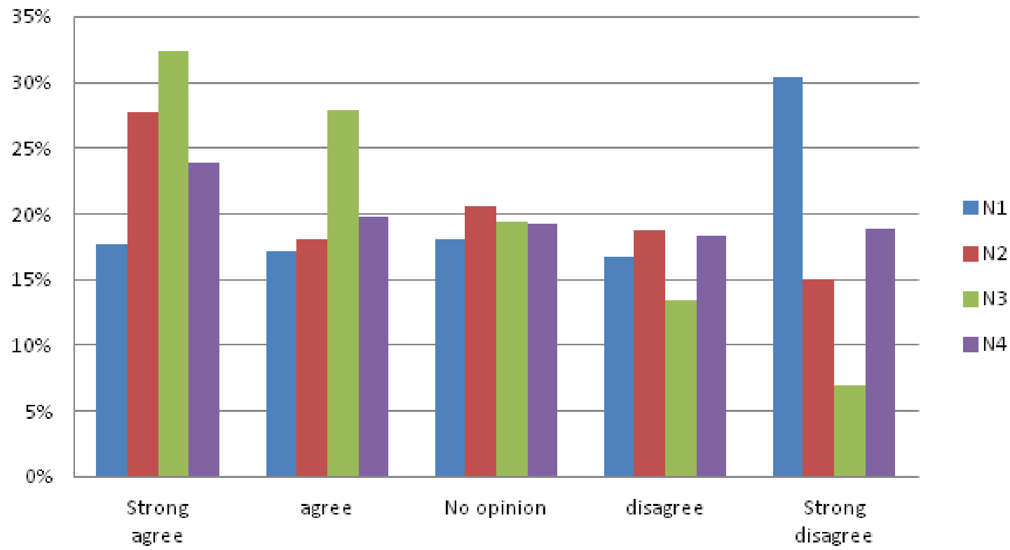


Figure 53. Graph. Number of agents with different attitudes in neighborhood 4.



Note: N1 = Neighborhood 1, N2 = Neighborhood 2, N3 = Neighborhood 3, and N4 = Neighborhood 4.

Figure 54. Graph. Attitude distribution in neighborhoods 1–4 of base scenario.

For comparison of the neighborhoods, the following performance measures are used:

- Time (ticks) for opinion value to converge.
- Number of interactions until convergence.

From figure 50 through figure 53, it is evident that neighborhood 1 needs the most time to converge, and neighborhood 3 can reach a stable status the fastest among the neighborhoods. Additionally, neighborhood 3 had the largest number of interactions.

Simulation Experiments and Results

With new information from outside the neighborhood, the attitudes toward more sustainable modes of transportation can be influenced. Influencing the attitudes of travellers from outside can be accomplished through a variety of ways (e.g., through targeted advertisements to influence attitudes, operational targeting via positive feedback for sustainable traveler choices, or by incentivizing the use of sustainable transport). By observing the people around them and by sharing their experience with their neighbors, the attitude diffusion process given an initial change can then be initiated. The model presented in this chapter is designed to answer the question: If we want to sustain the change in attitudes, who needs to be influenced? Additionally, how many (what fraction of) agents will change their attitude? In order to study how agents are affected by the diffusion of information under outside interventions, the following two scenarios are designed: random targeting of agents and targetting network opinion leaders. For each experiment, the stable solution described in the previous sections uses the initial network.

Random Targeting of Agents

In this scenario shown in figure 55, 30 percent of agents with the attitude "strongly disagree" were selected randomly and induced to change their attitude from "strongly disagree" to "agree." This scenario simulates a non-targeted external influence shown in figure 56.

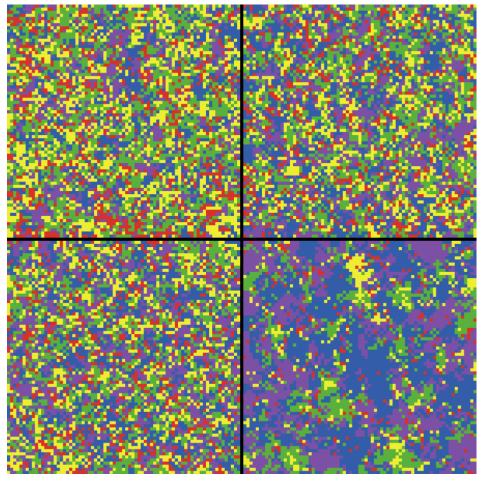
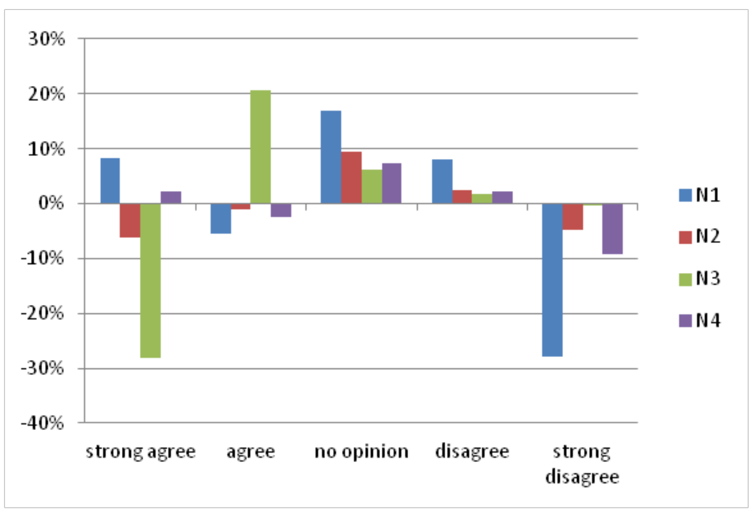


Figure 55. Illustration. Simulation results for scenario 1: random targeting simulation results.



Note: N1 = Neighborhood 1, N2 = Neighborhood 2, N3 = Neighborhood 3, and N4 = Neighborhood 4.

Figure 56. Graph. Simulation results for scenario 1: random targeting percentage change of attitudes.

In figure 55, outside influence effects neigborhood 3 (lower left corner) and neigborhood 1 (upper right corner) the most. Whereas in neighborhood 3, where already a majority of the agents had a positive attitude, the change cannot be sustained. The change in neighborhood 1 can be nearly sustained, as the group with "strongly disagree" attitude nearly maintain the outside change. In general, the more homogenous neighborhoods where a higher intensity of interaction is simulated are more affected by an outside intervention, whereas the heterogenous neighborhoods tend to retain the same attitude share as in the base scenario.

Figure 57 shows the compliance of the neighborhood under outside influence. The number of people rejecting the new attitude decreases in neighborhoods 1, 2, and 4. The change in neighborhood 1 is the most visible. The number of people accepting new information decreases in neighborhoods 2, 3 and 4 and increases in neighborhood 1.

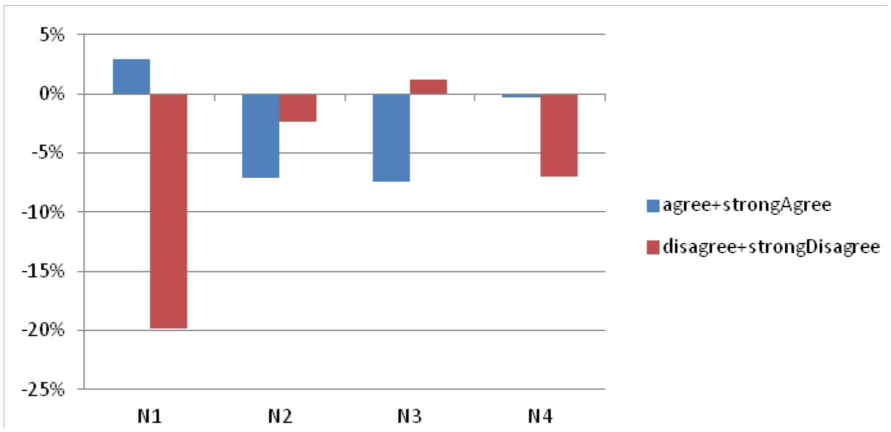


Figure 57. Graph. Percentage change of attitudes aggregated in positive and negative attitude bins.

Targetting Network Opinion Leaders

In this second scenario, targeted influence from the outside was tested, with 30 percent of the opinion leaders selected randomly and induced to change their attitude from “strongly disagree” to “agree.” Figure 58 shows similar results as in scenario 1. However, as expected, influencing opinion leaders had a stronger impact overall. The outside influence affected the homogenous neighborhoods the most. Whereas in neighborhood 3, where already a majority of the agents had a positive attitude, the change could be sustained. The change in neighborhood 1 was sustained and expanded, as the group with “strongly disagree” attitude grew in excess of outside influence.

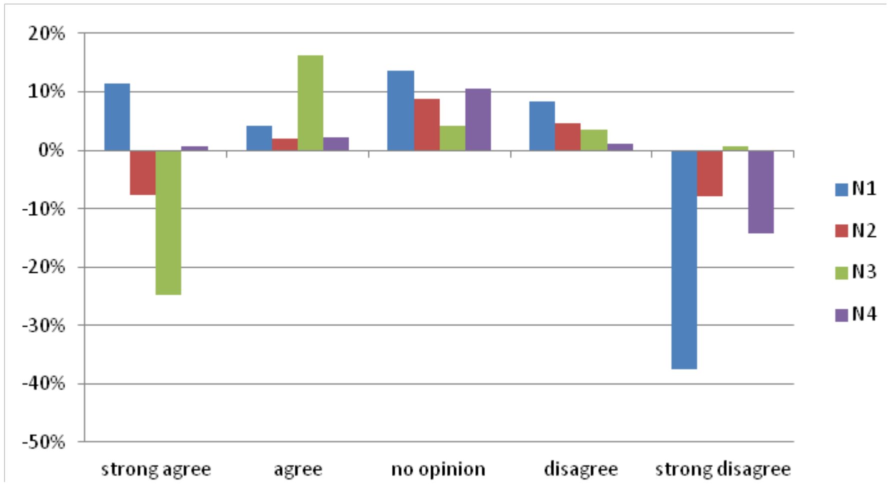


Figure 58. Graph. Percentage change of attitudes in the different neighorhoods under scenario 2: targeting opinion leaders.

Figure 59 shows that the number of people who rejected new information under the outside influence decreased in neighborhoods 1, 2, and 4. The change in neighborhood 1 is the most striking. The number of people accepting new information decreased in neighborhoods 2 and 3 and increased in neighborhoods 1 and 4. Comparing these results with the results from scenario 1, the influence of outside factors is stronger under scenario 2.

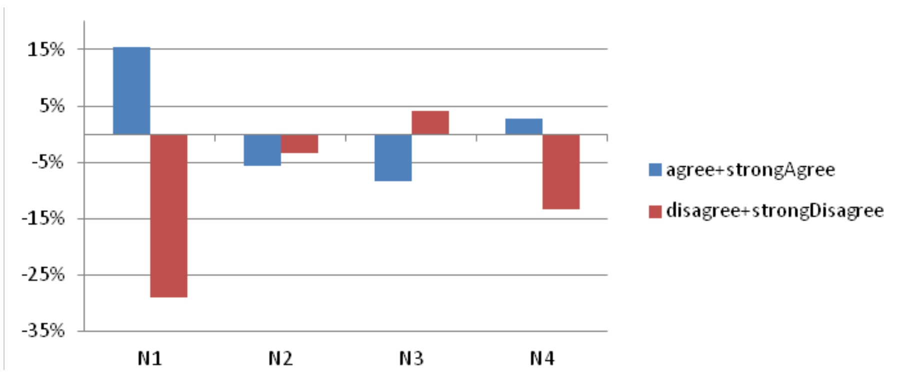


Figure 59. Graph. Percentage change of attitude aggregated in positive and negative attitude bins.

Limitations

This case study is primarily intended as an exploratory piece, providing an outlook for future research rather than a modeling tool ready for immediate implementation. Nevertheless, information and attitudes in individual decision processes are very important and are increasingly being incorporated or considered into choice models. Especially for demand management purposes, it is important to understand the information dissemination and attitude evolution processes. Better understanding and modeling of these processes can enable agencies and policymakers to exert greater control over demand and how demand could be influenced. This does not only have to be in one direction towards more sustainable attitudes but can also be used to understand strong positive attitudes towards less sustainable behavior and how such attitudes could be reversed or mitigated.

The most significant limitation in this case study is that the models are not calibrated based on actual observations but only serve illustrative purposes to show the different processes involved in an attitude formation model and how these processes can be formulated in an agent-based modeling framework. This work underscores the large data gaps and needs in the realm of user attitudes and associated dynamic mechanisms as well as the potential value in terms of policy effectiveness of investing to deploy data gathering and user behavior observatories.

RECOMMENDED NEXT STEPS AND RESEARCH

Although attitudinal questions have been integrated into recent travel surveys, these attitudes are assumed to be static and introduced in the models as being constant.[134,135] The case study in this chapter built a model to understand the processes behind these attitudes and to the research team's knowledge. There is no data available to calibrate the developed model. Instead of relying on existing data, the model is based on concepts and processes known from literature, where similar models have been developed. As in all areas, the responses of travelers to information, messages, guidance, and controls are essential to the overall effectiveness of management strategies. Understanding the process of information dissemination and attitude formation can be an important contribution in understanding and evaluating demand management strategies, which involve information. But as attitudes and their formation dissemination may take place over a longer period, a travel behavior and attitude tracking survey would be needed to dynamically collect travel behavior and attitudinal data.

A next step would be to design an experimental survey where people would be tracked over a longer period of time and be exposed to stimuli conditioning. The survey would track how the participants learn their attitudes. Such stimuli conditioning could be through advertisements toward a particular attitude or with incentive stimuli. In a second step, participants could discuss their attitudes with the other participants around them and learn from each other.

The methodology applied in this case study provides the necessary framework and structure to capture the processes of how people learn their attitudes and could be validated and calibrated with the observation of such an experimental study and reformulated if necessary.

CHAPTER 7. AERIS CASE STUDY II: INFLO AND SPEED COMPLIANCE

PROGRAM INTERVENTION: SPEED HARMONIZATION

The U.S. Department of Transportation (USDOT) DMA program has identified 10 high-priority mobility applications to improve the individual mobility, safety, and environmental impacts through connecting vehicles, infrastructure, and travelers.(142) Figure 60 shows these USDOT DMA bundles. INFLO is part of these mobility applications, which includes queue warning, cooperative adaptive cruise control, and speed harmonization.(143) Among these applications, this study focuses on speed harmonization, which is an ATM strategy that adjusts the speed limit based on traffic, weather, and road surface condition to improve mobility, safety, and negative environmental impacts.(140)

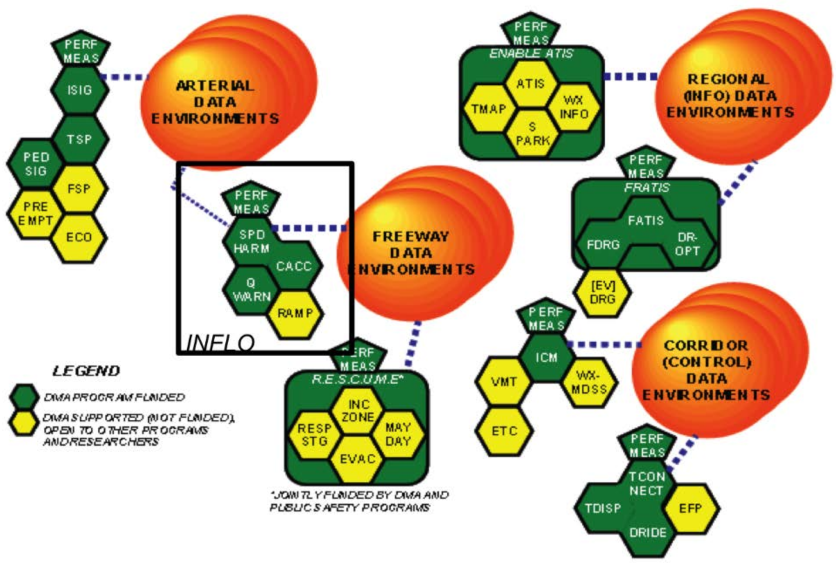


Figure 60. Illustration. USDOT DMA bundles.(144)

USDOT's AERIS program also identifies speed harmonization as an effective application to control negative environmental impacts.(144) The AERIS program examines ways to reduce environmental impacts resulting from transportation-related emissions and fuel consumption, and as such, AERIS projects leverage other USDOT research areas for environmental management. The AERIS program has developed six transformative concepts, bundling applications to achieve additional benefits beyond what each can achieve alone. Connected vehicle technology is a central component of the AERIS program, so information and how it is communicated to travelers and their vehicles is of interest. Figure 61 shows the USDOT AERIS bundles, where speed harmonization is characterized as an eco-lanes application.

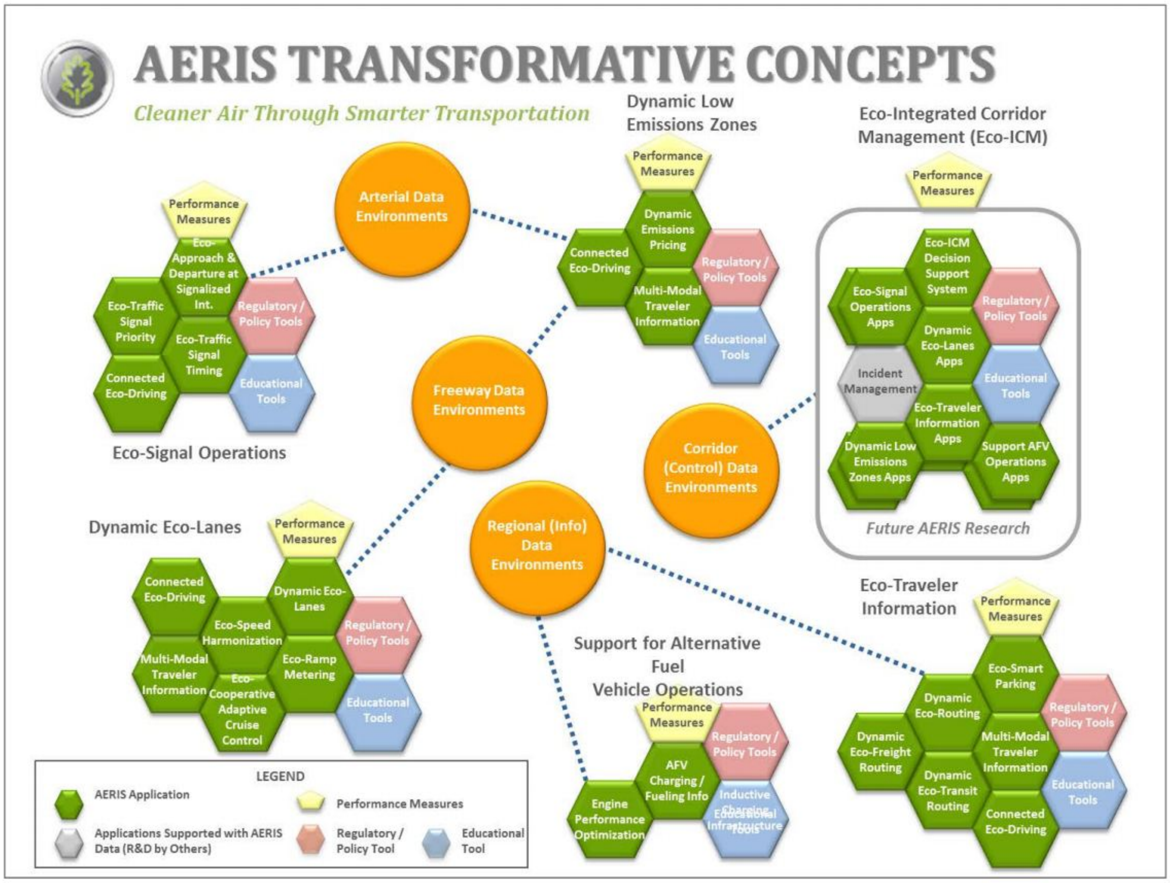


Figure 61. Illustration. USDOT AERIS application bundles.[144]

Speed harmonization was first introduced in Germany and the Netherlands in the 1970s; however, it was not widely implemented until the 2000s.[145] The literature has adopted both empirical and simulation approaches to analyze the effectiveness of speed harmonization systems. Empirical-based approaches focus on evaluating the effectiveness of the existing systems. (See references 143–150.) These studies mainly compare certain performance measures (e.g., flow rate, travel time, crash rate, etc.), based on the empirical data in a before and after study to investigate the effectiveness of speed harmonization systems. Unlike empirical-based approaches, simulation-based approaches mostly investigate the algorithms and methods with the objective of improving the performance of the speed harmonization systems. (See references 151–157.) These studies mainly focus on improving the speed limit selection algorithms.

Current practice of speed harmonization systems can benefit from connected vehicles technology. Connected vehicles technology will provide the means to detect and collect the individual vehicles' trajectories. These trajectories can be used in traffic control algorithms to improve the performance of Intelligent Transportation Systems (ITS), enhance safety, control congestion, and reduce emissions. However, further behavioral based studies are required to incorporate the information provided by connected vehicles into speed harmonization systems.[140] The main objective of this study was to investigate the impacts of early shockwave detection based on the information from the connected vehicles on congestion and emission control using speed harmonization as the control strategy. The performance of the speed harmonization system under different drivers' compliance levels was also investigated to understand what level of behavioral compliance was needed to achieve intervention targets. The speed harmonization system implemented in this study was first introduced by Talebpour et al.[140] This system adopts the wavelet transform method to generate a reliable shockwave detection algorithm.[158] The speed limit is selected based on a predefined decision tree.[159] The microsimulation model of Hamdar et al. was used to implement the speed harmonization system.[160]

The following section presents the effects of the speed harmonization systems on travel behavior. Formulation of the microscopic model, the logic behind the speed harmonization and ramp metering algorithms, the simulation framework, and the corresponding heterogeneity considerations are discussed next. The study sections are described followed by experimental results on each section.

FRAMEWORK FOR EVALUATION

Connected vehicle technology is intended to help drivers avoid making bad driving decisions en route. Speed harmonization, like ramp metering and VMSs, requires drivers to comply with the advised policy in order for it to be effective. As such, the key decision for drivers is whether to comply with this information or not (see figure 62). The level of compliance with advised (and in some cases required) information directly influences the acceleration and deceleration of vehicles on the network. These vehicles are then assigned to the network using multi-criterion DTA, which indirectly produces new network travel times and travel costs. Over time, these travel costs influence travelers' mode choice utility and perceived accessibility (e.g., travel time to their preferred destinations). There is little existing research on how speed harmonization might influence travelers' accessibility and mobility choices over time.

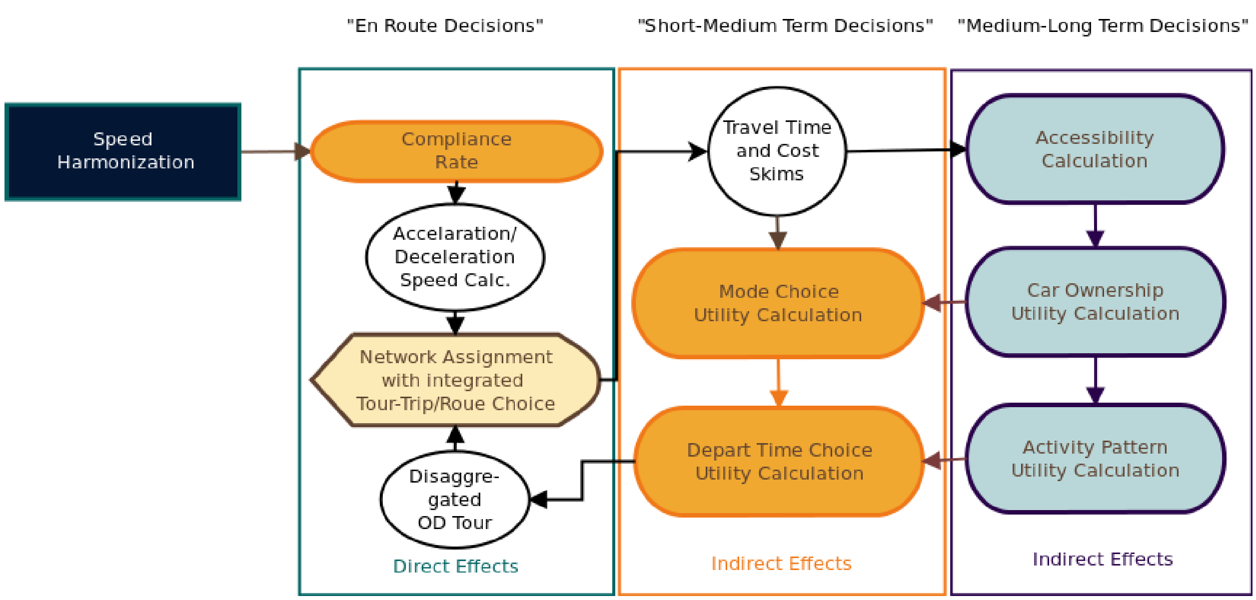


Figure 62. Illustration. Framework for evaluation of speed harmonization and related en-route interventions.

DATA AVAILABLE AND USED IN CASE STUDY

In this study, two highway segments were selected for the simulation case studies: a hypothetical segment and a real-world segment. The hypothetical segment is a two-lane segment with a lane drop. Figure 63 illustrates the geometric characteristics of this hypothetical segment. The segment is 6 mi long, and the lane drop is located 3.5 mi downstream of the start location. The inflow rate is set to be 1,500 vehicles/h. The simple geometric characteristics of this segment provide a controlled environment to fulfill the objectives of this study.

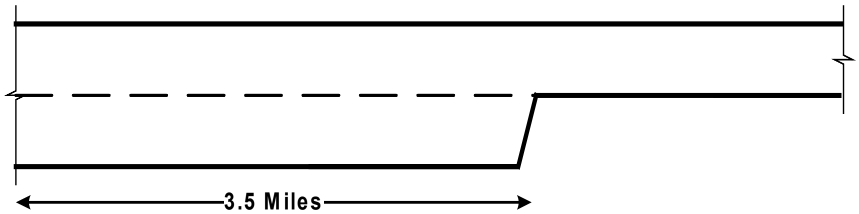
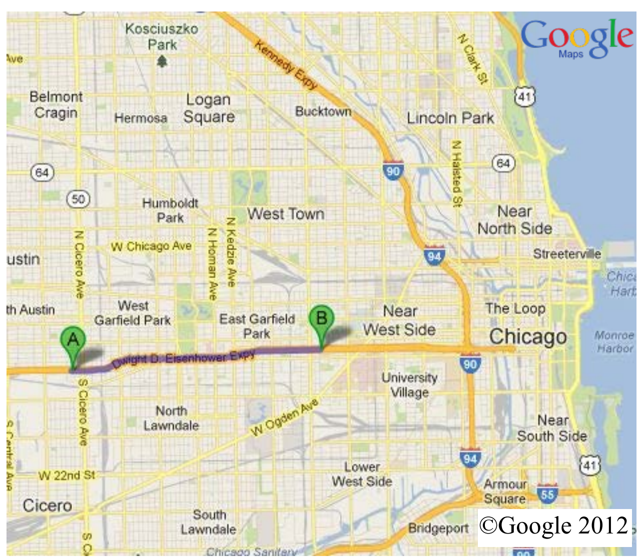


Figure 63. Illustration. Geometric characteristics of the hypothetical two-lane highway.

A four-lane highway was also selected for the simulation case study. The segment is located on the eastbound direction of I-290 near Chicago, IL. This 3.5-mi-long segment has four on-ramps and three off-ramps, each with different characteristics and different merging length. Figure 64 and figure 65 show the geographic and geometric characteristics of this segment, respectively. The loop detector data (speed, flow, and occupancy) is only available for the main section. Therefore, the output of the DYNASMART mesoscopic model for the morning peak period was used to calculate the flow pattern in the segment. The loop detector data were then used to adjust these flows to their actual values on an average day. The individual vehicles' paths were determined by utilizing the DYNASMART output. The information on these paths (i.e., start section, end section, and departure time) was then combined to calculate the ramps and main section entry flows.



©Google Maps® 2012

Figure 64. Illustration. Geographic characterization of the selected segment in Chicago, IL.(161)

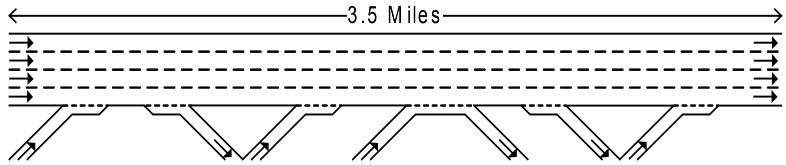


Figure 65. Illustration. Geometric characterization of the selected segment in Chicago, IL.

MODEL DEVELOPMENT AND CALIBRATION

In this study, the microsimulation model of Hamdar et al. was used in conjunction with the speed harmonization system introduced by Talebpour et al. to investigate the effects of speed harmonization on traffic breakdown and carbon dioxide emission.[160,140] In the following section, the formulation of the microscopic model is presented. The speed harmonization system and the logic behind the shockwave detection and speed limit selection algorithms are discussed, followed by a presentation of the ramp metering algorithm and the model calibration results.

Microscopic Model Formulation

Acceleration modeling and lane change modeling are core elements of microsimulation traffic models. Acceleration models are intended to capture the operational decisionmaking process, while lane changing models aim to capture the tactical driving decisionmaking process. This study builds on the simulation model presented by Hamdar et al., which adopts a duration-based framework at the tactical level and a utility-based framework at the operational level.[160] Additional details on the model formulation can be found in Hamdar and Hamdar and Mahmassani.[162,163]

Duration Framework

In the duration framework, the hazard-based duration models were used to capture the tactical decisionmaking process. The driving process was divided into different episodes characterized by a termination probability (given that the episode has not ended before) and an episode duration (the time elapsed before the driver enters another episode). The episodes could be divided into car-following episodes and free-flow episodes based on the corresponding inter-vehicle follower-leader interactions.

A free-flow episode ends when either the distance between the vehicle and its leader decreases to the point that the new episode can be considered as a car-following episode or the vehicle changes lane (the vehicle can enter another car-following episode or free-flow episode depending on the interaction between the vehicle and the leader). The car-following episode ends when either the vehicle changes lane (similar to the car-following episode, the outcome can be either a free-flow episode or a car-following episode) or the distance between the vehicle and its leader increases to the point that the new episode can be considered as free-flow episode.

The hazard at time *u* is defined as the conditional probability of termination of the current episode at small time period δ after u as follows:

$$\lambda_{iq} = \lim_{\delta \to 0^+} \frac{P\left(u \leq T_{iq} < u + \delta \mid T_{iq} < u\right)}{\delta} = \lambda_{0q} \emptyset \left(x_{iq}, \beta_q\right)$$

Figure 66. Equation. Hazard equation for time *t*.

Where:

i = The driver.
q = The exit strategy of an episode.
T_{iq} = The duration of the episode for driver i and exit strategy q.[163]
λ_{0q} = The base line hazard value at time u.
x_{iq} = The vector of explanatory variables for driver i at time u.
β_q = The vector of corresponding parameters to be estimated.

Hamdar and Mahmassani used the exponential form for the function of exogenous covariates shown in table 19.[163]

Table 19. External covariates and their definition.[163]

Data Number	Data Type	Definition	Unit
1	Vehicle ID (VehID)	ID (ascending by entry time into study section).	Number
2	Episode ID (EpID)	ID (following vehicle ID ordering).	Number
3	Episode duration (duration)	Duration of the car-following episode.	s
4	Episode type (EpType)	$q = 1, \ldots, Q$ where $Q = 4$.	Number
5	Left censuring variable (LeftCens)	LeftCens = 1 if episode is the first episode corresponding to a vehicle and = 0 otherwise.	Number
6	Vehicle type x0 (VehType)	1 = motorcycle, 2 = auto, and 3 = truck.	Number
7	x1 (LCL)	Number of leaders changing lanes during episode.	Number
8	x2 (V)	Driver's speed.	m/s
9	x3 (DXL1)	Headway between driver i and leader $i - 1$ (front-to-front bumper).	m
10	x4 (DVL1)	Relative speed between driver i and leader $i - 1$.	m/s
11	x5 (DXF1)	Distance headway between driver i and follower $i + 1$ (front-to-front bumper).	m
12	x6 (DVF1)	Relative speed between driver i and follower i + 1.	m/s
13	x7 (DXL2)	Distance headway between driver i and driver $i - 2$ (front-to-front bumper).	m
14	x8 (DVL2)	Relative speed between driver i and driver $i - 2$.	m/s
15	x9 (DXL1R)	Distance headway between driver i and the leader on the right lane.	m
16	x10 (DVL1R)	Relative speed between driver i and the leader on the right lane.	m/s
17	x11 (DXF1R)	Distance headway between driver i and the follower on the right lane.	m
18	x12 (DVF1R)	Relative speed between driver i and the follower on the right lane.	m/s
19	x13 (DXL1L)	Distance headway between driver i and the leader on the left lane.	m
20	x14 (DVL1L)	Relative speed between driver i and the leader on the left lane.	m/s
21	x15 (DXF1L)	Distance headway between driver i and the follower on the left lane.	m
22	x16 (DVF1L)	Relative speed between driver i and the follower on the left lane.	m/s
23	x17 (K)	Driver's average surrounding density.	Veh/km/lane
24	x18 (KR)	Driver's average surrounding density in adjacent lane 1 (to the right).	Veh/km/lane
25	x19 (KL)	Driver's average surrounding density in adjacent lane 2 (to the left).	Veh/km/lane

1 m/s = 3.28 ft/s
1 m = 3.28 ft
1 km = 0.621 mi

Acceleration Framework

Drivers select their acceleration based on the evaluation of the potential gains and losses. Hamdar et al. modeled this decisionmaking process using Kahneman and Tversky's prospect theory.(160,164) Based on this theory, the decisionmaker first assigns different utilities to different alternatives by considering corresponding gain and losses (framing or editing phase). He/she then evaluates these alternatives based on the prospect index (evaluation phase). The prospect index is calculated similar to the expected utility using subjective decision weights instead of expected probability of each outcome. Based on this theory and to evaluate the acceleration choice, the following value function is introduced by Hamdar et al.:(160)

$$U_{PT}(a_n) = \frac{\left[w_m + (1 - w_m)\left(\tanh\left(\frac{a_n}{a_0}\right) + 1\right)\right]}{2}\left[\frac{\left(\frac{a_n}{a_0}\right)}{1 + \left(\frac{a_n}{a_0}\right)^2}\right]^{\gamma}$$

Figure 67. Equation. Acceleration value function.

Where:

U_{PT} = The acceleration value function.
a_0 = Normalization parameter.
a_n = *acceleration*
$\gamma > 0$ and w_m = Parameters to be estimated.(160)

The drivers will gain U_{PT} by choosing a_n as the acceleration unless there exists a crash possibility. Hamdar et al. used the crash seriousness term, $k(v, \Delta v)$, to determine the disutility resulting from the crash as follows:

$$U(a_n) = (1 - p_{n,i})U_{PT}(a_n) - p_{n,i} w_c k(v,\Delta v)$$

Figure 68. Equation. Crash disutility.

Where $p_{n,i}$ is the probability of being involved in a rear-end collision.(160) $U_{PT}(a_n)$ is derived from Figure 67, and w_c is a crash weighting parameter which is lower for aggressive drivers.

Capturing the stochastic nature of the acceleration choice, Hamdar et al. obtained the logistic functional form as follows:(160)

$$f(a_n) = \begin{cases} \dfrac{e^{(\beta_{PT} \times U(a_n))}}{\int_{a_{min}}^{a_{max}} e^{(\beta_{PT} \times U(a'))} da'} & a_{min} \le a_n \le a_{max} \\ 0 & Otherwise \end{cases}$$

Figure 69. Equation. Stochastic nature of the acceleration.

Where:

β_{PT} = Sensitivity of choice to the total utility.
a_{min}, a_{max} = Minimum and maximum vehicle acceleration.
da = Integral.

Speed Harmonization Algorithm

The model introduced in the previous section is used in a simulation framework that considers inter-driver heterogeneity. The objective is to examine the effectiveness of the speed harmonization system in improving traffic conditions, reducing the number and amplitude of the shockwaves, and delaying breakdown formation particularly under congested conditions. This section describes the speed limit selection algorithm for the speed harmonization system, as well as the approach followed in the algorithm for early determination of shockwave formation. More detail on these algorithms can be found in Talebpour *et al*.[151]

Shockwave Detection Framework

In this study, the wavelet transform method of Zheng et al. was used to identify the shockwave formation process based on individual vehicle information.[158] The authors defined an *oscillation* as a process in which an instance of acceleration behavior is followed by one of deceleration behavior, and used the wavelet-base energy to identify the location of the vehicle responsible for the start of the oscillation.

The concept of wavelet transform developed in 1980s refers to a transformation from continuous time series data into scale components based on a real or complex function, $\psi(t)$. The general formulation for the continuous wavelet transform (CWT) of a general signal $x(t)$ can be written as follows:

$$CWT(\alpha,\beta) = \omega(\alpha)\int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-\beta}{\alpha}\right)\mathrm{d}t$$

Figure 70. Equation. CWT function.

Where:

CWT = Continuous wavelet transform function.
α = The scale parameter.
β = The translation parameter.
$\omega(\alpha)$ = The weighting function typically set to be $\frac{1}{\sqrt{\alpha}}$ to normalize the energy across scales.[158]

In this study, the Mexican hat wavelet, as defined in equation 71, is selected as the mother wavelet; where $\alpha = 1$ and $\beta = 0$, the ψ function is termed the mother wavelet.

$$\psi\left(\frac{t-\beta}{\alpha}\right) = \left(1-\left(\frac{t-\beta}{\alpha}\right)^2\right)e^{-\left(\frac{t-\beta}{2\alpha}\right)^2}$$

Figure 71. Equation. Mother wavelet function.

Based on the work of Zheng et al., velocity is selected as the input signal to the wavelet transformation. Inserting figure 71 into figure 70, the CWT used in this study can be formulated as follows:

$$CWT(\alpha,\beta)=\frac{1}{\sqrt{\alpha}}\int_{-\infty}^{\infty} v(t)\left(1-\left(\frac{t-\beta}{\alpha}\right)^2\right)\, e^{-\left(\frac{t-\beta}{2\alpha}\right)^2} dt$$

Figure 72. Equation. CWT function (simplified).

The dimensionless average wavelet energy can be then calculated by averaging figure 72 across different scales as follows:

$$E(\beta)=\frac{1}{\max(\alpha)}\int_{0}^{\infty}|CWT(\alpha,\beta)|^2 d\alpha$$

Figure 73. Equation. Average wavelet energy function.

Averaging makes this method a powerful tool to analyze the non-stationary signal measures such as traffic speed and acceleration and locating the abrupt changes in the values of these measures. Based on the recommendation made by Zheng et al., for each vehicle, the upper bound for α is set to be 6.4 s, and β is calculated for all time steps during which the vehicle is present in the study segment.(158) Figure 74 through figure 77 illustrate the application of the wavelet transform to identify the abrupt changes in speed using a vehicle trajectory from I-80 Next-Generation Simulation (NGSIM) data. Figure 74 shows the actual speed diagram with small and large fluctuations. Figure 75 shows the wavelet transform coefficient, $CWT(\alpha, \beta)$, computed for the entire range of β and $\alpha = 4$. The figure shows that fluctuations in CWT match the fluctuations in actual speed while having less noise compare to the actual speed data. Figure 76 presents the distribution of the absolute values of CWT function, $|CWT(\alpha,\beta)|$, for the entire range of $\alpha = 1$ to 64. The lighter areas in the figure correspond to the higher energy values. Finally, the distribution of the wavelet energy (figure 73) is presented in figure 77. The local peaks correspond to the abrupt speed drops in the actual time series data.

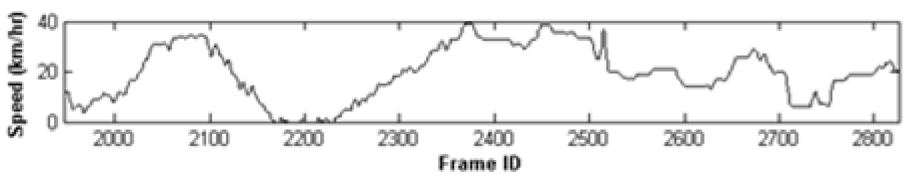


Figure 74. Graph. Wavelet energy calculation—actual speed of a vehicle.

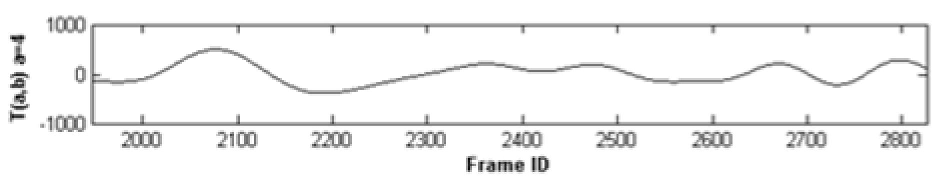


Figure 75. Graph. Wavelet energy calculation—CWT of the actual speed data.

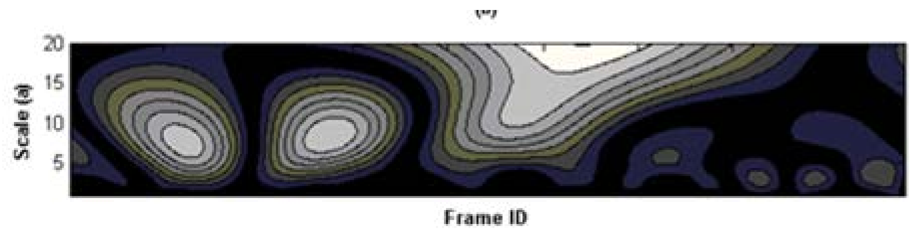


Figure 76. Graph. Wavelet energy calculation—absolute values of the CWT coefficient across scales.

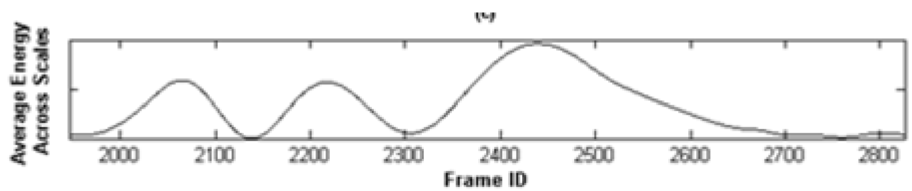


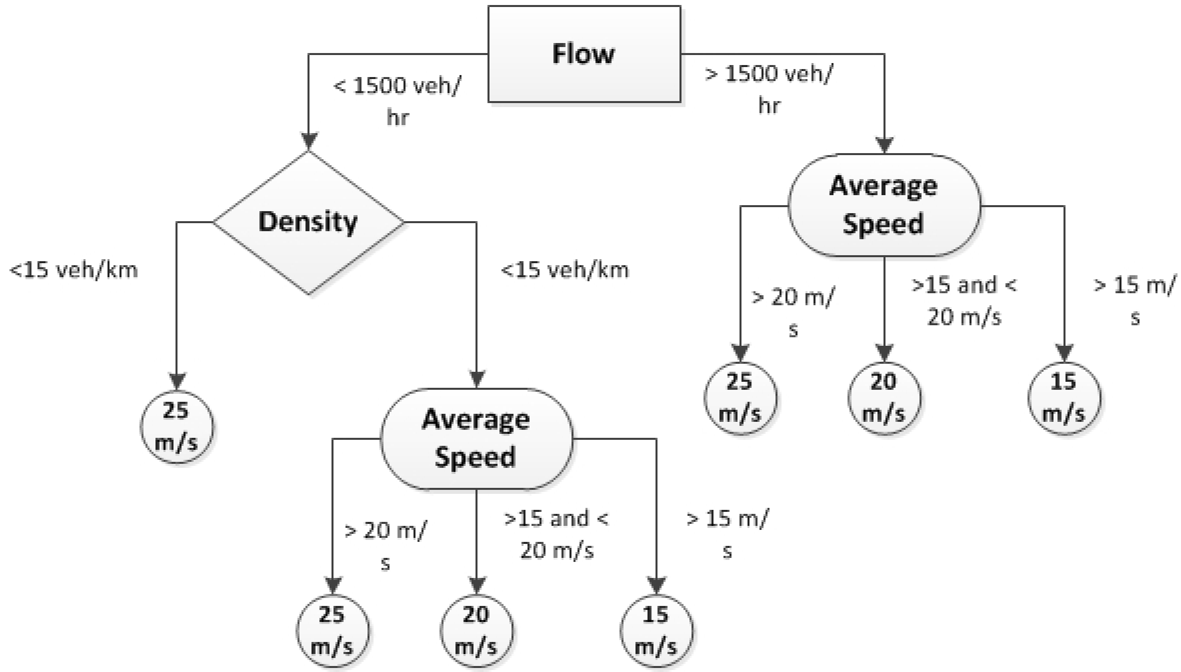
Figure 77. Graph. Wavelet energy calculation—average wavelet energy across scales.

Detecting the shockwave in its early stages is an important first step in the implementation of the proposed speed harmonization system. In the next section, the second step of this process, speed limit selection, is discussed in detail.

Speed Limit Selection

The speed limit selection algorithm is the core component in the speed harmonization system. Several different approaches have been proposed, which can be categorized into reactive and predictive approaches. The reactive algorithms set the speed limit based on the current traffic, road, and weather conditions, while predictive algorithms use current traffic, road, and weather conditions in conjunction with a prediction module to select the speed limit.

Figure 78 shows the decision tree for the speed limit selection, which is based on the decision tree introduced by Allaby et al.[159] The decision is based on the prevailing traffic condition (i.e., speed, flow, and density) at the shockwave detection point. Note that once a speed is updated on a sub-segment, it cannot be changed for 10 min to prevent rapid fluctuations in the speed limit.



1 ft = 0.305 m

Figure 78. Flowchart. Speed harmonization decision tree.

Ramp Metering Algorithm

Ramp metering is a common strategy in the current practice of congestion control in highway systems. To provide a more realistic simulation, this study incorporates Asservissement lin´eaire d'entr´ee autorouti`ere' (ALINEA) as the ramp metering algorithm.(165) ALINEA calculates the metering rate based on the difference between the desired and measured occupancy using the following equation:

$$r(t)= r(t-1) + K_r[O - O_{out}(t)]$$

Figure 79. Equation. Ramp metering rate.

Where:

r = Ramp metering rate.
t = Time.
K_r = Regulatory parameter set to be 70 vehicles/h in this study based on recommendations presented by Chaudhary et al.(165)
O = Desired occupancy.
O_{out} = Measured occupancy.

Simulation Framework

The simulation framework is based on the model formulation and the speed limit selection logic presented earlier, with particular focus on the shockwave formation. The wavelet energy value is considered as an indicator of shockwave formation and computed using figure 79 for each vehicle at each time step of 0.1 s. For the purpose of early shockwave detection, the numerical derivation of the wavelet energy is calculated to find the peak points in the wavelet energy corresponding to the sudden changes in the speed as follows:

$$\frac{\mathrm{d}E(\beta)}{\mathrm{d}\beta} = \frac{-E(\beta - 2h) + 8E(\beta - h) - 8E(\beta + h) + E(\beta + 2h)}{12h}$$

Figure 80. Equation. Wavelet energy rate.

Where:

h = Predefined value set to be 1 sec in this study.
E = Energy.

The wavelet energy is calculated and examined continuously during the simulation. Once a sudden change in speed is found for a vehicle, all the vehicles following that car in the range of 0.5 mi on that lane will be checked to find other sudden changes upstream of the original location for the next 10 seconds. Note that these values are used here primarily for illustrative purposes. It can be expected that performance could be improved adaptively in a deployment context. If these calculations indicate a shockwave occurrence (the backward moving wave is found) then the appropriate speed limit to suppress this shockwave is selected based on the speed limit selection decision tree and the traffic conditions at the shockwave occurrence point.

The experienced hazard is also considered as a safety indicator, and computed using figure 81 for individual drivers at each time step. Following the aggregation procedure presented by Talebpour et al., this study computed the weighted average of experienced hazard to evaluate safety. For a segment with length L at time step u, the average hazard is calculated as follows:

$$\bar{\lambda}_u = \left(\sum_{i=1}^{N} \sum_{q=1}^{4} \lambda_{iq}^{u} \delta_{iq}^{u} \Big/ N_u \right)$$

Figure 81. Equation. Average hazard.

Where:

$\bar{\lambda}_u$ = The average hazard at time step u.
λ_{iq} = The hazard value vehicle *i* and episode type *q*.
δ_{iq} = A binary variable determining which exit strategy is active.
N_u = The total number of vehicles at time step *u*.[166]

Heterogeneity Considerations

The behavioral parameters of drivers in microscopic simulation models are expected to be correlated. Kim and Mahmassani presented a methodology to capture this correlation across the parameters of each driver.[167] They showed that sampling from the empirical data while accounting for the correlation between the parameters of each sample (individual drivers) was the best method to capture heterogeneity in microscopic simulation models. In this study and based on their findings, the NGSIM data were used to generate the correlated set of parameters. The data were previously used by Talebpour et al. to generate the set of correlated parameters and were collected on April, 13, 2005, on a segment of Interstate I-80 in San Francisco, CA, from 4:00 to 4:15 p.m. (2,052 vehicles).[166] The correlated parameters from 35 vehicles were used to generate the correlated set of parameters used in the simulation exercise. Based on the proposed method by Kim and Mahmassani, the parameters of each generated vehicle in the simulation exercise corresponded to a particular vehicle in the actual data.[167]

Table 20 shows the calibration results, and table 21 shows the correlation among the parameters of individual drivers. The Pearson correlation coefficients reveal strong correlation between the model parameters.

Table 20. Descriptive statistics of calibrated parameters.[140]

Parameter	Mean	S.D.
Reaction time (R_t)	0.86	0.78
Sensitivity exponents of the generalized utility (γ)	0.47	0.41
Velocity uncertainty variation coefficient (α)	0.10	0.09
Logit uncertainty parameter (β)	5.24	2.15
Maximum anticipation time horizon (τ_{max})	5.35	2.47
Asymmetry factor for negative utilities (ω_m)	3.56	2.17
Weighing factor for accidents (ω_c)	99,315.79	21,240.08
Correlation time of intra-driver variability (τ_{corr})	19.50	4.20

Table 21. Pearson correlation coefficients and *p*-values (in parentheses).[140]

	R_t	γ	α	β	τ_{max}	ω_m	ω_c	τ_{corr}
R_t	1.0000	-0.0845	0.0792	-0.0642	0.2155	0.1769	-0.0020	0.0439
	(0.0000)	(0.6141)	(0.6365)	(0.7019)	(0.1939)	(0.2881)	(0.9905)	(0.7934)
γ	-0.0845	1.0000	-0.0005	0.1137	0.2545	0.2370	-0.0336	-0.1575
	(0.6141)	(0.0000)	(0.9977)	(0.4967)	(0.1231)	(0.152)	(0.8414)	(0.3450)
α	0.0792	-0.0005	1.0000	-0.1328	-0.1606	0.2947	-0.0380	0.0459
	(0.6365)	(0.9977)	(0.0000)	(0.4266)	(0.3355)	(0.0725)	(0.8210)	(0.7843)
β	-0.0642	0.1137	-0.1328	1.0000	0.0327	-0.1505	-0.3580	-0.0887
	(0.7019)	(0.4967)	(0.4266)	(0.0000)	(0.8457)	(0.3670)	(0.0273)	(0.5964)
τ_{max}	0.2155	0.2545	-0.1606	0.0327	1.0000	0.2330	0.4509	0.1739
	(0.1939)	(0.1231)	(0.3355)	(0.8457)	(0.0000)	(0.1592)	(0.0045)	(0.2963)
ω_m	0.1769	0.2370	0.2947	-0.1505	0.2330	1.0000	0.0969	0.2712
	(0.2881)	(0.1520)	(0.0725)	(0.3670)	(0.1592)	(0.0000)	(0.5626)	(0.0995)
ω_c	-0.0020	-0.0336	-0.0380	-0.3580	0.4509	0.0969	1.0000	0.1305
	(0.9905)	(0.8414)	(0.8210)	(0.0273)	(0.0045)	(0.5626)	(0.0000)	(0.4349)
τ_{corr}	0.0439	-0.1575	0.0459	-0.0887	0.1739	0.2712	0.1305	1.0000
	(0.7934)	(0.3450)	(0.7843)	(0.5964)	(0.2963)	(0.0995)	(0.4349)	(0.0000)

SENSITIVITY TESTS USING SIMULATION

Numerical Experiments and Results

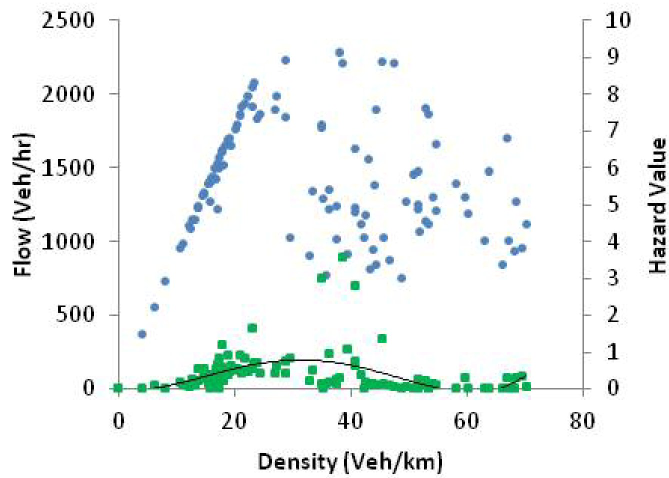
The purpose of the simulation experiments was to investigate the effectiveness of the proposed speed harmonization system in controlling breakdown formation, to analyze the effect of drivers' compliance with the speed limit on the performance of the speed harmonization system, and to study the effects of the proposed speed harmonization system on the emission production. Two scenarios were designed for each segment.

The first scenario focused on the effects of the proposed speed harmonization system on the breakdown and emission control. Note that full compliance with the suggested speed limit was applied to these scenarios. The effects of ramp metering on the performance of the proposed speed harmonization system are also discussed for the segment in Chicago, IL.

The second scenario involves analysis of the effect of drivers' compliance with the suggested speed limit on the performance of the speed harmonization system. Different levels of compliance were considered to conduct a sensitivity analysis.

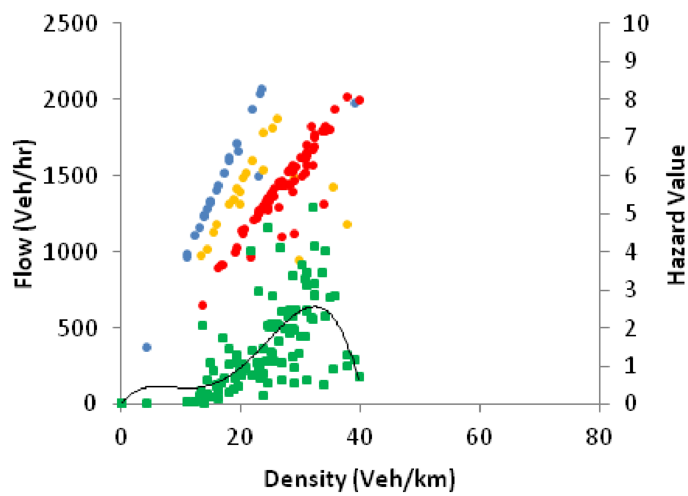
Hypothetical Segment

Figure 82 through figure 87 show the fundamental diagram, hazard-density diagram, temporal evolution of speed and flow, and emission production for the sub-segment starting 0.6 mi upstream of the lane drop location with and without active speed harmonization. Note that in all of the simulations presented for the hypothetical segment, the speed limit changes were applied 0.6 mi upstream of the shockwave detection point. The figures clearly reveal the effectiveness of the speed harmonization system in controlling breakdown formation, preventing speed drop, and maintaining higher flow rates. However, the hazard values are higher for the simulation with active speed harmonization. This is mainly due to drivers' adaptation effort to the new speed limit. It is expected that gradual change of speed over space can decrease the perceived risk by the drivers in this adaptation process. The figures also reveal the positive effect of speed harmonization on the emission production. This is mainly due to the effect of the speed harmonization system on breakdown formation. High acceleration rates, which result in more emission production, are more likely to happen in a congested condition. Thus, eliminating shockwaves and preventing breakdown formation can reduce the emission production.



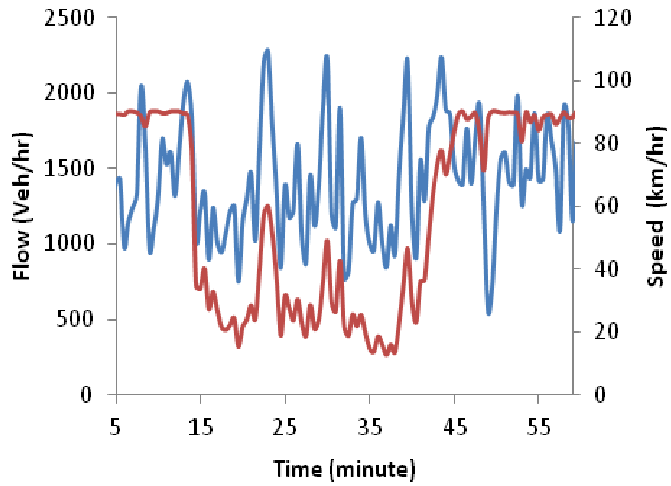
Note: Blue denotes fundamental diagram for 25 m/s speed limit and green denotes hazard value.
1 m/s = 3.28 ft/s

Figure 82. Graph. Fundamental diagram and hazard value for simulation with no active speed harmonization.



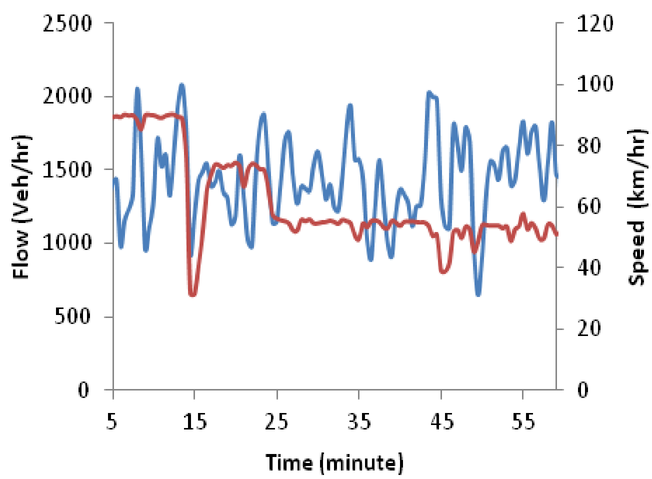
Note: Blue, orange, and red donate fundamental diagram for 25, 20, and 15 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s

Figure 83. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization.



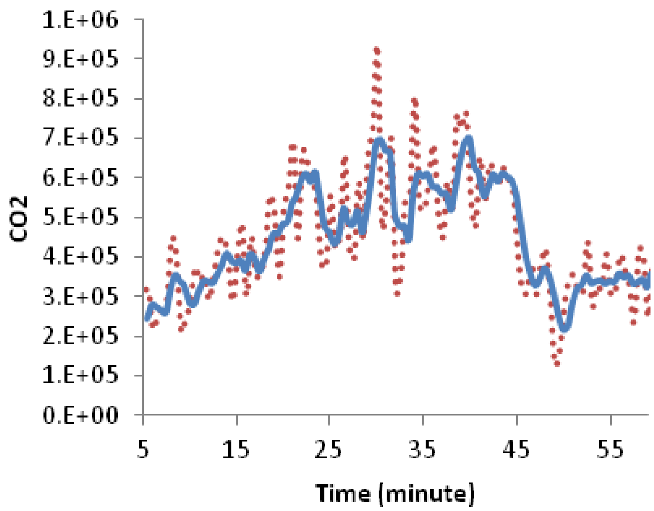
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 84. Graph. Flow and speed evolution over time for simulation with no active speed harmonization.



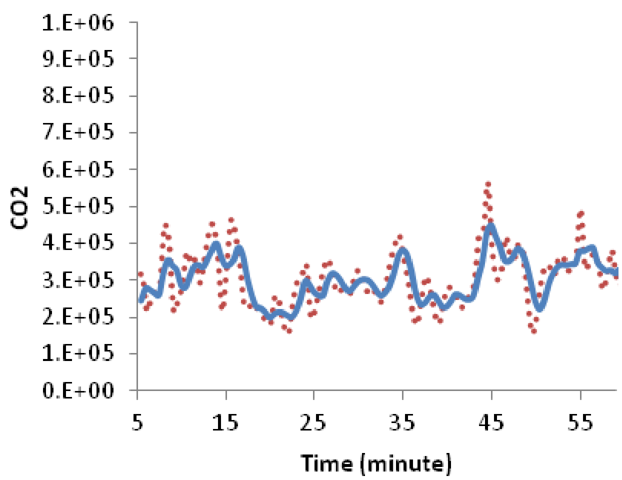
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 85. Graph. Flow and speed evolution over time for simulation with active speed harmonization.



Note: Red donates actual emission, and blue denotes moving average.

Figure 86. Graph. Emission and moving average evolution over time for simulation with no active speed harmonization.

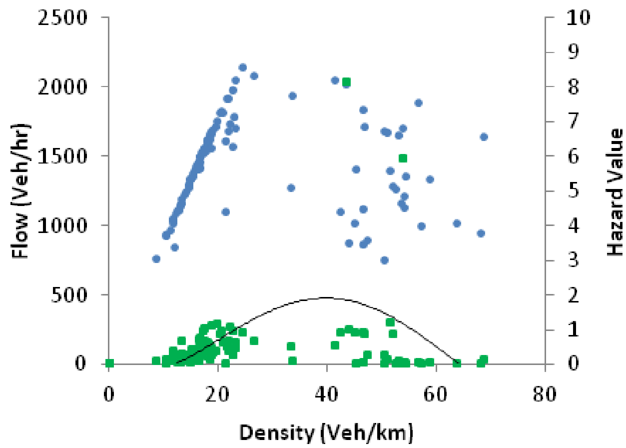


Note: Red denotes actual emission, and blue denotes moving average.

Figure 87. Graph. Emission and moving average evolution over time for simulation with active speed harmonization.

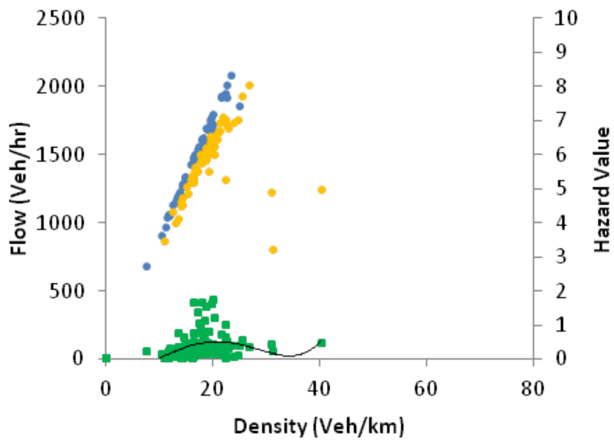
Figure 88 through figure 96 show the effects of compliance on the fundamental diagram, hazard-density diagram, temporal evolution of speed and flow, and emission production for the sub-segment starting 0.6 mi upstream of the lane drop location. Three levels of compliance with the suggested speed limit (0, 10, and 90 percent) are considered where drivers are able to drive with speeds up to 15 percent higher than the suggested speed limit. These figures reveal the importance of compliance with the suggested speed limit for the success of the speed harmonization system.

In a congested driving environment, drivers mostly operate in the car-following mode where they should either follow their leaders or change lane to avoid a crash. This implies that once a certain number of vehicles slows down to the suggested speed limit, the rest of the vehicles should slow down to the same speed to avoid a crash. The simulation results presented in figure 88 through figure 96 also confirm this hypothesis. While higher compliance levels are more favorable, the system is still capable of controlling breakdown formation at 10 percent compliance level. More detailed sensitivity analysis on the effect of compliance on the speed harmonization system is presented in the next section. Note that compliance with the posted speed limit is a major concern in speed harmonization systems. This observation can facilitate the effective implementation of these systems as attaining 10 percent compliance level is less challenging and well within the levels of compliance observed today.



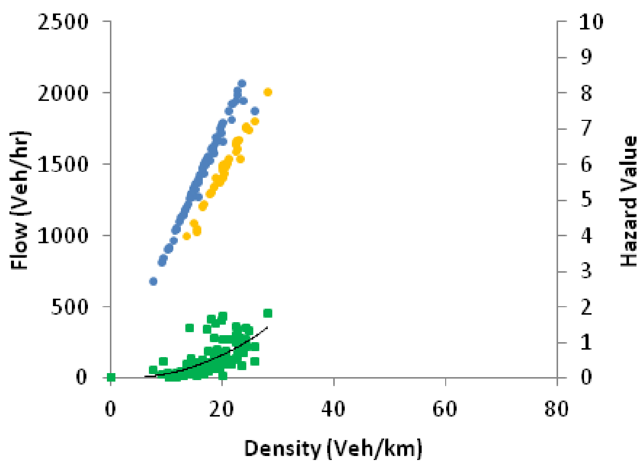
Note: Blue denotes 25 m/s speed limit, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 88. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization and 0 percent compliance.



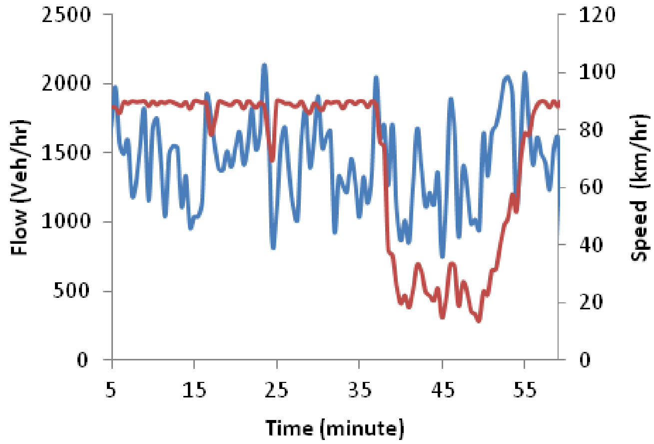
Note: Blue and orange denote 25 and 20 m/s speed limits, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 89. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization and 10 percent compliance.



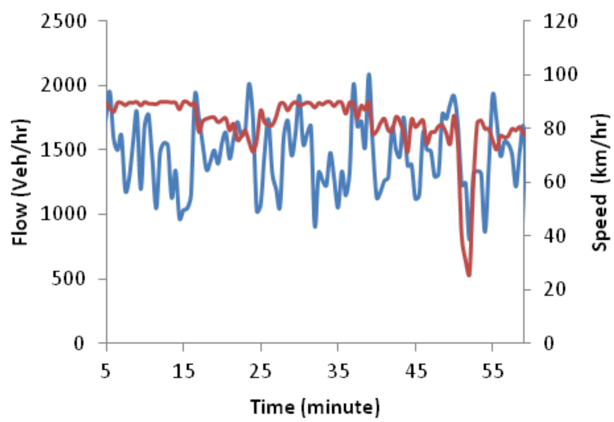
Note: Blue and orange denote 25 and 20 m/s speed limits, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 90. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization and 90 percent compliance.



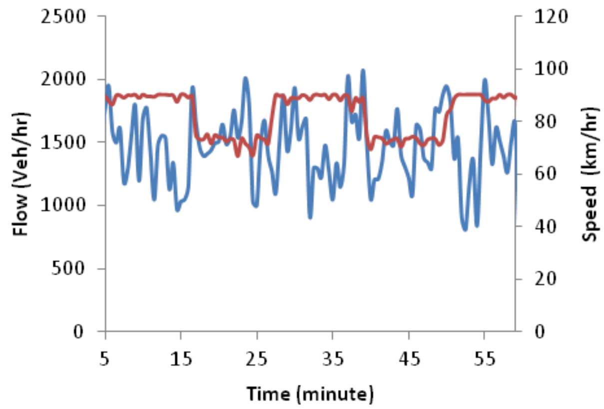
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 91. Graph. Flow and speed evolution over time for simulation with active speed harmonization and 0 percent compliance.



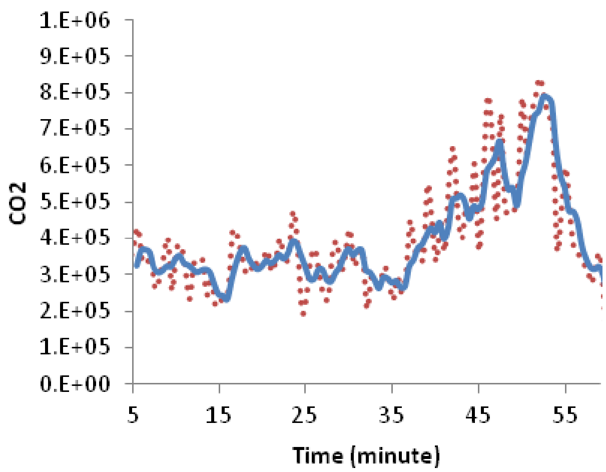
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 92. Graph. Flow and speed evolution over time for simulation with active speed harmonization and 10 percent compliance.



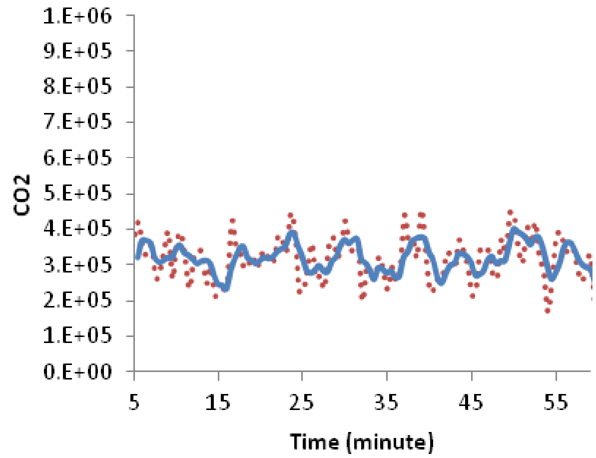
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 93. Graph. Flow and speed evolution over time for simulation with active speed harmonization and 90 percent compliance.



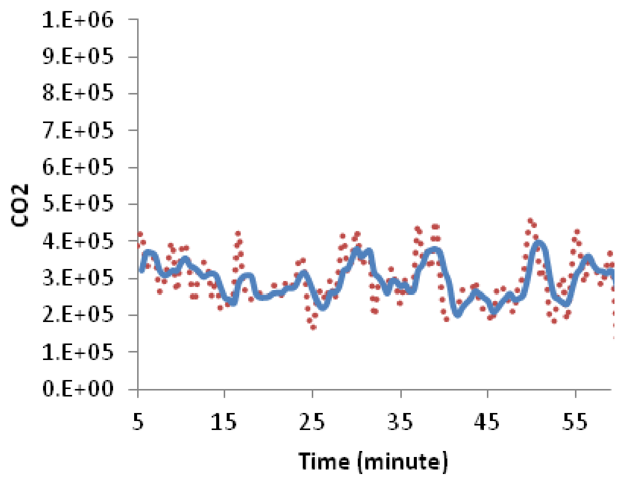
Note: Red denotes actual emission, and blue denotes moving average.

Figure 94. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and 0 percent compliance.



Note: Red denotes actual emission, and blue denotes moving average.

Figure 95. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and 10 percent compliance.



Note: Red denotes actual emission, and blue denotes moving average.

Figure 96. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and 90 percent compliance.

Chicago, IL

Figure 97 through figure 100 illustrate the effectiveness of the speed harmonization system in suppressing shockwaves and preventing breakdown formation while maintaining flow rate along the segment. Note that the drivers fully complied with the suggested speed limit in these simulations. In figure 97, the shockwave starts 2 mi downstream of the start point and propagates upstream. The speed harmonization system detects this shockwave at its onset and triggers the new speed limit. Reducing the speed limit to a lower value prevents the shockwave formation and propagation (see figure 99).

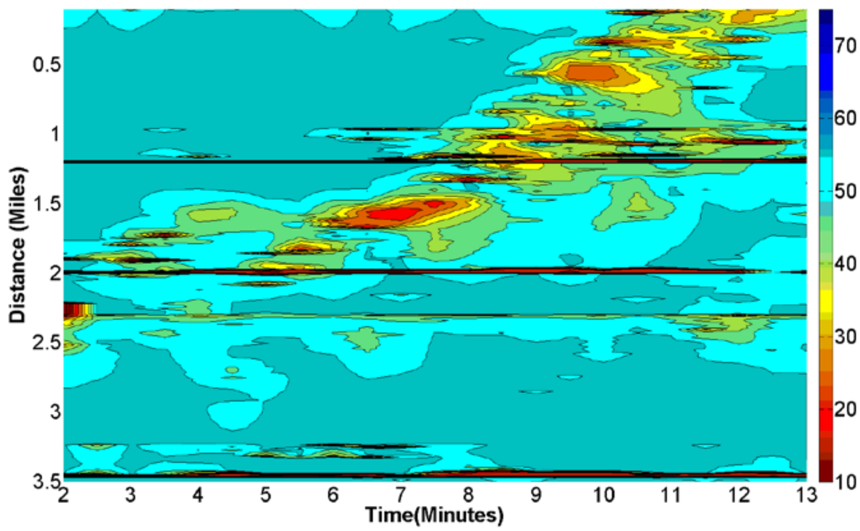
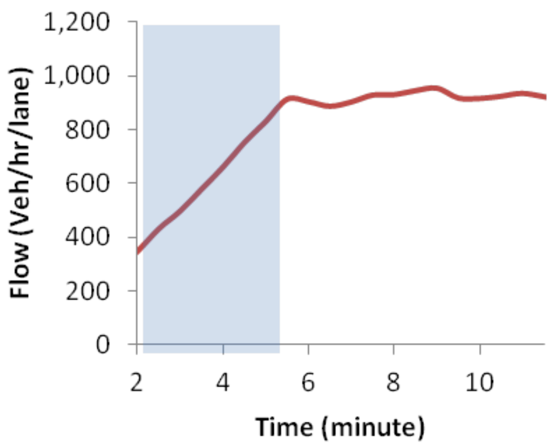


Figure 97. Graph. Smoothed speed variations in time-space diagram for simulation without active speed harmonization.



Note: Blue box shows the warm-up period.

Figure 98. Graph. Flow-time diagram for simulation without active speed harmonization.

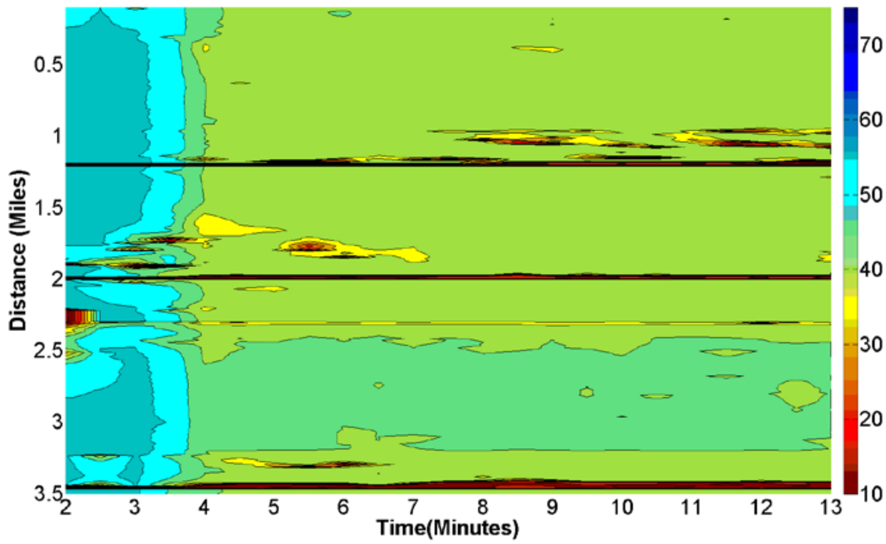
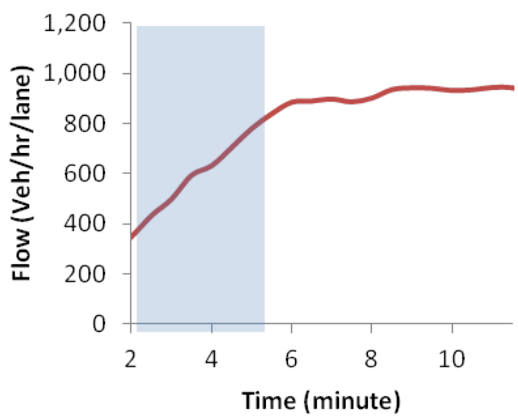


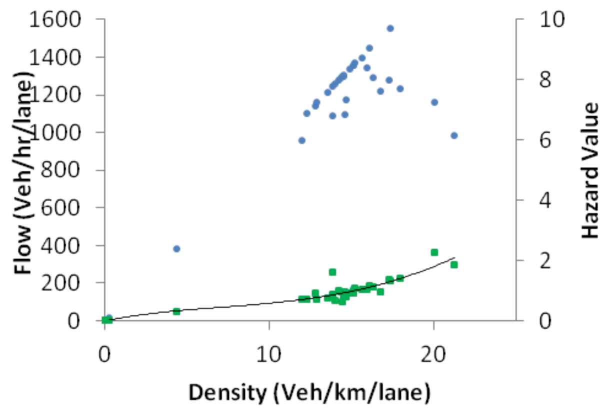
Figure 99. Graph. Smoothed speed variations in time-space diagram for simulation with active speed harmonization.



Note: Blue box shows the warm-up period.

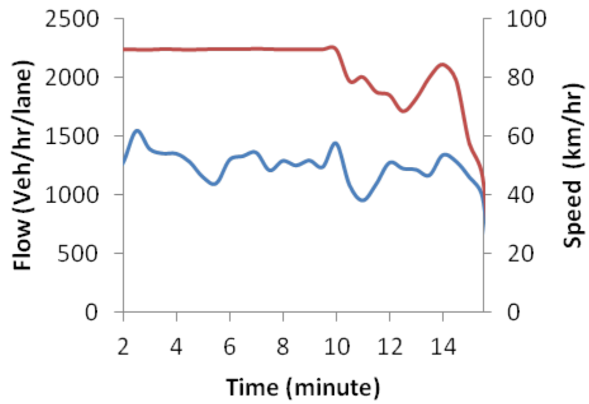
Figure 100. Graph. Flow-time diagram for simulation with active speed harmonization.

Figure 101 through figure 115 show the effects of compliance level on the fundamental diagram, hazard-density diagram, temporal evolution of speed and flow, and emission production for the sub-segment between milepost 0.6 and 1.2 with active speed harmonization but without active ramp metering. Five levels of compliance with the suggested speed limit (0, 10, 20, 40, and 90 percent) were considered where drivers were able to drive with the speed up to 10 percent higher than the suggested speed limit. These figures clearly reveal the effectiveness of the speed harmonization system in controlling breakdown formation, preventing speed drop, maintaining higher flow rates, and controlling emission production. They confirm that once certain number of vehicles slow down to the posted speed limit, the rest of the vehicles should reduce their speed accordingly to avoid a crash. However, in this case, a minimum of 20 percent compliance is required for the success of the speed harmonization, while in the hypothetical network, the speed harmonization system is capable of controlling breakdown formation at 10 percent compliance level. This occurs due to different geometric characteristics (different number of lanes and the existence of on and off-ramps in the segment in Chicago, IL) and different flow patterns.



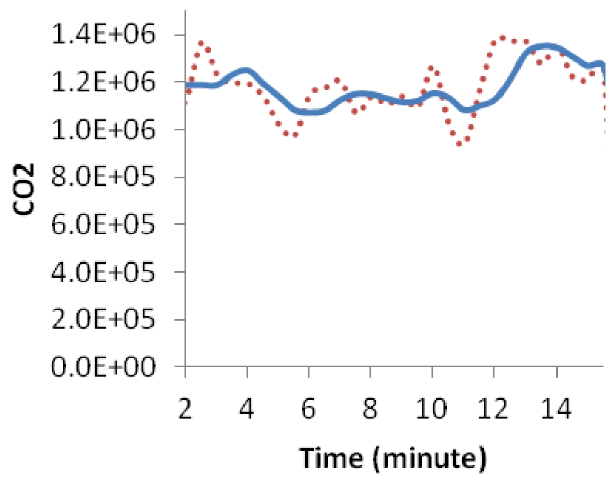
Note: Blue denotes 25 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 101. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization without active ramp metering at 0 percent compliance.



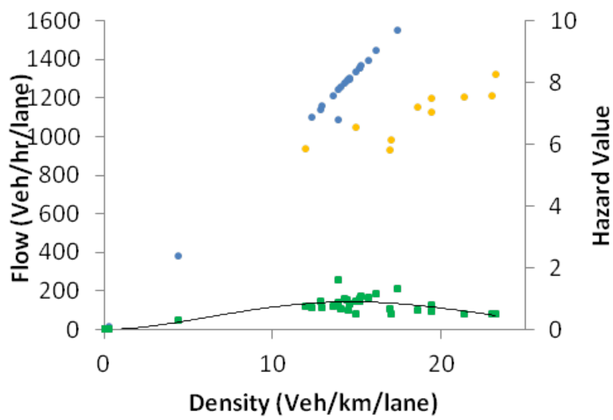
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 102. Graph. Flow and speed evolution over time for simulation with active speed harmonization without active ramp metering at 0 percent compliance.



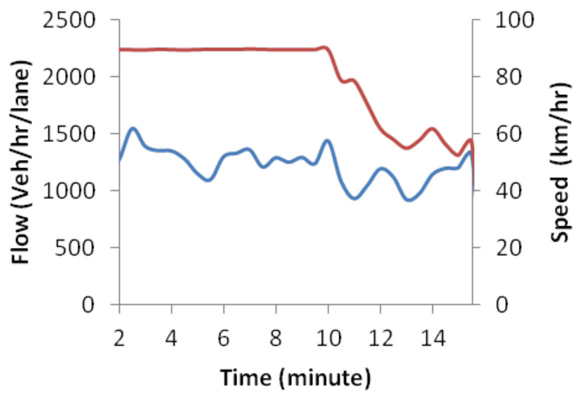
Note: Red denotes actual emission, and blue denotes moving average.

Figure 103. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and without active ramp metering at 0 percent compliance.



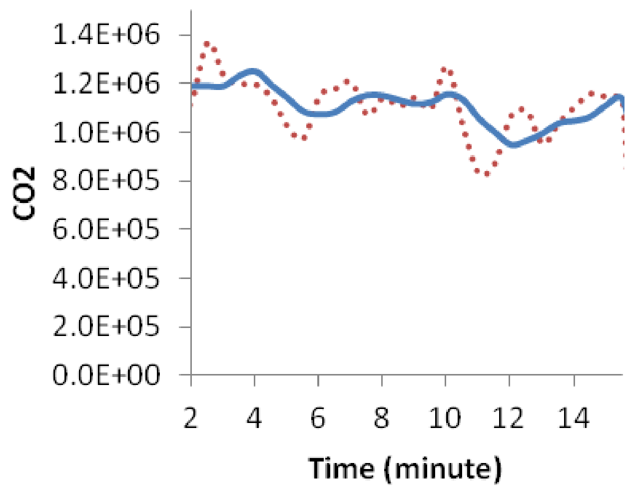
Note: Blue and orange denote 25 and 20 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 104. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization without active ramp metering at 10 percent compliance.



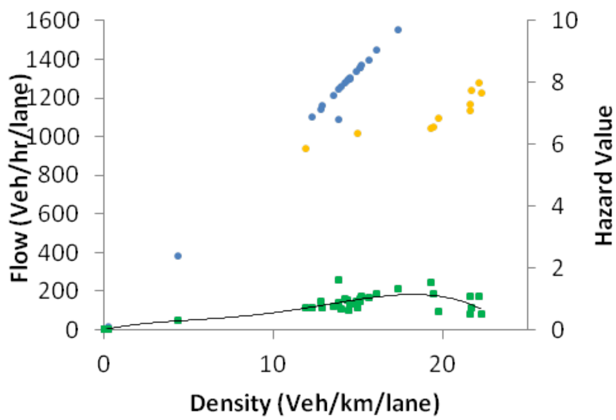
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 105. Graph. Flow and speed evolution over time for simulation with active speed harmonization without active ramp metering at 10 percent compliance.



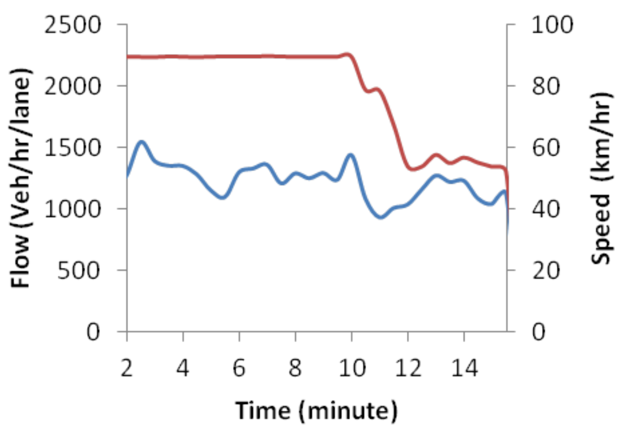
Note: Red denotes actual emission, and blue denotes moving average.

Figure 106. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and without active ramp metering at 10 percent compliance.



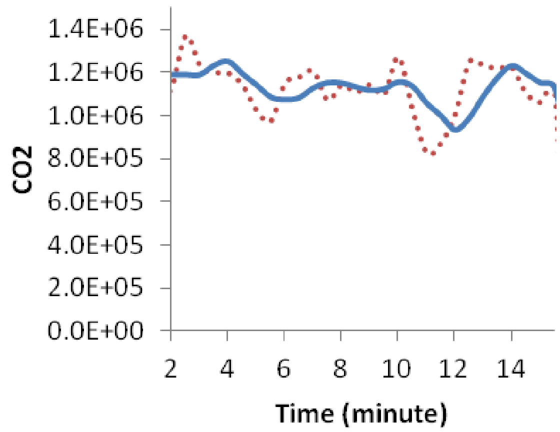
Note: Blue and orange denote 25 and 20 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 107. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization without active ramp metering at 20 percent compliance.



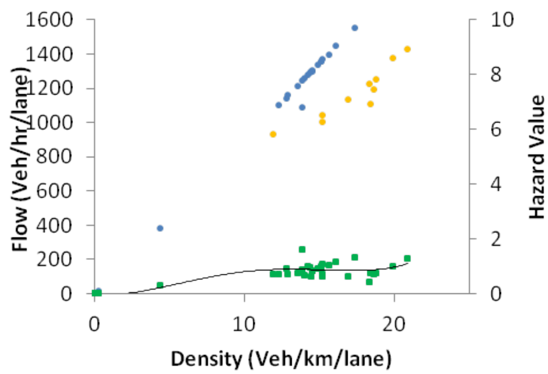
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 108. Graph. Flow and speed evolution over time for simulation with active speed harmonization without active ramp metering at 20 percent compliance.



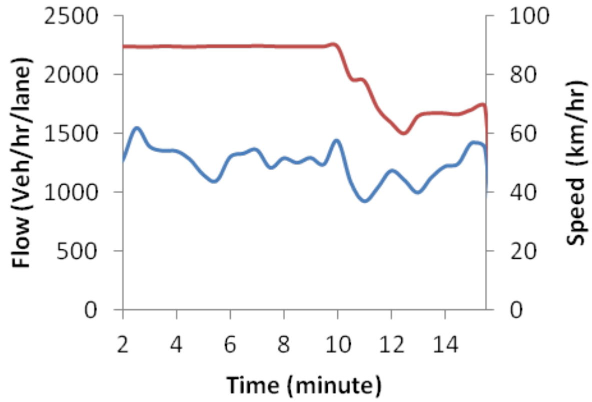
Note: Red denotes actual emission, and blue denotes moving average.

Figure 109. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and without active ramp metering at 20 percent compliance.



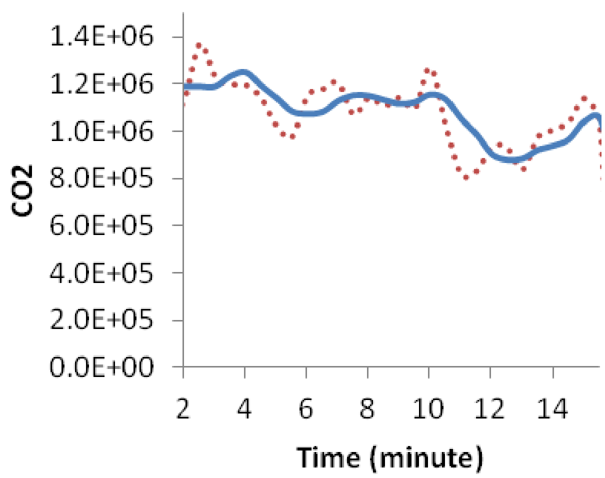
Note: Blue and orange denote 25 and 20 m/s speed limit, respectively, and green denotes hazard value.
1 km = 0.621 mi

Figure 110. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization without active ramp metering at 40 percent compliance.



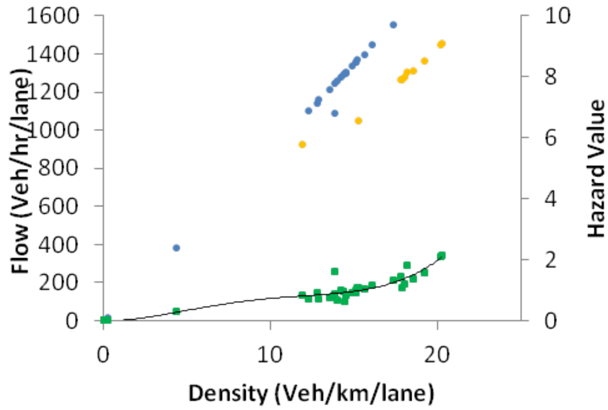
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 111. Graph. Flow and speed evolution over time for simulation with active speed harmonization without active ramp metering at 40 percent compliance.



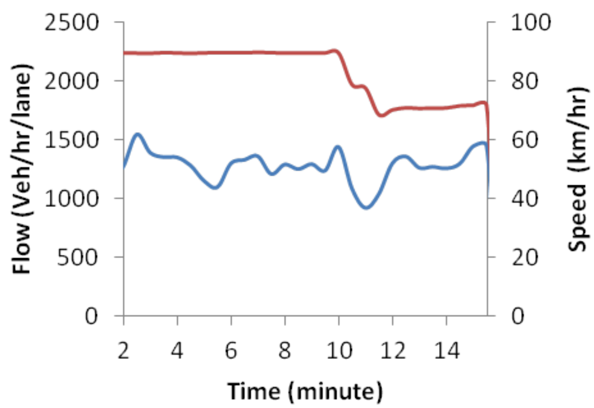
Note: Red denotes actual emission, and blue denotes moving average.

Figure 112. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and without active ramp metering at 40 percent compliance.



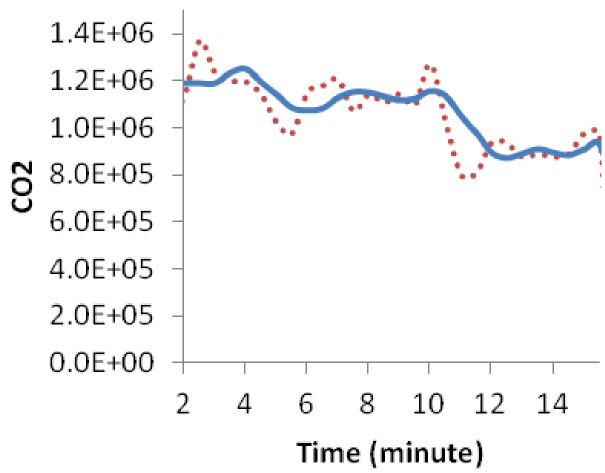
Note: Blue and orange denote 25 and 20 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 113. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization without active ramp metering at 90 percent compliance.



Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 114. Graph. Flow and speed evolution over time for simulation with active speed harmonization without active ramp metering at 90 percent compliance.



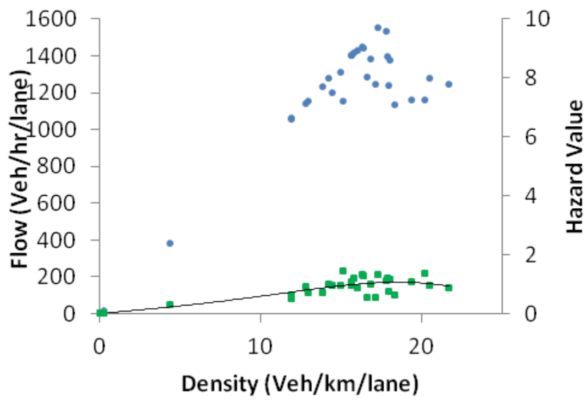
Note: Red denotes actual emission, and blue denotes moving average.

Figure 115. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and without active ramp metering at 90 percent compliance.

The combined effect of ramp metering and speed harmonization on the breakdown formation and control is also investigated. Figure 116 through figure 130 show the effects of compliance level on the fundamental diagram, hazard-density diagram, temporal evolution of speed and flow, and emission production for the sub-segment between milepost 0.6 and 1.2 with active speed harmonization and active ramp metering. The combination of two systems is still capable of controlling breakdown formation; however, the performance of the combined system is lower than the performance of the speed harmonization system itself. It is important for the ramp metering system to keep the ramp flows at appropriate levels to avoid further breakdown formation while the speed harmonization system is actively controlling the breakdown formation and propagation. This implies that the speed harmonization and the ramp metering systems should be calibrated jointly to provide the required coordination.

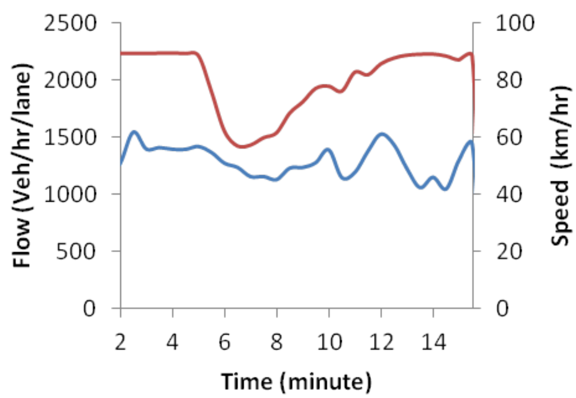
The hazard values are higher for the simulations with higher compliance levels (see figure 105 and figure 120). This is mainly due to drivers' adaptation effort to the new speed limit. As mentioned for the hypothetical network, it is expected that gradual change of speed over space can decrease the perceived risk by the drivers in this adaptation process.

It should be noted that the presented logic may allow optimal implementation through the connected vehicle technology. However, with current practice in implementing speed harmonization systems, it is challenging to achieve this optimality.



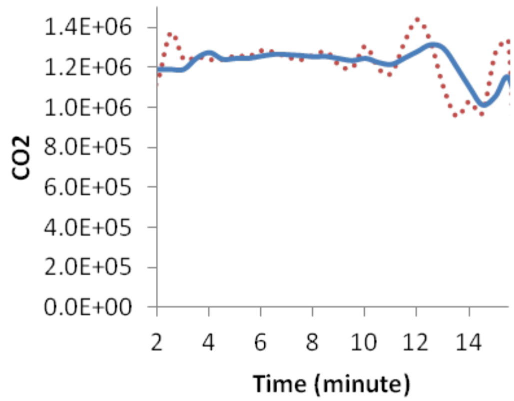
Note: Blue denotes 25 m/s speed limit, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 116. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization and active ramp metering at 0 percent compliance.



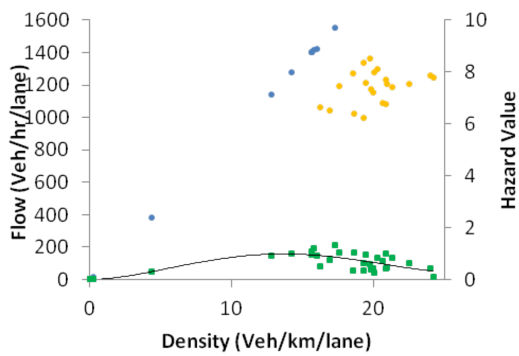
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 117. Graph. Flow and speed evolution over time for simulation with active speed harmonization and active ramp metering at 0 percent compliance.



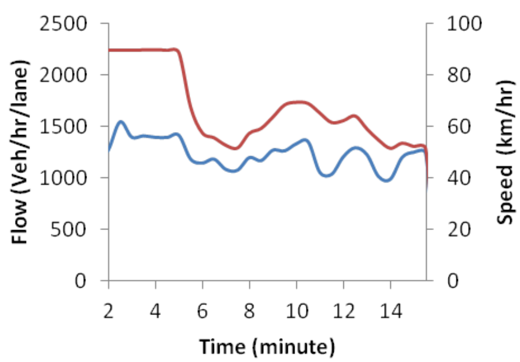
Note: Red denotes actual emission, and blue denotes moving average.

Figure 118. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and active ramp metering at 0 percent compliance.



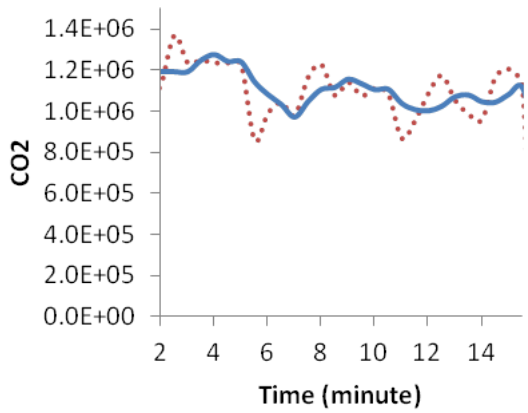
Note: Blue and orange denote 25 and 20 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 119. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization and active ramp metering at 10 percent compliance.



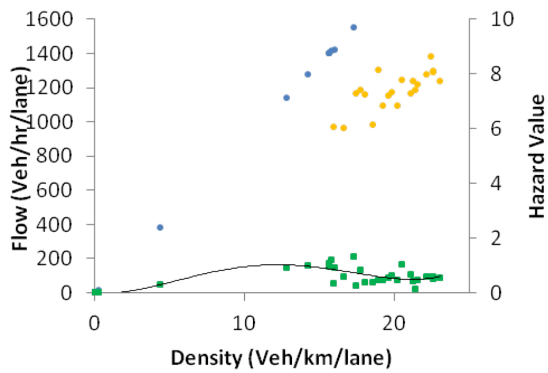
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 120. Graph. Flow and speed evolution over time for simulation with active speed harmonization and active ramp metering at 10 percent compliance.



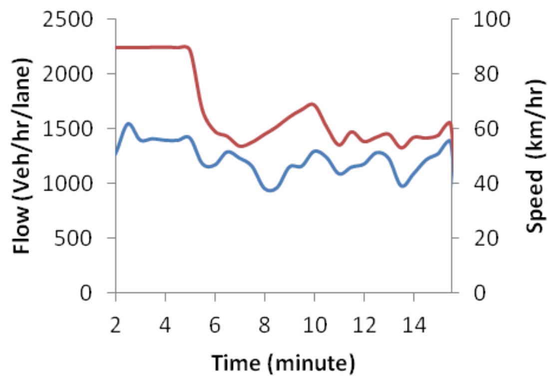
Note: Red denotes actual emission, and blue denotes moving average.

Figure 121. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and active ramp metering at 10 percent compliance.



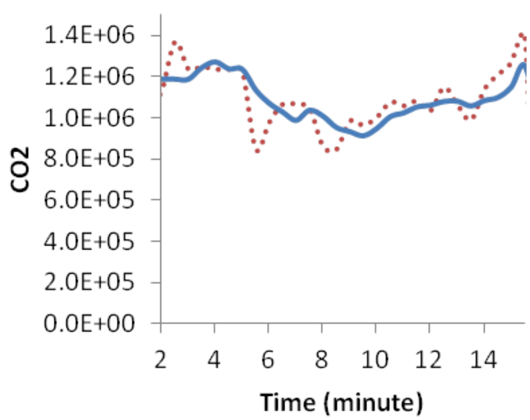
Note: Blue and orange denote 25 and 20 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 122. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization and active ramp metering at 20 percent compliance.



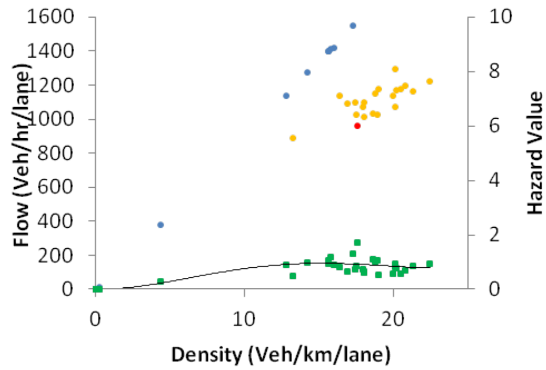
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 123. Graph. Flow and speed evolution over time for simulation with active speed harmonization and active ramp metering at 20 percent compliance.



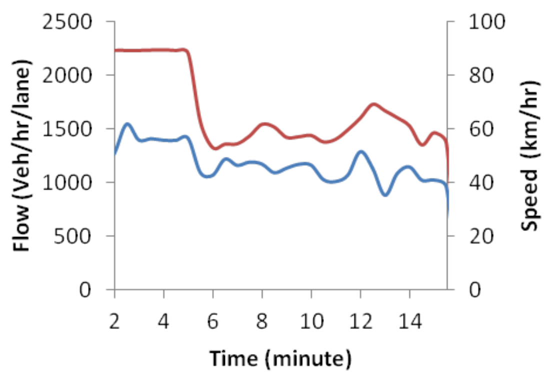
Note: Red denotes actual emission, and blue denotes moving average.

Figure 124. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and active ramp metering at 20 percent compliance.



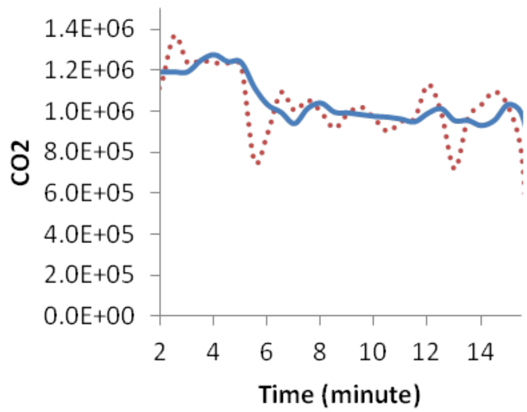
Note: Blue and orange denote 25 and 20 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 125. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization and active ramp metering at 40 percent compliance.



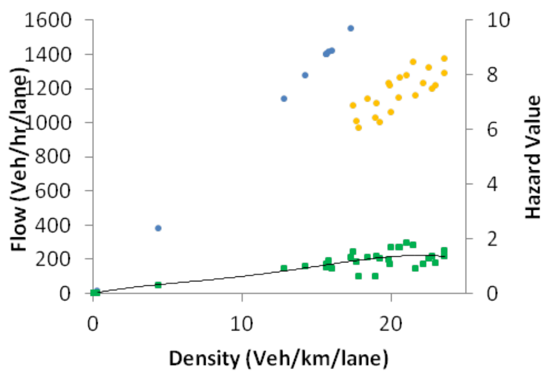
Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 126. Graph. Flow and speed evolution over time for simulation with active speed harmonization and active ramp metering at 40 percent compliance.



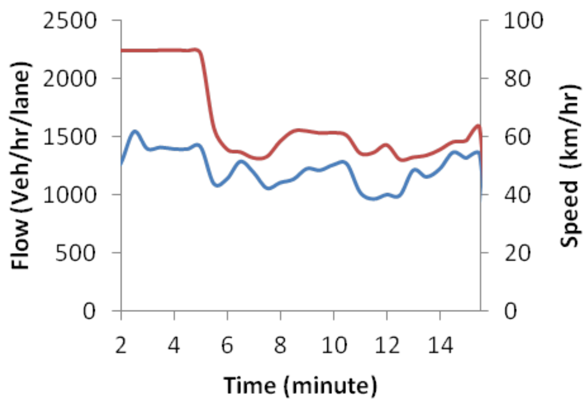
Note: Red denotes actual emission, and blue denotes moving average.

Figure 127. Graph. Emission and moving average evolution over time for simulation with active speed harmonization and active ramp metering at 40 percent compliance.



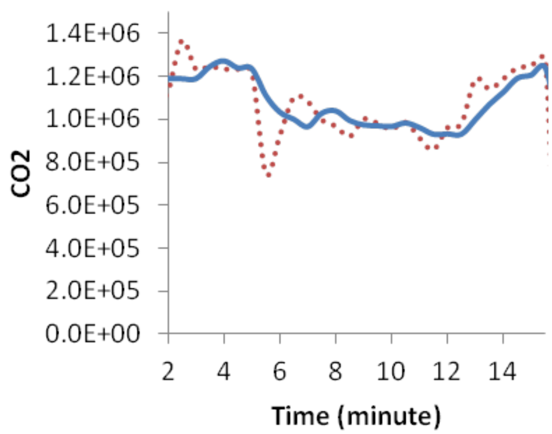
Note: Blue and orange denote 25 and 20 m/s speed limit, respectively, and green denotes hazard value.
1 m/s = 3.28 ft/s
1 km = 0.621 mi

Figure 128. Graph. Fundamental diagram and hazard value for simulation with active speed harmonization and active ramp metering at 90 percent compliance.



Note: Blue denotes flow, and red denotes speed.
1 km = 0.621 mi

Figure 129. Graph. Flow and speed evolution over time for simulation with active speed harmonization and active ramp metering at 90 percent compliance.



Note: Red denotes actual emission, and blue denotes moving average.

Figure 130. Emission and moving average evolution over time for simulation with active speed harmonization and active ramp metering at 90 percent compliance.

LIMITATIONS

The speed harmonization system implemented in this study is primarily reactive. The performance of the proposed speed harmonization algorithm can be improved by adopting a predictive speed limit selection algorithm. It is expected that the prediction module could predict traffic evolution with greater accuracy when using the individual vehicles data.

Introducing vehicle-to-vehicle communication (which provides drivers with the information about other drivers' decisions, road conditions, weather conditions, etc.) can also improve the performance of the proposed system. Furthermore, the potential for optimizing the speed limit for the individual vehicles can be investigated. This requires behavioral-based models with adaptation capability.

Investigating drivers' reaction and their response time to the speed limit changes in the connected vehicle environment is also necessary to improve the performance of the system, especially in a predictive speed harmonization system.

RECOMMENDED NEXT STEPS AND RESEARCH IN SPEED HARMONIZATION

Speed harmonization is an ATM strategy that adjusts the speed limit based on the prevailing traffic condition, road surface condition, and weather condition to improve mobility, safety, and environmental impacts.[140] This study investigated the effects of early shockwave detection based on the information from the connected vehicles on congestion and emission control using speed harmonization as the control strategy. The performance of the speed harmonization system under different drivers' compliance levels was also investigated. The wavelet transform method was used to identify shockwaves at their early stages. This robust shockwave detection algorithm is combined by a reactive speed limit selection algorithm to provide the appropriate speed limit based on the prevailing traffic condition. The microsimulation model of Hamdar et al. was used to implement the speed harmonization system, which was calibrated against the NGSIM data.[160]

Two highway segments, a two-lane hypothetical segment and a four-lane highway segment in Chicago, IL, were selected for the simulation. The simulation results confirm the effectiveness of the speed harmonization system in controlling breakdown formation, preventing speed drop, maintaining higher flow rates, and controlling emission production.

The effect of compliance on the performance of the speed harmonization system was also studied. The results indicate that low levels of compliance with the suggested speed limit were sufficient for the success of the system. However, the minimum required compliance level varied based on the geometric characteristics of the highway segment and its flow rate.

The simulation results also confirm the importance of having a coordinated ramp metering and speed harmonization systems. The uncoordinated ramp metering system can create further congestion while speed harmonization is actively controlling the congestion.

CHAPTER 8. ATIS

WRTM CASE STUDY

Simulate the Degree to Which Weather-Related Information Influences Travelers' Pre-Trip Travel Decisions

Background

Weather events such as precipitation, fog, high winds, and extreme temperatures cause low visibility, slick pavement, reduced roadway capacity, and other hazardous conditions on roadways. The disruptive effect of inclement weather on traffic has staggering impact on safety. About 28 percent of all highway crashes and 19 percent of all fatalities involve weather-related adverse conditions. Additionally, adverse weather accounts for about 25 percent of delays on freeways due to reduced service capacity (often at the most critical of times) and greater risk of accident involvement. To mitigate the impacts of adverse weather on highway travel, the FHWA WRTM program has been involved in research, development, and deployment of WRTM strategies and tools. Dealing with adverse weather requires not only sensing traffic conditions, but also the ability to forecast weather in real time for operational purposes. Recognizing the importance of tying weather and traffic management together in areas exposed to extreme weather situations, such as hurricanes and floods, some TMCs, such as the Houston TranStar® TMC, co-locate the weather service personnel with the usual traffic management agencies (police, traffic operators, emergency medical services, etc.). The most ambitious initiative in this regard is the Clarus weather system, which intended to provide TMCs with accurate real-time weather information.[(168–170)] Weather information, along with roadway traffic information obtained from ITS sensors, enables promising opportunities to improve traffic operations and management under inclement weather.

To reduce the impacts of inclement weather events and prevent congestion before it occurs, weather-related advisory and control measures could be determined for predicted traffic conditions consistent with the forecast weather (i.e., anticipatory road weather information, which then can be used to inform travelers and influence their behavior). This calls for integrated WRTM and a traffic estimation and prediction system (TrEPS) together with an integrated demand model to estimate user behavior changes due to en-route and pre-trip road weather-related information. Because the dynamics of traffic systems are complex, many situations necessitate strategies that anticipate unfolding conditions instead of adopting a purely reactive approach.

In a previous FHWA project, a methodology for incorporating weather impacts in TrEPS was developed.[(171,172)] The project addressed supply and en-route demand aspects of the traffic response to adverse weather. The methodology was incorporated and tested in connection with the DYNASMART simulation-based DTA system, thereby providing a tool for modeling the effect of adverse weather on traffic system properties and performance and for supporting the analysis and design of traffic management strategies targeted at such conditions. The projects concluded that to be able to retain a similar level of service (LOS) as observed in clear weather conditions, en-route WRTM strategies need to be combined with ATDM strategies to reach a demand reduction between 15 and 20 percent.

The purpose of the current case study was to integrate demand models into weather responsive TrEPS to study and simulate behavior responses from travelers on different behavioral levels due to WRTM strategies in conjunction with ATDM strategies and policies to estimate and simulate traveler behavior responses due to pre-trip information and policy integration.

Simulate WRTM Strategies Integrated with Demand Models

TrEPS is an essential methodology to enable implementation and evaluation of traffic management, as it estimates and predicts network states. DYNASMART, developed largely under FHWA support, uses a simulation-based DTA approach for traffic estimation and prediction.[173,174] TrEPS must recognize the fact that origin-destination demand can only be reliably available if they are integrated with the corresponding demand models, estimating and predicting demand changes with underlying disaggregated behavioral models. Conversely, demand models will only be able to realistically reflect behavior if they incorporate dynamic and disaggregated LOS variables. Such disaggregated LOS variables are only available in the connection with a DTA approach. As a state-of-the-art TrEPS, DYNASMART combines advanced network algorithms and models en-route tripmaker behavior route choices in response to information in an assignment-simulation-based framework to provide estimates of network traffic conditions, predictions of network flow patterns in response to various en-route contemplated traffic control measures and information dissemination strategies, and anticipatory traveler and routing information to guide tripmakers in their travel.[175] In the previous FHWA project, the principal supply side and en-route demand side elements affected by adverse weather were systematically identified and modeled in the TrEPS framework (see figure 131).[171,172] The models and relations were calibrated using available observations of traffic and en-route user behavior in conjunction with prevailing weather events. The proposed weather-related features have been implemented in DYNASMART and demonstrated through successful application to a real world network, focusing on two aspects: assessing the impacts of adverse weather on transportation networks and evaluating effectiveness of en-route weather-related advisory/control strategies in alleviating traffic congestion due to adverse weather conditions. The procedures implemented immediately provide applicable tools that capture knowledge accumulated to date regarding weather effects on traffic. The application to a real-world network shows that the proposed model can be used to evaluate weather impacts on transportation networks and the effectiveness of weather-related VMSs and other strategies.

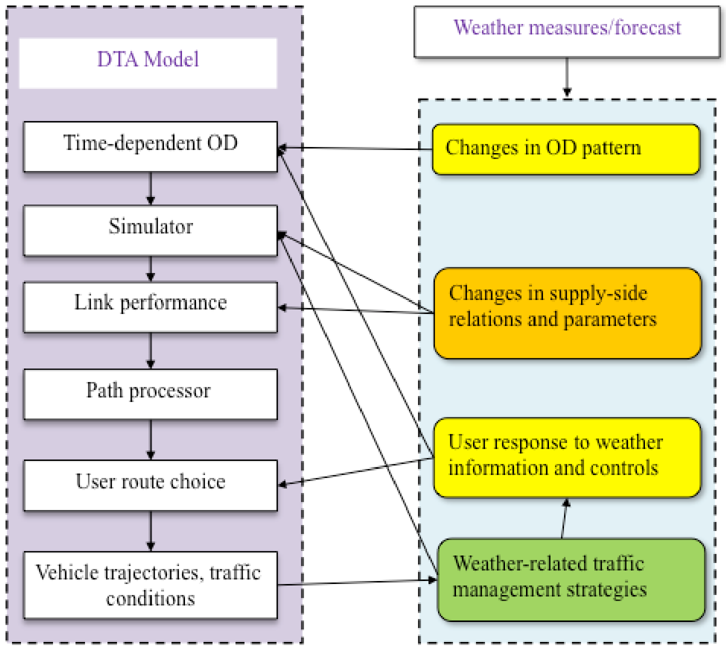


Figure 131. Illustration. Integrated DTA model with weather measures/forecast.[171]

Program Intervention: WRTM Strategies

Road weather information, such as en-route weather warning and route guidance, can be disseminated through radio, Internet, mobile devices, roadside VMS, etc. Pre-trip traveler information can be disseminated trough similar media channels and using social networking tools such as Twitter®.

Weather warning VMSs have been implemented in the field and are shown to be effective in decreasing the average speed as well as the variance in speed and hence helpful in increasing safety and reliability for the traveling public.[176,177] Weather VMSs also proved most effective when adverse weather and road conditions were not easy to detect. Weather advisory VMSs, in the form of slippery road condition sign and fog (low visibility) sign, have been implemented and tested in Europe. For example, in Finland, a slippery road condition sign, implemented in combination with a minimum headway sign, decreased the mean speed by 0.75 mi/h with the steady display and by 1.31 mi/h when the sign was flashing.[176] Hogema and van der Horst showed that the Dutch fog warning signs, implemented in conjunction with variable speed limits, decreased the mean speed in fog by 5 to 6 mi/h.[178] Conversely, Cooper and Sawyer found that the automatic fog-warning system on the A16 motorway in England reduced the mean vehicle speed by approximately 2 mi/h.[179] A comprehensive synthesis of recent developments and applications focusing on U.S. practice is presented in *Developments in Weather Responsive Traffic Management Strategies.*[180]

Weather-related pre-trip information has not been studied in depth so far, but pre-trip traveler information in general as part of ATIS strategies has been studied. It has been found that traveler information influences route, departure-time, and mode choice. Abdel-Aty et al. studied route changes in Los Angeles, CA.[181] Only a small share of the respondents (15 percent) reported using more than one route on their commute. Of that 15 percent, 34 percent said they changed routes after actually seeing traffic conditions. Higher incomes and education levels predicted more route changes, perhaps reflecting schedule flexibility and arrival times expectations for such workers. Mahmassani et al. performed a survey of commuters in Austin, TX, to study information dissemination and traveler behavior. Information in the form of radio traffic reports appeared to have a strong impact in that regular listeners to traffic were more likely to switch their behavior with new information.(40)

Mahmassani and Chang studied an adjustment and experience-based model of perceived travel time for departure time choice.(58) Under the myopic adjustment rule, the perceived travel time is only a function of the latest day's outcome. In laboratory experiments conducted to study the effectiveness of different information strategies on user responses to information, Srinivasan and Mahmassani found that route switching model specifications, which predict whether a user will switch paths in a given time interval, consistently outperformed models that view the process as a new choice at every opportunity.(182) The authors designed an experiment whereby virtual commuters were given trip times on three facilities (at decision locations), information about congestion on the facilities, a message alerting the driver when they are stuck in a queue, and post-trip feedback consisting of departure time, arrival time, and trip time on the chosen path. Their empirical findings suggest that an individual's negative experience with ATIS information has mixed effects on inertia, but congestion and information quality tend to reduce inertia. Drivers who experience lower switching costs and increased trip time savings tend to comply with information. In the sequential treatment, past negative experience relative to preferred arrival time seemed to increase the likelihood of compliance. Inaccurate information decreased drivers' compliance propensity.

Beyond these dimensions, only a couple of studies have addressed destination adjustment in response to information for discretionary (shopping) travel.(44)

Managing demand in this case study encompasses providing travelers with information aimed at creating a shift in their departure times, a mode shift, or a trip cancelation so that the total travel demand during the peak periods can be reduced. The objective was how much demand should be reduced under different weather conditions in order to maintain a certain level of network performance and how this demand reduction could be achieved. It is critical for the traffic operators to provide reliable information to maintain credibility with roadway users. It is also important to try to minimize the potential economic losses by setting the target demand to its necessary level. Attempting to reduce demand beyond this level might cause significant financial loss to the local business and community. As such, the goal of using TrEPS is to provide traffic operators with the information on the optimal level of demand that can improve the network performance but not negatively affect the productivity under given weather conditions, information on which strategies the appropriate demand reduction can be achieved.

Behavioral Dimensions: Route Choice, Departure Timing, Mode Choice, and Trip Cancellation

The previous discussion of prior work reveals that efforts to devise WRTM systems have remained limited to a few countries and locales, although recognition of the need for such intervention continues to increase. Furthermore, the incorporation of demand models into existing tools responsive to WRTM are missing so far and constitute an important link for the usefulness of WRTM applications in practice. Whereas the studies so far highlighted the en-route information influence through VMS on route choice decisions, this case study focuses on simulated behavior responses based on pre-trip information. Since WRTM strategies target short- to medium-term decisions due to the limited time frame of weather forecasts, the immediate behavioral dimensions that can be influenced with pre-trip and en-route weather-related traffic information are route choice departure time choice, mode choice, and trip cancellation. To capture the behavior in a responsive way, spatially and temporally disaggregated individual-based models were used in conjunction with the mesoscopic DTA simulation.

The advantages of using disaggregated individual demand models on WRTM strategies can be grouped into the following categories:

- They can identify the influence of on-time trip attributes.
- They capture disaggregated individual characteristics beyond aggregate TAZs in conjunction with DTA tools.
- They could capture longer-term behavior, overcoming the limitations of tour-based models by including activity patterns outside the daily schedule in addition to time dependency, destination, and mode (in this case study, there was no full-blown activity-based model implemented).
- They capture short-term decision shifts, which may have substantial impacts at the network level.

The modeled behavior choices for households and individuals were organized sequentially on the basis of the time frame over which they might take place. As a result, longer-term decisions were modeled first, followed by medium- and then short-term decisions. Thus, each of the models imposes certain restrictions on the sub-sequential decisions on a shorter time horizon. This conceptual framework was used for integrating the demand model with the network assignment procedure to evaluate WRTM strategies and is further explained in the following section.

Framework for Evaluation

When analyzing WRTM strategies in terms of their impacts on the flows in the network, one has to consider that demand, which is used as an input for the network assignment, is affected by the changes in the generalized cost function values produced in the traffic assignment. Thus, the integration of transport supply and demand models is important, as the demand and supply models are each formulated to use forecast outputs from the other model.

This section discusses the feedbacks between the demand and supply models as well as what level of intersection for the feedback loops is appropriate to study and analyze WRTM strategies so that the level of service input to the demand models is the same as the output from the supply models and the demand input to supply models is the same as that output from the demand models.

The integration of demand models and the network assignment to evaluate WRTM strategies has several parts. First, a base travel demand with calibrated travel costs and skims was generated, which was then used to update the travel times and cost skims by solving for the multi-criterion dynamic user equilibrium. Second, bad weather scenarios were introduced on the network level with weather adjustment factors (WAFs). The changed supply on the network level was then used to update the travel time and cost skims by solving again for the multi-criterion dynamic user equilibrium. Third, the generated disaggregated user time and cost skims were fed back to the individual disaggregated demand model, where the travel time and cost skims propagated through the sequence of interrelated choices and affect particularly all the short- and medium-term traveler decisions shown in figure 132. This includes direct impacts of weather on mode and departure time choice (as well as location choice, which is not shown here) through generalized cost functions included in the utility expressions for each choice alternative.

However, in the medium to long term, bad weather scenarios in places where they occur frequently can also indirectly affect further user decisions, such as activity pattern changes and accessibility, as well as even longer-term choices of home, workplace, and school location (not illustrated).

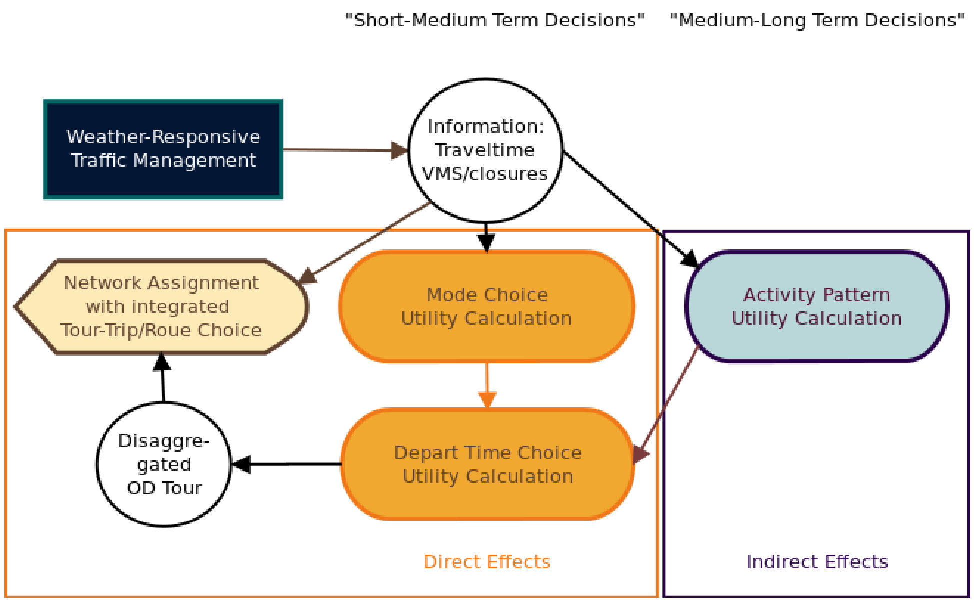


Figure 132. Illustration. WRTM modeling framework.

The supply side used in this case study was calibrated based on a previous study and is discussed in more detail in Mahmassani et al.[171,172] Supply-side parameters that are expected to be affected by the weather condition are identified in table 22.

Table 22. Supply-side properties related with weather impact in DYNASMART.(171)

Category	mi/h	Parameter Description
Traffic flow model[1]	1	Speed-intercept (mi/h)[1]
	2	Minimal speed (mi/h)
	3	Density break point (pcpmpl)[1]
	4	Jam density (pcpmpl)
	5	Shape term alpha
Link performance	6	Maximum service flow rate (pcphpl or vphpl)
	7	Saturation flow rate (vphpl)
	8	Posted speed limit adjustment margin (mi/h)
Left-turn capacity	9	Effective green-to-cycle length (g/c) ratio
Two-way stop sign capacity	10	Saturation flow rate for left-turn vehicles (vphpl)
	11	Saturation flow rate for through vehicles (vphpl)
	12	Saturation flow rate for right-turn vehicles (vphpl)
Four-way stop sign capacity	13	Discharge rate for left-turn vehicles(vphpl)
	14	Discharge rate for through vehicles (vphpl)
	15	Discharge rate for right-turn vehicles (vphpl)
Yield sign capacity	16	Saturation flow rate for left-turn vehicles (vphpl)
	17	Saturation flow rate for through vehicles (vphpl)
	18	Saturation flow rate for right-turn vehicles (vphpl)

[1]Only available in dual-regime model.
pcpmpl = Passenger cars per mile per lane, pcphpl = Passenger cars per hour per lane, and vphpl = Vehicles per hour per lane.

The inclement weather impact on each of these parameters is represented by a corresponding WAF as follows:

$$f_i^{Weather\ Event} = F_i \cdot f_i^{Normal}$$

Figure 133. Equation. WAF.

Where:

$f_i^{Weather\ Event}$ = The value of parameter i under a certain weather event.
f_i^{Normal} = The value of parameter i under the normal condition.
F_i = The WAF for parameter i.(172)

Behavioral Models

Utility-based econometric models have their roots in economic consumer choice theory. These model the individual's activity and travel decisions. In addition to discrete choice alternatives, these models can be enriched by other utility-based models such as hazard models to represent time durations. Overall, the set of economic equations provide the structure to model the relationship between the traveler's characteristics, the network characteristics, and the environment's characteristics, which describe the place to perform activities and also any further restrictions on the traveler's behavior.

The utility-based choice models used to represent the mode and departure time choices follow the concept of an overarching daily activity travel pattern proposed by Bowman and Ben-Akiva.[183] These models are based on an underlying system of logit models in a particular hierarchy. Detailed model forms and specifications are presented later in this chapter.

Data Available and Used in Case Study

Urban Network and Associated Weather Conditions

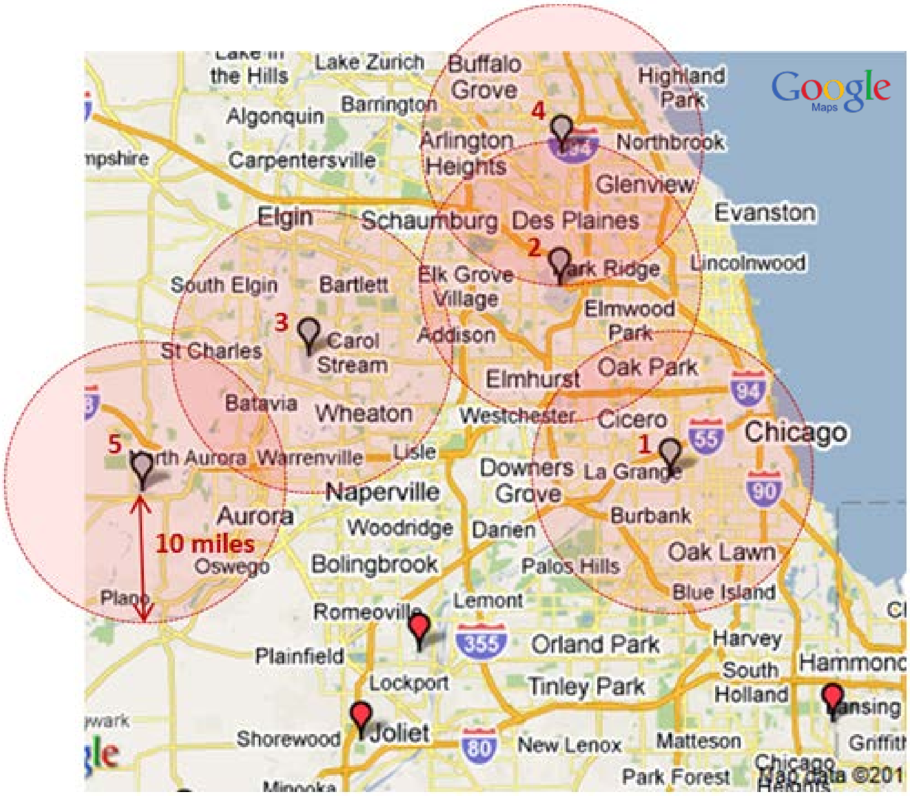
The network used in this case study included the Chicago, IL, downtown area along the Kennedy and Edens Expressways. The network is bounded on the east by Lake Michigan and on the west by Cicero Avenue and Harlem Avenue. Roosevelt Road and Lake Avenue bound the sub-network from the south and north, respectively. The network description is illustrated in figure 134. The network description is as follows:

- 4,805 links.
  - No tolled links.
  - 150 freeways.
  - 47 highways.
  - 247 ramps (59 of them are metered).
  - 4,361 arterials.
- 1,578 nodes.
  - 545 signalized intersections.
  - 218 zones.
- Demand period.
  - 5–11 a.m. hourly demand.
  - ~800,000 total demand.

Figure 134. Illustration. Network configuration and description for Chicago, IL, network.

Weather Data

Weather data are available from two sources; the Automated Surface Observing System (ASOS) stations located at airports and the roadside environmental sensor stations (ESSs) available on the Clarus Web site. As the historical weather data from ESS have a time resolution of 20 min and are only available from 2009 to the present, ASOS data with 5-min resolution were used in conjunction with traffic detector data collected and aggregated over a 5-min interval. ASOS 5-min weather data are available on the National Oceanic and Atmospheric Administration's National Climatic Data Center Web site. The spatial distribution of ASOS stations used in this case study is shown in figure 135, and their location and further information are listed in table 23.



©Google Maps® 2012

Figure 135. Illustration. Chicago, IL, study area and adjacent ASOS stations.(184)

Table 23. Airports with ASOS stations and available time periods for data.

No.	Airport	Location	ICAO Airport Code	ASOS Data
1	Midway International Airport	Chicago, IL	KMDW	2005–Present
2	O'Hare International Airport	Chicago, IL	KORD	2000–Present
3	Dupage County Airport	Dupage, IL	KDPA	2005–Present
4	Chicago Executive Airport	Cook, IL	KPWK	2005–Present
5	Aurora Municipal Airport	Kane, IL	KARR	2005–Present

ICAO = International Civil Aviation Organization.

Traffic Data

In conjunction with the weather data described in the previous section, traffic data for supply side parameter calibration and aggregated analysis of demand data was obtained from loop detectors installed on freeway lanes. Historical data with the 5-min aggregation interval were used, and the time periods for the data varied with the study site over the 2005–2011 period.

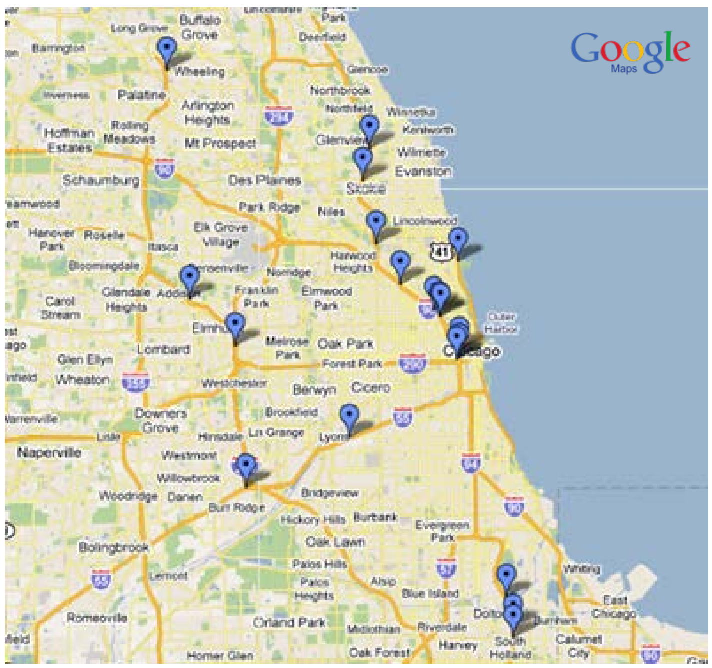
In selecting detector locations and collecting the data, the following criteria were mainly considered:

- Choose detectors as close as possible to ASOS stations no farther than 10 mi from ASOS.

- Remove the influence of other external events such as incidents/accidents, work zones, and planned special events.

Note that the process for removing the effect of external events is highly dependent on the availability of other event data. In case where there is difficulty obtaining detailed data for incidents, work zones, and special events, one could focus on traffic data and clean outliers in the dataset only. Since average measures are extracted over a longer period of time (i.e., at least 1 year), the influence of other external events on traffic parameters is expected to be small. The selected loop detector locations are illustrated in figure 136.

For the Chicago, IL, network, traffic data were obtained from the Illinois Department of Transportation; 5-min aggregated data from 2009 were used. Figure 136 shows a map of the selected detector locations in Chicago, IL. At each location, traffic data from northbound or southbound directions were obtained. There was no HOV lane at any of the selected locations.



©Google Maps® 2012

Figure 136. Illustration. Selected detector locations in Chicago, IL.[185]

Behavioral Model Data

This section presents details of data preparation and model estimation for the individual behavioral models (mode choice and departure time choice).

Mode Choice:

The main source of data used to develop the mode choice and departure choice models in this study was the Chicago Household Travel Survey and National Transit Database (NTD), which were used to estimate travel times for the non-chosen modes (public transit in this case study).[186,187] Table 24 shows the average speeds obtained from the reported travel times of the chosen alternatives in the travel survey data.

Table 24 shows mode-specific average speeds obtained from the NTD for CTA, Pace, and Metra in 2011. The average speeds were calculated by dividing the annual vehicle revenue miles by the annual vehicle revenue hours for each mode. The average speeds obtained in the NTD are higher relative to the reported average speeds from the Chicago Household Travel Survey. Although the NTD speeds seem to be more realistic, the average speeds from the Chicago Household Travel Survey represent experienced travel time by transit users, perhaps including waiting time and travel time in all the segments of a transit trip (e.g., walking to/from transit stop). Therefore, for the purpose of this study, an average speed of 14.4 mi/h was used for the transit mode, and an average speed of 17.7 mi/h was used for the park & ride mode.

Table 24. Mode-specific average speeds from the 2011 NTD.

Mode	Average Speed (mi/h)
CTA bus	9.3
Pace bus	13.9
CTA rail	18.4
Metra rail	30.7

Travel costs for auto and transit are estimated using the following expressions:

$$\text{Auto cost (\$)} = 0.505 \times \text{distance} + \text{toll(s)}$$

Figure 137. Equation. Auto travel cost estimation.

$$\text{Transit cost (\$)} = 2.25 + 0.25 \times \text{number of transfer(s)}$$

Figure 138. Equation. Transit travel cost estimation.

Since the number of transfers was unknown, three different assumptions were made to estimate transit cost. First, it was assumed that all the transit trips were made with no transfers. Thus, transit cost for all the origins and destinations were fixed and equal to $2.25. The second assumption was that those trips that started and ended at non-CBD zones included one transfer, and the rest of the trips included no transfers. The third assumption was that those trips that started or ended outside Chicago's boundary had an average transit cost of $4.50, while the rest of the trips with transit cost $2.50. Results of the mode choice model, which are described in the next section, suggest that assumption two provides more realistic values of time.

For the park & ride mode, the following equation was used to estimate travel cost (including transit fare and parking):

$$\text{Park \& ride (Metra) cost (\$)} = 0.1856 \times \text{distance} + 3.5$$

Figure 139. Equation. Park & ride travel cost estimation.

Departure Time Choice

For the departure time choice model, the initial demand as sliced into 0.5-h bins, and the dynamic travel times for the clear weather scenario and snow weather scenario were used to infer travel times.

If for the specific disaggregated origin-destination pair, based on network nodes ($1,578^2$ combinations in the Chicago network), individual trips fall within the departure time bin, the average observed travel time for this origin-destination and half hour bin was used. If there were no observations from the DTA for a specific origin-destination and time bin were available, the free flow travel time was used.

It is assumed that the preferred arrival time for each individual was the arrival time under clear weather condition and the too late or too early arrival times under the snow weather conditions were then inferred based on the new travel times for each departure time bin.

Model Development and Calibration

Mode Choice

The empirical analysis of mode choice in this study applies the discrete choice modeling framework developed by Domencich and McFadden and Ben-Akiva and Lerman.[(188,189)] The model is segmented by trips from and to the CBD and trips occurring outside of the CBD. This market segmentation was applied, as the transit system in Chicago focused on commuting trips to and from the CBD. Transit shares for trips with origin and destination outside of the CBD had a very low share of 3.25 percent, where the shares for trips with origin or destination in the CBD were 44.73 percent. In addition, there are several park & ride locations that connect people in the Chicago suburbs to the commuter rail system, which is included as a separate mode in the mode choice model for CBD trips.

To realistically capture the substitution patterns between the different modes available, it is essential to consider the similarities between park & ride options and public transit option alone, as these two modes share unobserved attributes among each other, which violates the independence of irrelevant alternatives property of the multinomial logit model. To capture the similarity of park & ride trips and transit trips, a nested multinomial logit model was estimated for trips from and to the CBD and for trips outside the CBD a standard logit model is estimated with only the two alternatives auto and transit. The two models are described in table 25 and table 26.

Table 25 and table 26 show the parameter estimates for the nested logit model for the Chicago metropolitan area trips from and to the CBD and the parameter estimates for the logit model for the Chicago metropolitan area trips outside of the CBD, respectively.

Table 25. Nested logit model estimation results for trips from and to the CBD.

Variables	Estimate	Standard Error	*t*-Value	p-value
Travel time	-0.01	0.00	-12.00	0.00
Cost	-0.07	0.01	-10.97	0.00
Park & ride intercept	-0.71	0.12	-6.10	0.00
Transit intercept	-0.07	0.06	-1.17	0.24
Park & ride departure time after 7 a.m.	-0.96	0.09	-10.99	0.00
Transit departure time after 7 a.m.	-0.55	0.06	-9.16	0.00
ϑ_{PT} (scale parameter)	0.70	0.06	12.47	0.00
Correlation	0.51	0.10	-5.29*	0.00

*Denotes that this *t*-value compares the difference betweennthis parameter estimate and a value of 1.0.

Based on this information, the likelihood at convergence is -17,965.64, and the value of time is 8.35, which is calculated as the ratio of the parameter for time over the parameter for cost. It is comparable to value of time obtained for Chicago in other studies. The value of time is on average slightly higher for trips to and from the CBD compared to trips outside of the CBD.

Table 26. Logit model estimation results for trips outside of the CBD.

Variables	Estimate	Standard Error	*t*-Value	***p-value***
Travel time	-0.01	0.00	-9.26	0.00
Cost	-0.09	0.02	-4.30	0.00
Transit intercept	-2.16	0.16	-13.15	0.00
Transit departure time after 7 a.m.	-0.77	0.16	-4.68	0.00

Based on this information, the likelihood at convergence is -2,748.41, and the value of time is 6.31.

Figure 140 and figure 141 showcase the nesting structure for the nested logit and logit models, respectively. The parameter estimates are consistent for both models. All estimates are as expected and highly significant. The nesting coefficient shows a medium correlation of park & ride with transit and is highly significant different from 0 and 1, where 0 would indicate perfect correlation and 1 no correlation. The transit and park & ride intercepts show the average attractiveness of each alternative compared to auto for all unobserved factors. In both models, the auto is the relative preferred mode of choice given all observed attributes being the same. Public transit options are rather used during rush hour period compared to off peak periods.

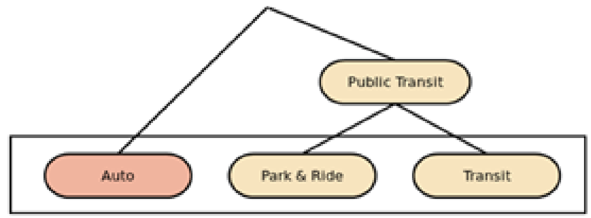


Figure 140. Illustration. Nested and non-nested mode choice model structure—structure for trips to and from the CBD.

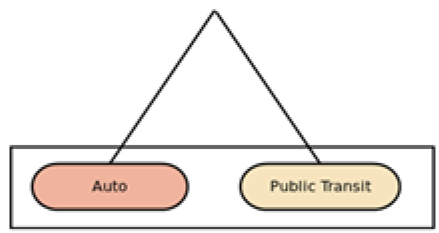


Figure 141. Illustration. Nested and non-nested mode choice model structure—structure for trips outside the CBD.

In the nested logit model framework, the utility of each alternative j to an individual i can be represented as follows:

$$U_{ij} = x_{ij}b + e_{ij}$$

Figure 142. Equation. Random utility model.

Where:

U_{ij} = Utility of alternative j for individual i.
x_{ij} = Exogenous characteristics of individual i and alternative j.
b = Set of parameters.
e_{ij} = Error term distributed Gumbel with mode 0 and scale 1.

For the nested case, the utility for park & ride and transit can be rewritten with a shared error component as follows:

$$U_{P\&R} = V_{P\&R} + e_{PT} + e_{P\&R}$$
$$U_{Transit} = V_{Transit} + e_{PT} + e_{Transit}$$

Figure 143. Equation. Utility of park & ride and transit.

Where:

$U_{P\&R}$ = Utility of park & ride.
$V_{P\&R}$ = Vector of park & ride.
e_{PT} = Shared component.
$e_{P\&R}$ =Error of park & ride.
$U_{Transit}$ = Utility of transit.
$V_{Transit}$ = Vector of transit.
$e_{Transit}$ = Error of transit.

The unobserved component of park & ride and transit are divided into two components. The distinct error components for park & ride and transit are represented by independent and identically distributed Gumbel random variables with variance parameter ϑ_{PT}. The shared component, e_{PT}, is distributed such that the sum of both distributions is Gumbel (0,1), as shown in the following equation.

$$e_{PT} + e_{P\&R} \sim G(0,1)$$
$$e_{PT} + e_{Transit} \sim G(0,1)$$

Figure 144. Equation. Distribution of nested logit error terms.

Where *G(a,b)* = The Gumbel distribution with mode *a* and scale *b*.

The problem can then be described as if there are two levels of choice: a marginal choice among auto and public transit and a conditional choice between park & ride and transit if public transit is chosen. Since $e_{P\&R}$ and $e_{Transit}$ are independent and identically distributed Gumbel(0, ϑ_{PT}), where ϑ_{PT} is the scale of the Gumbel distribution for the transit error term, the condition choice becomes the following:

$$P(j \mid \eta) = \frac{e^{\left(X_j\beta / \vartheta_{PT}\right)}}{\sum_{k \in J} e^{\left(X_k\beta / \vartheta_{PT}\right)}}$$

Figure 145. Equation. Conditional choice probability (nested logit).

Where:

i= The set of all individuals.
j = The set of all alternatives.
ϑ_{PT} = scale of the Gumbel distribution for the transit error term.

The marginal choice probability between auto and public transit is given by the following:

$$P(\text{Auto}) = \frac{\exp\left(X_{\text{Auto}}\beta_{\text{Auto}} / \vartheta_{\text{Auto}}\right)}{\exp\left(X_{\text{Auto}}\beta_{\text{Auto}} / \vartheta_{\text{Auto}}\right) + \exp\left(X_{PT}\beta_{PT} / \vartheta_{PT}\right)}$$

$$P(PT) = \frac{\exp\left(X_{PT}\beta_{PT} / \vartheta_{PT}\right)}{\exp\left(X_{\text{Auto}}\beta_{\text{Auto}} / \vartheta_{\text{Auto}}\right) + \exp\left(X_{PT}\beta_{PT} / \vartheta_{PT}\right)}$$

Figure 146. Equation. Marginal choice probabilities (nested logit).

The parameters in the nested logit probability formulation in figure 146 are estimated by maximizing the following log likelihood function:

$$LL(\beta) = \sum_{t} \sum_{m \in (Auto, PT)} y_{ij} \log \frac{\exp(V_m)}{\sum \exp(V_m)} + \sum_{t} \sum_{i \in (P\&R, Transit)} y_{ij} \log \frac{\exp(V_i / \vartheta_{PT})}{\sum \exp(V_i / \vartheta_{PT})}$$

$$L(\beta) = \sum_{i \in I} \sum_{j \in (\text{Auto}, PT)} y_{ij} \log \frac{\exp\left(X_j \beta_j\right)}{\sum_{q \in (\text{Auto, } PT)} \exp\left(\frac{X_q \beta_q}{\vartheta_{PT}}\right)} + \sum_{i \in I} \sum_{k \in (\text{P\&R, Transit})} y_{ik} \log \frac{\exp(\frac{X_k \beta_k}{\vartheta_{PT}})}{\sum_{r \in (\text{P\&R,Transit})} \exp(\frac{X_r \beta_r}{\vartheta_{PT}})}$$

Figure 147. Equation. Log-likelihood function (nested logit).

Where:

I = The set of all individuals.
y_{ij} = Choice indicator for alternative j and individual i, as defined in figure 148.
P&R = Park & ride.
PT = Public transit.

$$y_{ij} = \begin{cases} 1 & if\ i\ chooses\ j \\ 0 & otherwise \end{cases}$$

Figure 148. Equation. Choice indicator function.

In the case of non-CBD trips, the usual multinomial logit modeling framework is used, where the probability of choosing between auto and transit is given by the following:

$$P(j) = \frac{e^{(X_j \beta)}}{\sum_{k \in J} e^{(X_k \beta)}}$$

Figure 149. Equation. Choice probability.

Where $P(j)$ is the probability of decisionmaker i choosing mode j.

Departure Time Choice

For the departure time choice model, the discrete-choice modeling framework developed by Domencich and McFadden and Ben-Akiva and Lerman is used.[188,189] Since there are no data available to specifically estimate the departure time choice coefficients, the model is calibrated using coefficient estimates from the model developed by Noland and Small and recalibrating the alternative specific constants to match the departure time choices observed in Chicago.[190]

A cost function is postulated with a particular preferred arrival time, which empirically is taken to be the arrival time under clear weather condition. This scheduling cost function, *CS* is calculated as follows:

$$C_S = Const. + \beta_1 (T + T_W) + \beta_2 (SDE) + \beta_3 (SDL)$$

Figure 150. Equation. Scheduling cost function.

Where:

Const. = Alternative specific constant for each 30-min departure time bin.

T = Free-flow travel time plus the extra travel time due to recurrent congestion which we assume the commuter expects will occur daily during clear weather.
T_W = Added time due to non-recurrent (or unpredictable) congestion due to incident-related delays, which is the difference between the dynamic simulated travel time during bad weather condition and T.(191)
SDE = Schedule delay early.
SDL = Schedule delay late.
β_1, β_2, and β_3 = Costs per minute of travel time, arriving early, and arriving late, respectively.

As the expected travel time for the clear weather condition is *T*, *SDE* and *SDL* are zero in the clear weather condition since no delays are expected. *SDE* and *SDL* for bad weather conditions are defined as follows:

$$SDE = T_W, \forall (T + T_W) < T \text{ and otherwise } 0$$
$$SDL = T_W, \forall (T + T_W) > T \text{ and otherwise } 0$$

Figure 151. Equation. Definition of schedule delay early and late.

Table 27 shows the parameter estimates for the departure time choice model.

Table 27. Departure time choice model parameter estimates.

Variables	Estimate	Standard Error	*t*-Value	$P_r(>\|t\|)$	Significance Level
Travel time	-0.098	—	—	—	—
SDE	-0.097	—	—	—	—
SDL	-0.281	—	—	—	—
Alternative Specific Variables					
5:00–5:30 a.m.	Base category				
5:31–6:00 a.m.	1.406	0.23	11.62	0.00	0
6:01–6:30 a.m.	3.460	0.56	8.35	0.00	0
6:31–7:00 a.m.	4.939	0.92	6.45	0.00	0
7:01–7:30 a.m.	7.273	1.02	9.23	0.00	0
7:31–8:00 a.m.	9.506	1.23	12.23	0.00	0
8:01–8:30 a.m.	11.689	2.56	7.32	0.00	0
8:30–9:00 a.m.	13.698	2.34	13.11	0.00	0
9:01–9:30 a.m.	15.382	2.86	14.23	0.00	0
9:31–10:00 a.m.	17.123	3.21	9.10	0.00	0
10:01–10:30 a.m.	16.060	3.51	8.11	0.00	0
10:31–11:00 a.m.	13.110	2.32	8.32	0.00	0

— Indicates where data are not applicable since these parameters were not estimated in this model.

Based on the information in the table, the likelihood at convergence is -52,621.3.

Natural Reduction

For the base scenario with bad weather, the amount of natural reduction in demand must be determined, as several studies have found that traffic volumes decline during winter storms.(192–194) This natural demand reduction without demand management strategies may be due to several reasons, including trip cancelation, teleworking, mode shifts, and departure time shifts. Hanbali found demand reductions ranging from 7 to 56 percent during snow fall depending on time of day, day of the week, and roadway type as well as the strength of snowfall.(194)

For the Chicago, IL, case, the average traffic volumes for a moderate snow day and a clear weather day from several detectors on freeways (see figure 136) are compared to find an aggregated natural demand reduction to apply to the base weather scenario. The resulting difference in traffic is illustrated in figure 152. Overall, the observed reduction in traffic is 8.95 percent. Due to a lack of additional data sources (e.g., daily transit counts, detector data on peripheral roads, or Travel Household Survey data for bad and good weather days), it is unclear if a decrease in traffic volume is due to route choice, mode choices, departure time choice, or trip cancellation. However, the analysis of ICM case study suggests that the traffic reduction is mostly due to trip cancellation, as no mode shifts were observed, and the reductions were observed during non-peak hours when the infrastructure was not at capacity.

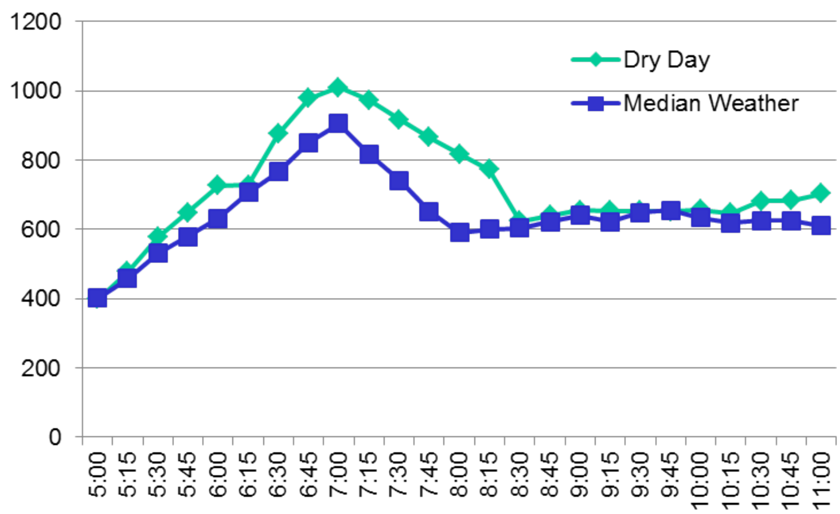


Figure 152. Graph. Traffic detector volumes on clear weather days and a median snow day in Chicago, IL.

Policy Intervention: Weather-Related Delay of Schools

A weather-related cancellation or delay of an institution, operation, or event as a result of inclement weather is common in many parts of the world, as well as in warmer parts of the United States, which are less likely to handle snow. Among institutions, schools are likely to close or delay when snow impairs travel. This is mostly due to concern about safety in order to keep those traveling to the location of the schools in an effort to prevent accidents.

Many countries and smaller jurisdictions have mandates for a minimum number of school days in a year. In order to meet these requirements, many public school systems and private schools that can expect to be closed at times during the year by inclement weather will often build a few extra days into their calendar for snow closures. Instead of cancelling an entire school day, some schools may delay opening by 1 or 2 h or announce a particular opening time. This can be advantageous in places where schools are not charged a snow day by delaying their opening. This is particularly common during lighter snowfalls in areas accustomed to moderate winter snowfall, such as the New York metropolitan area and adjacent southern New England; Washington, DC; Philadelphia, PA; and Baltimore, MD. In Chicago, there is no such policy in place. In order to prevent accidents as well as other problems that may result from travel in inclement weather, such a policy could be suggested and implemented on certain days in, especially as providing information to parents is simple and affordable through Internet media outlets.

In the event of snow, schools could delay opening by 1 or 2 h and extend the day for the time missed in the morning. Such a policy could have a significant effect since school-related trips have a very narrow departure time distribution during the peak hour. In Chicago, during the morning peak between 5 and 10 a.m., school-related trips constitute 8.9 percent of the traffic volume, and its departure time distribution is much narrower than work trips in the same time period. Figure 153 shows the distribution of work departure time and school trip departure time for autos. By shifting the school related trips by 1 h, the departure time distribution could be flattened and expanded toward later hours, which is especially interesting, as departure time interventions, such as earlier dissemination of information, shifts departure times toward earlier hours.

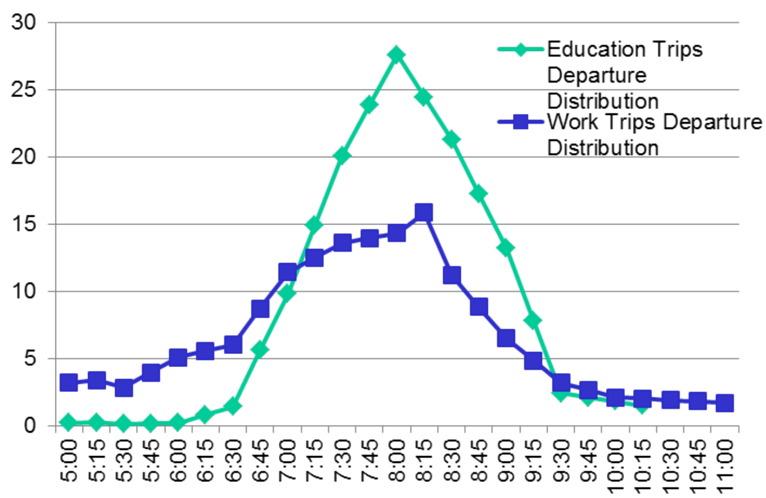


Figure 153. Graph. Morning peak departure time distribution for school trips and work trips.

Sensitivity Analysis Using Simulation for Different Scenarios

Experiment Design—Weather Scenario:

For the weather scenario, a median snow day on February 22, 2011, in Chicago, IL, was chosen. The entire simulation horizon was 8 h, where vehicles were generated and loaded onto the network during the first 6 h based on the origin-destination matrix, which represents the traffic demand between 5 and 11 a.m. For the remaining 2 h, vehicles were simulated so that the generated vehicles reached their destinations.

Experimental Design—Demand Scenarios:

A total of 12 demand scenarios were prepared: one for the benchmark case, which was 100 percent of the demand under the normal weather condition (i.e., no snow); and the other 11 scenarios with different demand levels under snow condition. For the generation of the 11 scenarios, researchers started with the full demand (100 percent) and reduced the total demand with different demand management strategies as shown in table 28.

Table 28. Demand scenario overview and description.

Scenario Number	Scenario Name	Demand Input	Description
1	Base— normal weather	Normal weather and normal traffic	Calibrated base scenario, which builds the basis for the subsequent scenarios
2	Base—weather	Moderate snow weather and normal traffic	Scenario to estimate the weather impact on the network LOS
3	Moderate weather—natural	Moderate weather, natural mode choice, and natural departure time spread	Scenario to estimate the LOS based on the natural reduction in trips and spread out of the peak hour
4	Moderate weather—natural and demand management	Moderate weather, natural mode choice, natural departure time spread, and VMS	Scenario to estimate the LOS based on the natural reduction in trips and spread out of the peak hour
4.1.1 and 4.1.2	Mode choice	50 and 100 percent information	Scenario to estimate the LOS based on the natural reduction in trips and mode choice
4.2.1 and 4.2.2	Departure time choice	50 and 100 percent information	Scenario to estimate the LOS based on the natural reduction in trips and departure time choice
5	Policy	Educational trips 1 h later	Scenario to estimate the LOS based on the natural reduction in trips and school opening delay of 1 h
6	Moderate weather—demand management and policy	Moderate weather, natural reduction, mode choice, departure time choice, and policy intervention	Scenario to reach the same LOS based on the natural reduction in trips and spread out of the peak hour, plus the on-route trip changes based on VMS, plus pre-trip changes based on earlier dissemination of weather information
6.1		4.1.1, 4.2.1, and 5	
6.2		4.1.2, 4.2.2, and 5	

Note: Blank cells indicate not applicable.

DYNASMART Simulation

Analysis of the Results:

The following network performance measures are defined to illustrate network-level traffic conditions under different weather and demand scenarios:

- **Accumulated percentage of out vehicles**: The percentage of vehicles arriving at their destinations from the start of the simulation until a given time stamp *t*. It can be expressed in the following form:

$$\%Accumulated\ Out\ Veh = \frac{Out\ Vehicle}{Total\ Vehicle} \times 100$$

Figure 154. Equation. Accumulated percentage of out vehicles.

Where:

OutVehicle = Accumulated number of vehicles arriving their destinations from time 0 till time *t* in each scenario.
*TotalVehicl*e =Accumulated total number of vehicles loaded onto the network from time 0 till time *t* in each scenario.

- **Percentage change in average travel time**: The percentage change in the travel time between a weather scenario and the base non-weather scenario:

$$\%change\ Avg(TTime) = \frac{Avg(TTime) - Avg(TTime_{Base})}{Avg(TTime_{Base})} \times 100$$

Figure 155. Equation. Percentage change in average travel time.

Where:

$Avg(TTime_{Base})$ = Average travel time for full demand in the base case without weather feature.
$Avg(TTime)$ = Average travel for each weather scenario.

- **Percentage change in average stop time:** The percentage change in the stop time between a weather scenario and the base non-weather scenario:

$$\%change\ Avg(STime) = \frac{Avg(STime) - Avg(STime_{Base})}{Avg(STime_{Base})} \times 100$$

Figure 156. Equation. Percentage change in average stop time.

Where:

$Avg\ (STime)$ = Average stop time for *k* percent of full demand in weather scenario *i*.
$Avg\ (STime_{Base})$ = Average stop time for full demand in the base case without weather feature.

Scenarios 1 and 2:

Scenarios 1 and 2 are each used to establish a benchmark case to which the different other scenarios are compared. The first benchmark case, scenario 1, simulates traffic under clear weather condition with 100 percent demand. This scenario is used as the base scenario as described in figure 154 and figure 155. Scenario 1 is also used to establish a desired level of service which the different scenarios try to reach in order to maintain the same level of network performance as under clear weather condition.

Scenario 2 is used to establish the worst-case scenario under median snow condition with 100 percent demand and no management strategy, as well as no natural reduction. This scenario can be used to establish measures of improvement for the rest of the scenarios but also as an illustration of the impact of a median snow day on the network performance.

Figure 157 and figure 158 present the network density level using color coding where red = congested and green = uncongested for scenarios 1 and 2. In the figures, the time point for the current condition is set to 9:30 a.m. By comparing the two figures, it is clear that the network under clear weather is less congested than under median snow weather. Under snow weather condition, congested links (red) are more often observed and generally more widely spread in the network.

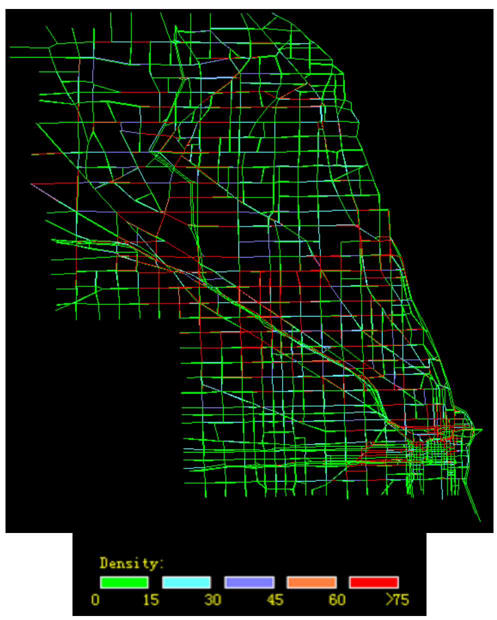


Figure 157. Illustration. Simulated network density for scenarios 1 and 2 with 100 percent demand—clear weather condition.

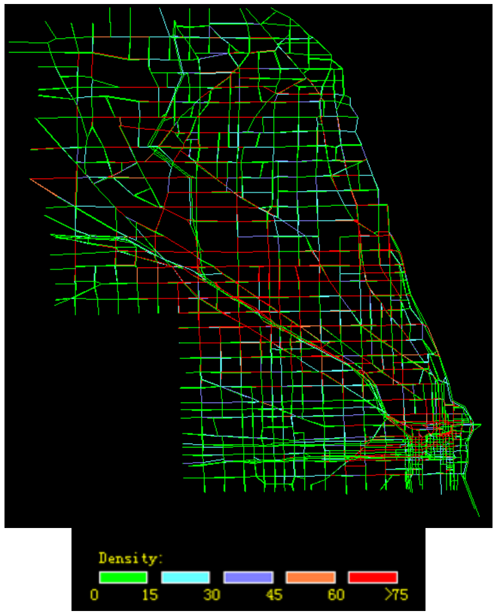


Figure 158. Illustration. Simulated network density for scenarios 1 and 2 with 100 percent demand—median snow day.

Figure 159 through figure 162 show a link-specific speed and flow distribution over the simulation time from 5 to 11 a.m. The selected link is the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

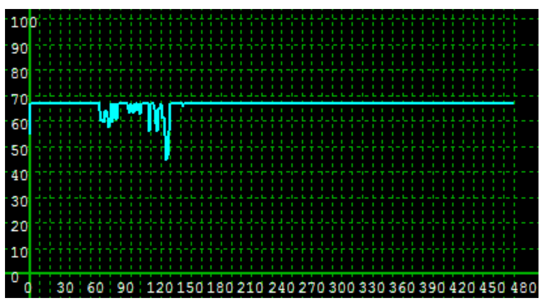


Figure 159. Illustration. Simulated link speed distribution for scenarios 1 and 2 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound—clear weather condition.

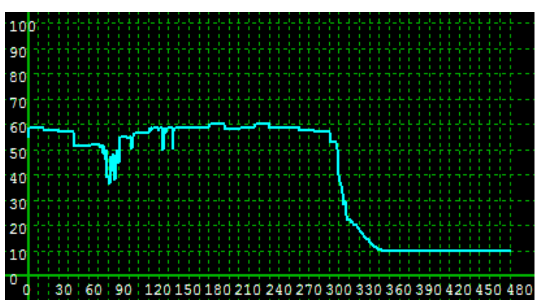


Figure 160. Illustration. Simulated link speed distribution for scenarios 1 and 2 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound—median snow day.

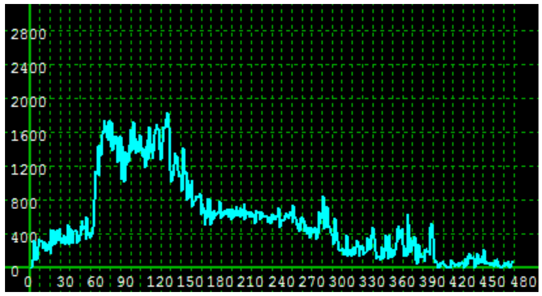


Figure 161. Illustration. Traffic volume distribution for scenarios 1 and 2 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound—clear weather condition.

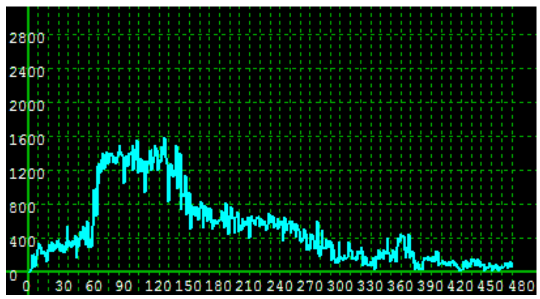


Figure 162. Illustration. Traffic volume distribution for scenarios 1 and 2 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound—median snow day.

Comparing figure 159 and figure 160 shows the impact of the weather condition drastically, as the speed on the link breaks down at around 10 a.m. in the morning, which can also be seen when comparing the traffic volumes of these two links. The average travel time increases from scenario 1 to scenario 2 from 30.2 to 38.6 min, which is an average increase of 27.81 percent. Considering a value of time in Chicago of around $8/h and a total demand of ~800,000 travelers, the additional travel time due to bad weather implies external costs of $896,000 for the morning period between 5 and 11 a.m.

Scenario 3:

Scenario 3 uses the natural demand reduction. No demand management strategies are in place. It includes the representation of individual behavior in canceling trips and teleworking due to bad weather. An 8.95 percent total reduction in demand is applied throughout the different departure time bins, as shown in figure 152 based on aggregated data obtained from traffic detectors. Figure 163 and figure 164 show the comparison of the network densities between scenarios 2 and 3. The comparison shows the reduction in congestion between these two scenarios, as there are fewer congested links visible on figure 164 compared to figure 163. The average travel time decreases from 38.6 to 35.41 min, which corresponds to a reduction in travel time of 8.26 percent.

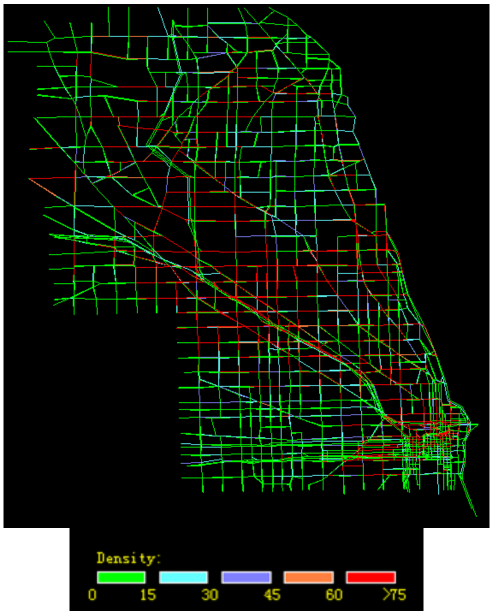


Figure 163. Illustration. Simulated network density for scenario 2 at 9:30 a.m.

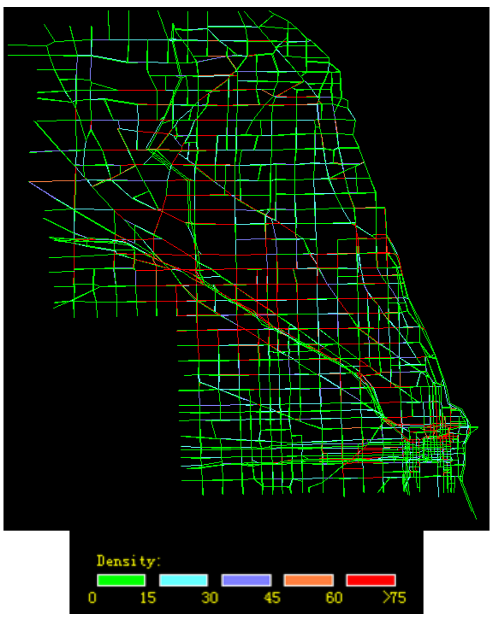


Figure 164. Illustration. Simulated network density for scenario 3 at 9:30 a.m.

Figure 165 through figure 168 show the comparison of link-specific speed and flow distribution over the simulation time from 5 to 11 a.m. similar to the one in figure 159 through figure 162. It can be seen that the flow is slightly lower in the beginning due to the demand reduction, but the free-flow speed can be obtained for a longer period of time. Whereas in scenario 1, the congestion reduces the speed to 10 mi/h by 10:30 a.m., and the speed with demand reduction maintains slightly higher for another 20 min. Similar observations can be made by comparing the flow distributions, where scenario 3 shows slightly higher volumes from 9:30 a.m. on.

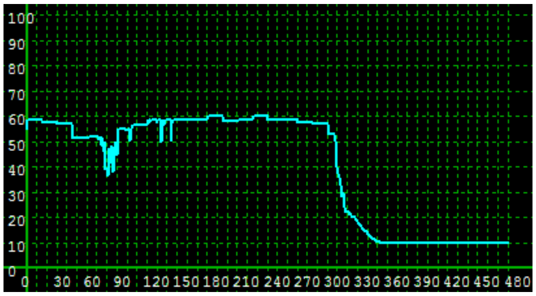


Figure 165. Illustration. Simulated link speed distribution for scenario 2 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

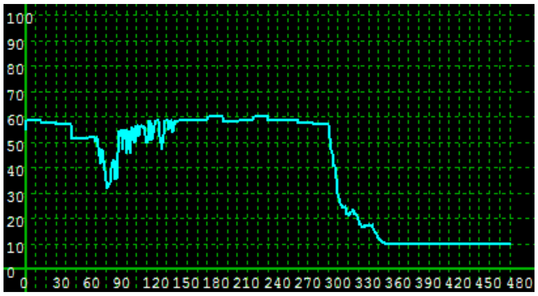


Figure 166. Illustration. Simulated link speed for scenario 3 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

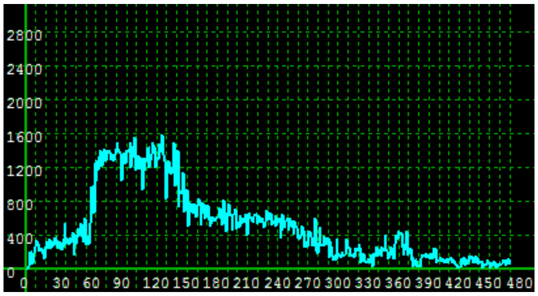


Figure 167. Illustration. Traffic volume distribution for scenario 2 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

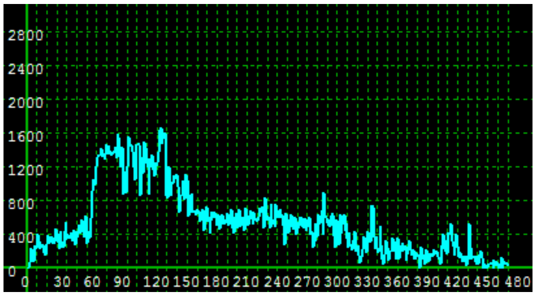


Figure 168. Illustration. Traffic volume distribution for scenario 3 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

Scenarios 4.1.1 and 4.1.2:

Scenarios 4.1.1 and 4.1.2 represent a demand management strategy on top of the natural demand reduction to inform travelers of the travel times with transit compared to the auto travel times. The two scenarios make the assumption that 50 and 100 percent of the travelers are receiving this information, respectively. The following figures only show the difference between scenarios 2 and 4.1.2, where 100 percent of the travelers are informed. Figure 163 and figure 169 illustrate the effect of the mode choice for scenario 2 compared to scenario 4.1.2 on the network density. The difference is especially visible when comparing the more congested CBD from scenario 2 to scenario 4.1.2, as the mode choice has mostly an effect on trips from and to the CBD, whereas trips outside the CBD remain nearly unaffected. In total, 7.31 percent of the to and from the CBD are projected to switch to transit under snowy condition and 100 percent information, whereas this number nearly halves when assuming 50 percent information to 3.67 percent.

Figure 169. Illustration. Simulated network density for scenario 4.1.2 at 9:30 a.m.

Figure 170 and figure 171 show the impact of the mode choice demand strategy on the link-specific speed and flow distribution. It can be seen that the free-flow speed recovers after the breakdown before it comes to a second breakdown with an overall slightly higher traffic volume.

The average travel time decreases from 38.6 to 34.62 and 32.16 min, respectively, for scenarios 4.1.1 and 4.1.2. This corresponds to travel time reduction of 10.31 and 16.68 percent.

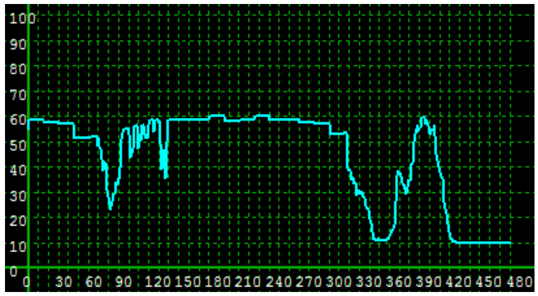


Figure 170. Illustration. Simulated link speed distribution for scenario 4.1.2 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

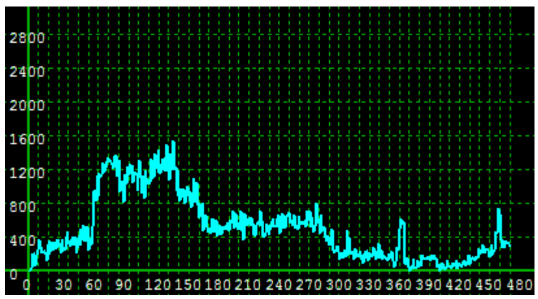


Figure 171. Illustration. Traffic volume distribution for scenario 4.1.2 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

Scenario 4.2.1 and Scenario 4.2.2:

Scenarios 4.2.1 and 4.2.2 represent a demand management strategy on top of the natural demand reduction to inform travelers of their expected auto travel time delays due to the weather condition to suggest leaving earlier or later to avoid delays. The two scenarios make the assumption that 50 and 100 percent of the travelers are receiving this information, respectively. The average expected delay for the trips is a minimum of 8 min small and a maximum of 31 min. The differences to scenario 2 are negligible, as the simulated mode shifts are too small to make an impact on the network wide traffic. Because of the small differences, the results are not shown here. The average travel time decreases from 38.6 min to 38.18 and 37.86 min for scenarios 4.2.1 and 4.2.2, respectively, which corresponds to a reduction in travel time of 1.08 and 1.91 percent.

Scenario 5:

Scenario 5 examines the effect of delaying school openings by 1 h during bad weather occurrences, as practiced in other States and cities (not including Illinois). Such policy interventions are mainly used for security reasons but also have an impact on traffic. The scenario is configured as described in the section, “Paragraph Policy Intervention: Weather-Related Delay of Schools” and illustrates the impact of such a policy on a median snow day on the network performance. School-related trips make up 8.9 percent of the traffic volume during the simulated morning hours, and its departure time distribution is much narrower distributed than work trips in the same time period. By shifting school related trips an hour later, the peak traffic can be flattened out, and the resulting difference in network densities are illustrated in figure 163 and figure 172.

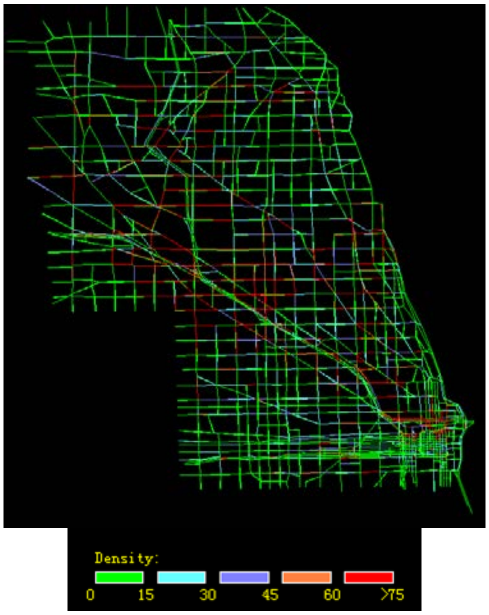


Figure 172. Illustration. Simulated network density for scenario 5 at 9:30 a.m.

Figure 173 through figure 174 show the comparison of a link speed and volume impact of school delay policy. In the comparison, it can be seen how the breakdown happens later and gets recovered soon after in the school delay policy scenario.

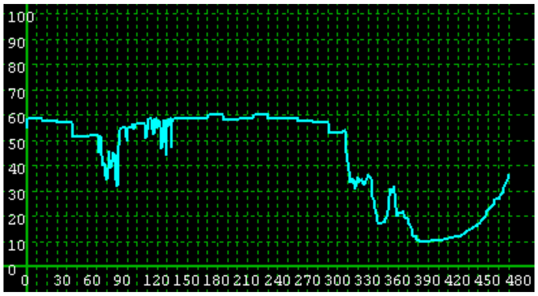


Figure 173. Illustration. Simulated link speed distribution for scenario 5 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

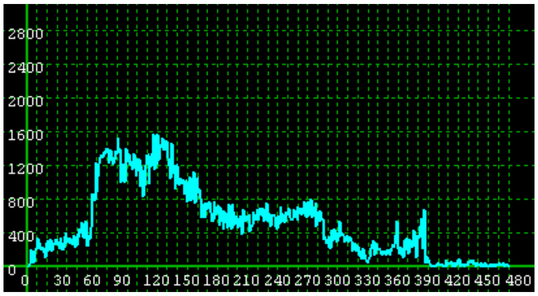


Figure 174. Illustration. Traffic volume distribution for scenario 5 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

Scenarios 6.1 and 6.2:

Scenarios 6.1 and 6.2 combine all demand management strategies and policy implementation, with 50 and 100 percent information, respectively. Figure 163 and figure 175 show the impact of scenario 2 in comparison to scenario 6.1. The speeds and densities are fully recovering the benchmark scenario 1.

Figure 175. Illustration. Simulated network density for scenario 6.1 at 9:30 a.m.

Figure 176 and figure 177 show the comparison of a link speed and volume impact of moderate weather, natural reduction, mode choice, departure time choice, and policy intervention.

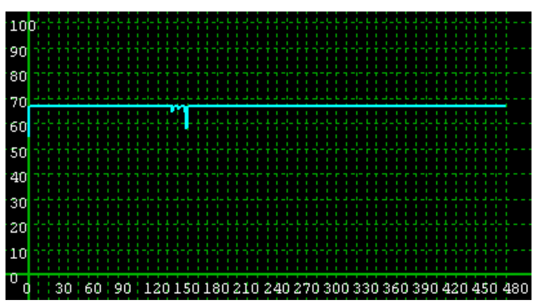


Figure 176. Illustration. Simulated link speed distribution for scenario 6.1 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

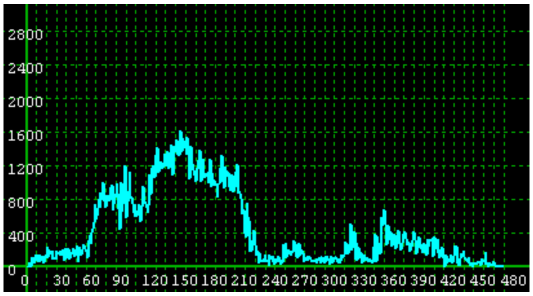


Figure 177. Illustration. Traffic volume distribution for scenario 6.1 for the Kennedy Expressway between Pulaski Road and North Cicero Avenue westbound.

Scenario Comparison and Discussion:

Figure 178 shows the accumulated percentage of out vehicles represented throughput of the network under different scenarios. One might notice that there are jumps around the 60-min mark. This is due to the time-dependent demand.

Compared to the benchmark case (i.e., scenario 1) where no snow event is present, the snow effect significantly deteriorates the network throughput if the original full demand is used and no demand management is applied (i.e., scenario 2 median snow with 100 percent demand). It can be seen that the network throughput decreases by about 7 percent due to weather at minute 120. The network performance improves as the demand level decreases. By utilizing all demand management strategies with 100 percent information, the throughput is slightly higher than the throughput of scenario 1, and with 50 percent information, the throughput is lower.

Figure 179 presents the percentage change in the average travel time and the average stop time for different scenarios relative to the benchmark case. With scenario 6.2, both measures are recovered to the level of the benchmark case.

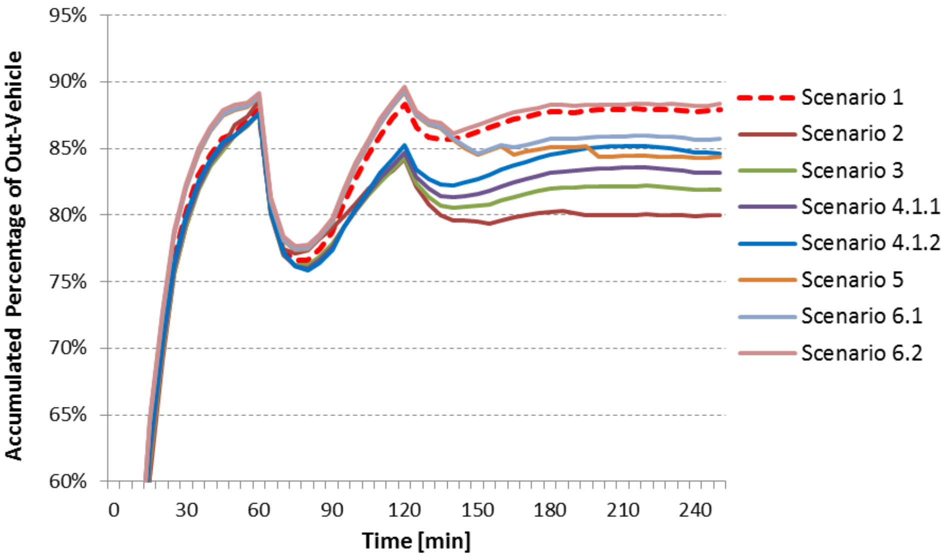


Figure 178. Graph. Accumulated percentage of out vehicle for different scenarios.

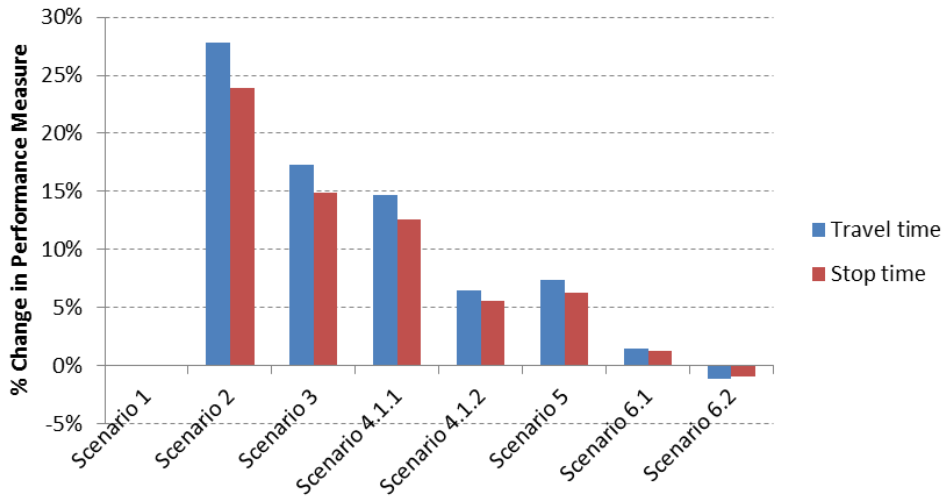


Figure 179. Graph. Changes in average travel time and average stop time relative to the benchmark.

These results depict a comprehensive list of demand management and policy strategy scenarios evaluated in this study and the corresponding improvement for network-wide travelers. In general, strategies that target mode choice and effective policies that target peak spreading have good potential to improve the cost and reliability of travel by reducing travel time. By distributing better information to the traveler and comparative travel times with transit mode alternatives, travel time can be reduced while also allowing users to exert greater control over their travel schedules.

Compared to the do-nothing case (scenarios 2 and 3), the integration of behavioral models that are sensitive to policy changes and management strategies, scenarios were simulated that significantly improve the time-dependent average travel time. Information and demand management strategies are highly effective in mitigating recurrent congestion, reducing travel time, and improving travel time reliability for both critical origin-destination pairs and networks.

Limitations

The limitations of this case study are mostly due to data unavailability and missing information for calibrating parameters used in the disaggregated choice models. For the simulated responses of individuals, a fixed compliance rate is assumed. In addition, the perfect/imperfect knowledge assumption used in the sensitivity analysis is chosen arbitrarily. The assumption of the natural reduction used in scenario 2 is based on aggregated information from loop detectors and is randomly applied to the travelers. Data to estimate individual behavioral models, such as travel surveys during bad weather and good weather, would help researchers to better understand the observed reduction as well as the nature of this reduction that travelers dodge to the peripheral network as part of their route choice behavior during bad weather conditions. Furthermore, certain individual decisions can only be understood when applied within a full-blown activity based model. Such decisions (e.g., substitution patterns, location choice changes, etc.) cannot be modeled with single decision models only for a part of the day. Also, longer-term effects for bad weather situations, where the occurrence is regularly, were not included in this case study but could be part of the observed natural reduction to some extent.

Further sensitivity analysis could be made to capture the exact combination of information compliance needed to reach the presented base scenario. This sensitivity analysis could also be coupled with VMS. DYNASMART has the capabilities to include VMS strategies during the simulation as part of the route choice algorithm. Also, the relative coarse time interval of 30 min for the departure time choice model could be refined to allow finer behavioral responses in the simulated departure time choices.

Recommended Next Steps and Research

The presented case study demonstrated how to include individual behavior models to evaluate and simulate the effectiveness of particular WRTM strategies in a given network during bad weather conditions. These allow the model user/agency personnel to compare network performance overall as well as portions of the network, origin-destination pairs or user segments with and without WRTM, as well as for different WRTM strategies. This provides an understandable method to quantify and characterize the need for and effectiveness of WRTM and to communicate these impacts to other personnel, decisionmakers, and system users as part of demand management strategies. This study conveys both the dynamic nature of the information, the network context, as well as the impact on users' decisions on trip cancellation, mode choice, departure time choice, and route choices.

The simulated demand strategies needed to offset the weather-induced network performance impairment and maintain the normal conditions level of service are a combination of transit travel time information given to auto users and policy implementation to shift school openings by an hour. The reduction depends on the nature, intensity, severity, and duration of the weather conditions. This information provides a practical target to attain through various information dissemination measures, activity cancellation or rescheduling measures, and possible incentive schemes to reach the desired level of reduction and shift in demand. The case scenario presented here shows one possible weather condition and a demand strategy of how to reduce the demand to reach LOS comparable to clear weather conditions. With different effort in dissemination of information to the auto user, a certain level of information, knowledge, and awareness could be reached to change mode and departure time decisions of individuals to reach the benchmark LOS. Models to estimate information and attitude/awareness dissemination are still relatively new to this field, but agent-based models as presented in chapter 6 are promising to model and simulate such scenarios.

In all areas, the responses of travelers to information, messaging, guidance, and controls are an essential ingredient to the overall effectiveness of management strategies. These decisions play a central role in this case study. While the methodology applied in this study provides the necessary framework and structure to capture these decisions and their evolution, it became clear during the study that a stronger observational basis is needed with regard to what users actually do in bad weather and under different interventions. The study team believes that a targeted application with tracking of a sample of users would contribute significantly to the ability of agencies to effectively deploy WRTM. Such a behavior tracking study that would allow observation of actual user responses to WRTM strategies, with particular focus on demand management strategies, would fill the data gap and minimize the assumptions, which have to be made for simulating best strategies. As noted, the lack of behavior tracking studies is an important gap in existing knowledge and a critical opportunity from the standpoint of agencies' abilities to mitigate inclement weather. The results would be incorporated in the presented methodology to improve its ability to predict ways to attain desired demand reduction targets.

In large metropolitan areas, it is also important to incorporate alternative transportation modes in the WRTM analysis, as shown in this case study. In the simulation of the Chicago, IL, network under snowy conditions, public transit plays an important role in providing and maintaining mobility.

This case study also showed that different strategies are not additive in their impacts, and a best combination needs to be carefully determined for specific weather conditions.

ICM CASE STUDY

Travel Behavior Variability and Intervention Following Active Traffic Management System (ATMS) Case Study

This section describes research performed on the Interstate 5 corridor in Seattle, WA, following the introduction of an automated ATMS on the corridor. It provides a summary of how information interventions are related to travel behavior variability and examines conditions of variability and demand. The other potential benefits associated with ATMS investments, such as improvements in safety, reductions in delays, and greenhouse gas emissions through speed harmonization, ramp metering, and other traffic management techniques were discussed previously in this chapter.

In the course of the research, variability in weather conditions was found to significantly influence some travel behaviors. Though weather conditions are not typically reported in the ATMS data (except for unusual circumstances), the effects of variable weather conditions are important in evaluating the larger context of the ATMS operational effects.

The purpose of this study has been to examine facility users' reactions to information (specifically ATMS-transmitted congestion, weather, and incidents information and operational guidance) provided by VMSs and supplemented by other freeway management techniques such as ramp metering. In this context, there are a number of behavioral dimensions that can be examined that affect behavior.

The ATMS system is an additional freeway management strategy that has not been widely used in the United States. Studying a corridor that has had a system in operation for some time allows for the recording of behavioral choices by travelers in the corridor who have had a chance to use the real-time information and adjust their behavior in response to the corridor's operations.

Program Interventions on Northbound Interstate 5 Corridor in Seattle, WA

Interstate 5 is the westernmost freeway that runs the length of the continental United States. The freeway traverses California, Oregon, and Washington. It also traverses the middle of several major metropolitan areas, including San Diego, Los Angeles, and Sacramento, CA; Portland, OR; and Seattle, WA.

Within the Seattle, WA, area, Interstate 5 is the major north-south freeway. As the major freeway, much of the alignment has four or five lanes in each direction as well as an HOV lane through much of the corridor.

The segment of Interstate 5 studied for this research is the northbound segment between Boeing Field and Interstate 90, almost entirely within the city limits of Seattle, WA. This portion of the corridor is recognized for having significant congestion throughout multiple hours of many weekdays as a result of merging traffic from Interstate 90. There are also lane reductions that occur with the opening and closing of the Interstate 5 reversible lanes that begin downtown. Finally, multiple movements as drivers enter and leave the local street system in the downtown area can contribute to congestion in this corridor segment.

To manage this congestion over the last few decades, the Washington State Department of Transportation (WSDOT) has implemented several tools to inform drivers of impending congestion. Improvements began by initiating ramp metering in the corridor. Other tools used include destination travel time signage and an ATMS that reports upstream warnings of traffic congestion as well as variable speed limits by lane. The primary purpose of the ATMS system was to reduce the occurrence of vehicle collisions and the related problem of additional non-recurring congestion. These signs are located on a series of gantries over the road at generally 0.5-mi spacing.

Behavioral Dimensions: Route Choice, Departure Timing, and Trip Cancellation

ATMS may influence a number of decisions that travelers make. These decisions include the following:

- **Trip cancellation**: A traveler must first decide whether or not to make a trip before choosing any elements of the trip. The tendency to make the same decisions over time is often referred to as "inertia." Information about traffic or weather conditions made public through media sources can influence whether or not to make a trip, and if so, which mode and route to take.

- **Destination choice:** A traveler may decide to change his/her destination. While many destinations are fixed from one day to another, such as work and school sites for most people, other trip destinations can vary, such as choices of retail stores.

- **Time-of-day choice:** A traveler may decide to change the time of day that a trip is made, presumably to a time when congestion is eased. A traveler is informed about travel times and congestion through a variety of sources in the media.

- **Mode choice:** A traveler can decide whether or not to drive alone, share a ride, or use another mode. A traveler may make this decision based on weather reports or on travel conditions in the media.

- **Path choice:** A traveler can decide while en-route to choose another path. Information on this choice is available from roadside signs, cell phone traffic applications, traffic radio reports, or other real-time sources.

Data Available and Used in Case Study

Traffic Volume and Speed Data

WSDOT maintains an FTP site with 6 months of performance data on area roadways. These data are available in 20-s or 5-min increments. As this deals with comparative travel demand choices, the 5-min data are the most applicable.

ATMS Activation Data

The ATMS system is automated so that no deliberate human decision is required for the signs to activate. A summary of the system design is available online. The signs contain advisory messages such as “slow traffic ahead” or “reduced speed zone,” with lane-assigned variable speed limits (between 30 and 50 mi/h) automatically activated when appropriate.

WSDOT maintains an internal log of signage registered each minute for each VMS in the region, including the ATMS system. The logs contain the mileage marker of each sign or sign gantry as well as time and the message indicated at each sign.

Weather Data and Selection of Weather Days

The ASOS program is a joint effort of the National Weather Service (NWS), the Federal Aviation Administration, and the Department of Defense. ASOS is designed to support weather forecast activities and aviation operations and, at the same time, support the needs of the meteorological, hydrological, and climatological research communities.

The program maintains a record of 5-min and hourly weather conditions at Boeing Field, which is adjacent to the corridor. Weather data are summarized hourly for temperature, conditions, recorded precipitation, wind speeds, and a number of other meteorological measurements. For this study, the weather conditions and the prior hour’s recorded precipitation were the primary conditions of interest in determining travel behavior choices.

The days selected for review were between Monday, September 11, 2012, and Thursday, December 6, 2012. Fridays were excluded for being atypical work days, and Saturdays and Sundays were excluded because weekend travel is different from weekdays. In addition, November 21 and 22, 2012, were excluded because of the variation in traffic that occurs on these days. Finally, home game days of the Seattle Mariners were excluded.

The remaining days were separated into the following three categories based on type of weather condition:

- **Dry days:** Days with no precipitation or unusual weather occurrences.
- **Drizzle days:** Days with at least 8 h of major travel periods (5 a.m. to 9 p.m.) experiencing precipitation, with the total daily amount under 0.10 inch.

- **Rainy days:** Days with at least 8 h of major travel periods (5 a.m. to 9 p.m.) experiencing precipitation, with the total daily amount exceeding 0.50 inch.

Days that were clearly transitional were excluded from the sampling. The days selected for these typologies are shown in table 29.

Table 29. Boeing Field weather data.

Date	Day	Precipitation Total (inches)	Recorded Hours Precipitation	Precipitation Hours (5 a.m.–9 p.m.)	Category of Day
9/10/12	Monday	None	None	None	Dry
9/11/12	Tuesday	None	None	None	Dry
9/12/12	Wednesday	None	None	None	Dry
9/13/12	Thursday	None	None	None	Dry
9/17/12	Monday	None	None	None	Exclude Seattle Mariners
9/18/12	Tuesday	None	None	None	Exclude Seattle Mariners
9/19/12	Wednesday	None	None	None	Exclude Seattle Mariners
9/20/12	Thursday	None	None	None	Dry
9/24/12	Monday	None	None	None	Dry
9/25/12	Tuesday	None	None	None	Dry
9/26/12	Wednesday	None	None	None	Dry
9/27/12	Thursday	None	None	None	Dry
10/1/12	Monday	None	None	None	Exclude Seattle Mariners
10/2/12	Tuesday	None	None	None	Exclude Seattle Mariners
10/3/12	Wednesday	None	None	None	Exclude Seattle Mariners
10/4/12	Thursday	None	None	None	Dry
10/8/12	Monday	None	None	None	Exclude Columbus Day
10/9/12	Tuesday	None	None	None	Dry
10/10/12	Wednesday	None	None	None	Dry
10/11/12	Thursday	None	None	None	Dry
10/15/12	Monday	0.3	12	11	Drizzle
10/16/12	Tuesday	None	None	None	Dry
10/17/12	Wednesday	None	None	None	Dry
10/18/12	Thursday	1.04	4	2	Transitional
10/22/12	Monday	0.35	10	9	Rain
10/23/12	Tuesday	T	4	2	Drizzle
10/24/12	Wednesday	0.19	17	10	Drizzle
10/25/12	Thursday	None	None	None	Dry
10/29/12	Monday	0.7	9	5	Rain
10/30/12	Tuesday	1.39	19	15	Rain
10/31/12	Wednesday	0.72	16	11	Rain
11/1/12	Thursday	0.39	10	5	Rain
11/5/12	Monday	0.05	1	0	Dry
11/6/12	Tuesday	0.01	1	1	Dry
11/7/12	Wednesday	None	None	None	Dry

Date	Day	Precipitation Total (inches)	Recorded Hours Precipitation	Precipitation Hours (5 a.m.–9 p.m.)	Category of Day
11/8/12	Thursday	None	None	None	Dry
11/12/12	Monday	0.16	6	2	Drizzle
11/13/12	Tuesday	0.19	9	4	Drizzle
11/14/12	Wednesday	None	None	None	Dry
11/15/12	Thursday	None	None	None	Dry
11/19/12	Monday	2.38	15	11	Rain
11/20/12	Tuesday	0.23	5	4	Rain
11/21/12	Wednesday	0.59	14	9	Excluded (Thanksgiving)
11/22/12	Thursday	0.02	2	0	Excluded (Thanksgiving)
11/26/12	Monday	None	None	None	Dry
11/27/12	Tuesday	None	None	None	Dry
11/28/12	Wednesday	0.12	8	8	Drizzle
11/29/12	Thursday	0.12	14	11	Drizzle
12/3/12	Monday	0.77		13	Rain
12/4/12	Tuesday	0.53	21	15	Rain
12/5/12	Wednesday	None	None	None	Dry
12/6/12	Thursday	0.07	9	7	Drizzle

Source: Boeing Field Weather Station Data, NWS

Transit Demand Data

Daily transit boardings were available for a number of bus, light rail, and commuter rail services that operate in the corridor under monitor by the Sound Transit District. An automated passenger counting (APC) system recorded northbound data on Sound Transit buses (Routes 577, 590, 592, 593, 594, 595, and 596) that operate on the Interstate 5 corridor and commuter rail services that operate on railroad tracks adjacent to the corridor for the study period. The link light rail system, which generally follows the corridor, did not have a recording of each transit trip, so a surrogate measure of the recorded trips from passengers' transit cards at the three southernmost stations (Sea-Tac Airport, Tukwila International Boulevard, and Rainier Beach) were used to determine variability. Additionally, King County Department of Transportation Metro Transit Division operates two routes in the corridor (routes 101 and 150), but the APC equipment on these routes was not comprehensively installed, so that these data were not examined.

In addition, there were two transit-related system changes that occurred that were accounted for in the mode choice data only. On September 29, 2012, the free-fare zone for transit riders in downtown Seattle was discontinued. That potentially could have affected the way that data were registered in the corridor (even though the fare policy change did not directly affect transit riders in the corridor). A second transit occurrence was the extending of the Sounder commuter rail from downtown Tacoma to South Tacoma and Lakewood station on October 8, 2012. For these reasons, mode choice data before October 8, 2012, were excluded.

Findings

The research yielded findings for a variety of circumstances. Note that these findings point to variability in observed aggregate travel conditions rather than individual travel behavior. As a result, the findings represent key observations, but the actual causes of the variability can only be interpreted. Future research should focus on behavioral tracking studies along ICM and ATMS corridors to capture individual responses over time.

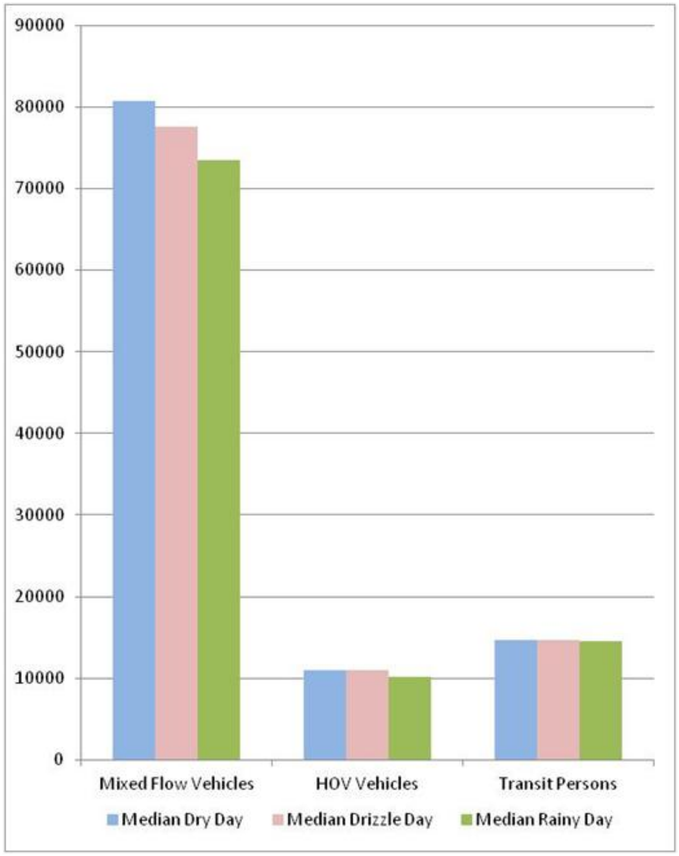
Inertia/Trip Cancellation

When examining the overall demand in the corridor, it is clear that there is variation in demand that is affected by weather conditions. To examine this, the median days of the three weather types were examined. The data examined in the corridor suggest that the total demand does vary with weather conditions. The findings are summarized in table 30 and illustrated in figure 180. For daily travel, there is a significant drop in demand for rainy days and a less significant drop for drizzle days.

Table 30. Summary of daily demand (October 10, 2012, to December 6, 2012).

Attribute/ Weather	Mixed Flow Vehicles	HOV Vehicles	Transit Persons
Median Day Type			
Dry	80,739	10,944	14,736
Drizzle	77,497	10,991	14,697
Rain	73,479	10,102	14,515
Percent—Standard Deviation ÷ Mean			
Dry	3	5	3
Drizzle	1	4	1
Rain	4	4	3
Percent of Dry Days			
Dry	100	100	100
Drizzle	96	100	100
Rain	91	92	99
Percent of Total Trips (not adjusted for auto occupancy)			
Dry	76	10	14
Drizzle	75	11	14
Rain	75	10	15

Sources: DKS Associates, 2013 using data from WSDOT and Sound Transit.



Source: DKS Associates

Figure 180. Graph. Summary of daily demand.

Destination Choice

The techniques applied did not produce results that indicated that information provided to travelers produced changes in destination choice. It is possible that daily reduction in travel could be due to destination choices, but it is more likely that trip cancellation created by more inertia not to travel was the cause of the observed travel reduction.

Mode Choice

The same data in figure 180 can be examined to suggest where daily mode choice changes might be occurring. There is clearly a reduction in traffic in mixed flow lanes, but corresponding increases in the daily demand in the HOV lane and in transit boardings are not demonstrated. This suggests that the primary reduction in activity is due to trip cancellation rather than shifting to another mode. Figure 181 summarizes the different mode shares for each type of day using medians from the various data sources. It should be noted that this figure does not account for the vehicle occupancies by mode, as these are not recorded in the analyzed datasets.

Source: DKS Associates

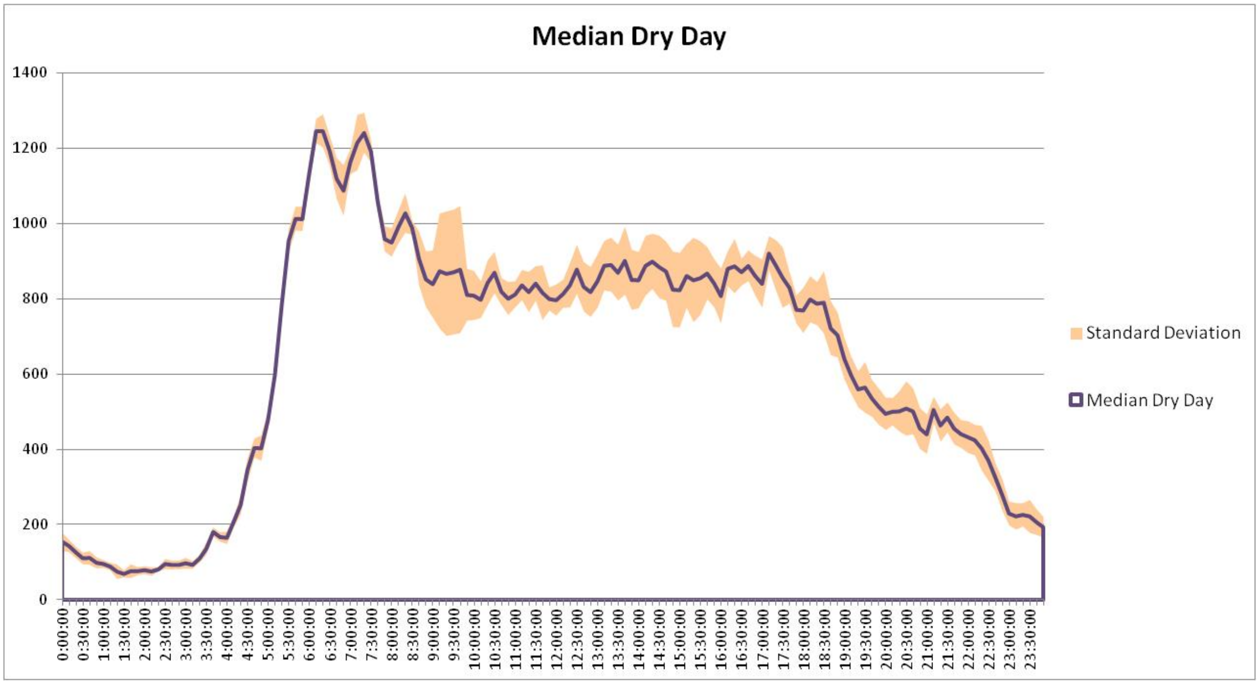
Figure 181. Graph. Comparison of transit usage to Interstate 5 northbound traffic.

Time of Day Choice

The data presented in figure 180 for mixed flow traffic have been disaggregated for 10-min periods throughout the day. The data for the median dry, drizzle, and rainy days are summarized by time-of-day in figure 182 through figure 184. To illustrate the magnitude of variability in each type of day, the graphs in the figures also include standard deviations. Because there are between 7 and 11 days included in the sampling, the applicability of the more statistically appropriate variable of 15 and 85 percent is not used. Instead, the standard deviation is used for illustrative purposes.

The location in the corridor that was examined was south of the Swift Avenue/Albro Place off-ramp (Boeing Access Road off-ramp) at monitoring location mile post 157.42. At this location, the effects of queuing in the corridor often are not reflected in the traffic speeds recorded. Mixed flow and HOV volumes are combined at this location.

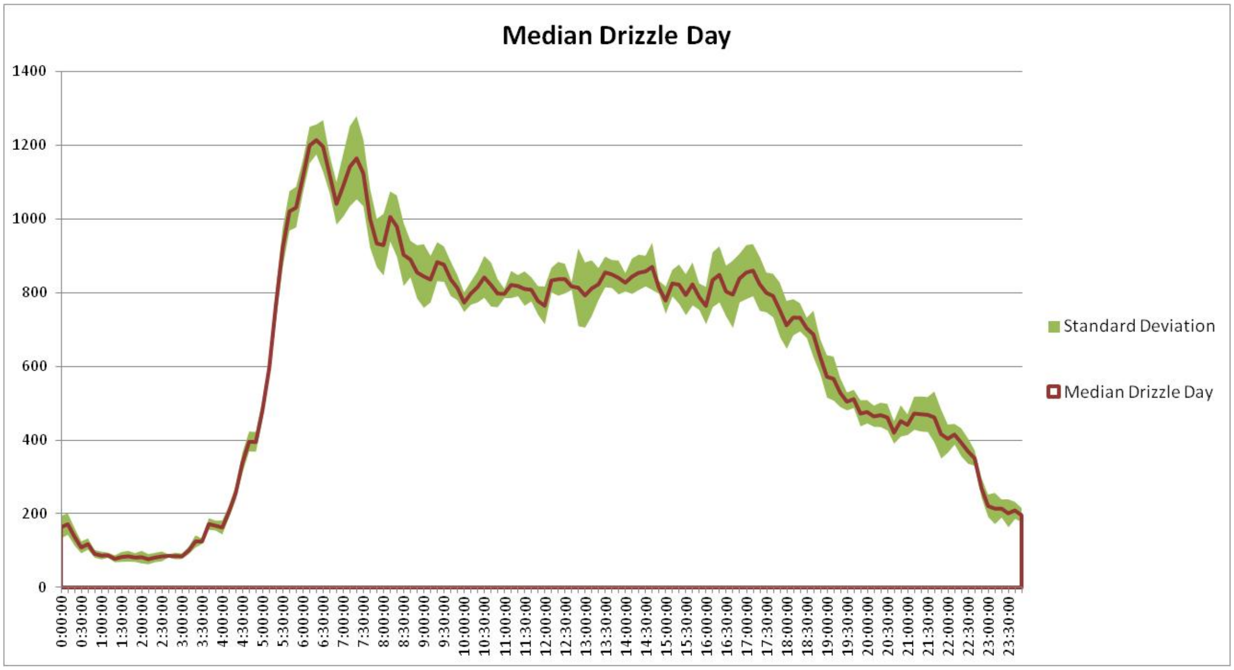
Figure 182 shows a median dry day. As is apparent from the graph, the early morning conditions are relatively constant, exhibiting little variation. The highest volumes occur in the morning peak period, with a maximum median of about 1,250 vehicles for the 10-min period (the morning peak period contains two peak volume periods as a result of arriving shift workers at nearby facilities). As the day progressed, some variability was observed later in the morning peak after 9:00 a.m., suggesting that the end of the morning peak period had variable congestion and that vehicle flows responded to this. Slight variability continued through the remainder of the day. Traffic generally remained steady at about 800 to 900 vehicles during each 10-min period. This continued to about 5:30 p.m.



Source: DKS Associates

Figure 182. Graph. Median dry day volumes by time of day—south of Boeing Access Road off-ramp.

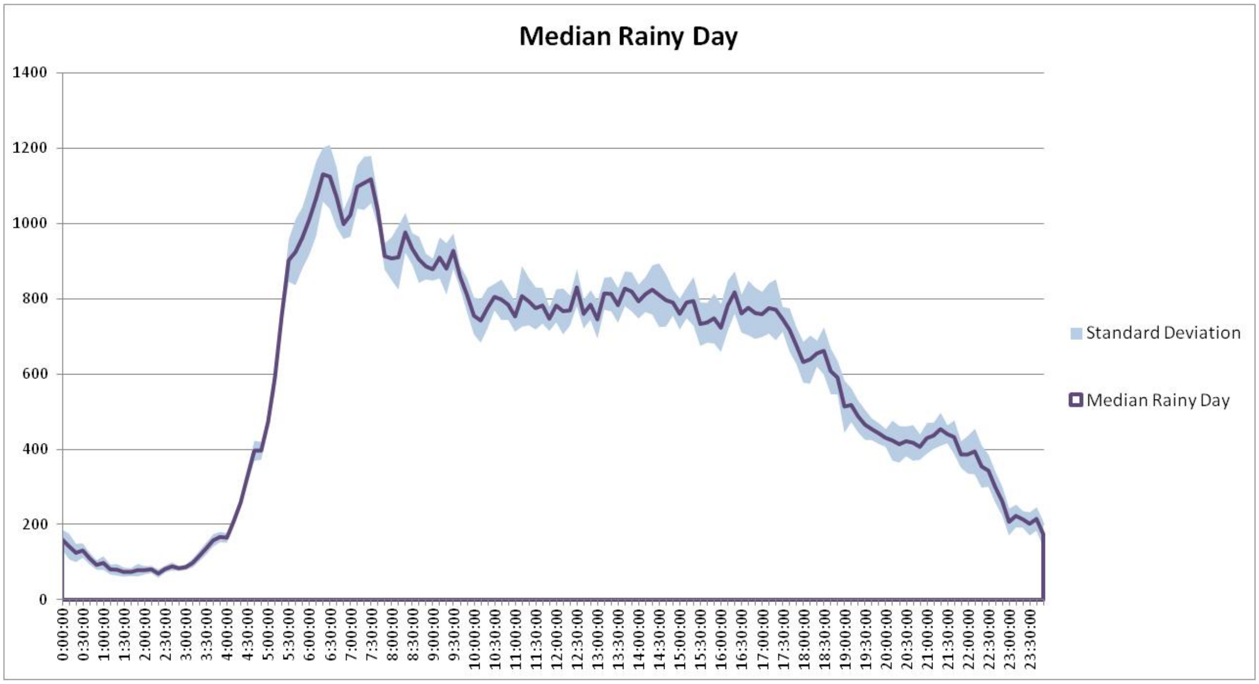
As is shown in figure 183 for the median drizzle day, the overall traffic demand began to decrease, but this decrease was slight through most of the day. The demand appears much more variable, although the median is comparable for dry days for many of the time periods. The second highest morning peak traffic median at about 7:20 a.m. is shown to be well below 1,200 vehicles. Another notable demand change is toward the end of the afternoon peak period. The median demand at 6:30 p.m. was about 700 vehicles for a 10-min period, while this was above 750 on dry days.



Source: DKS Associates

Figure 183. Graph. Median drizzle day volumes by time of day—south of Boeing Access Road off-ramp.

Rainy days showed significant decreases in demand as indicated in figure 184. The morning peak at about 6:30 a.m. had only about 900 vehicles for the 10-min period for mixed flow lanes. The median day showed volumes about or below 800 vehicles for much of the day, and the median demand time remained well under 800 vehicles for the 10-min period. The most notable demand change was toward the end of the afternoon peak period. An examination of the 6:30 p.m. occurrences showed that a median rainy day had about 600 vehicles for a 10-min period, while this was over 650 vehicles for drizzle days and 700 vehicles on dry days.



Source: DKS Associates

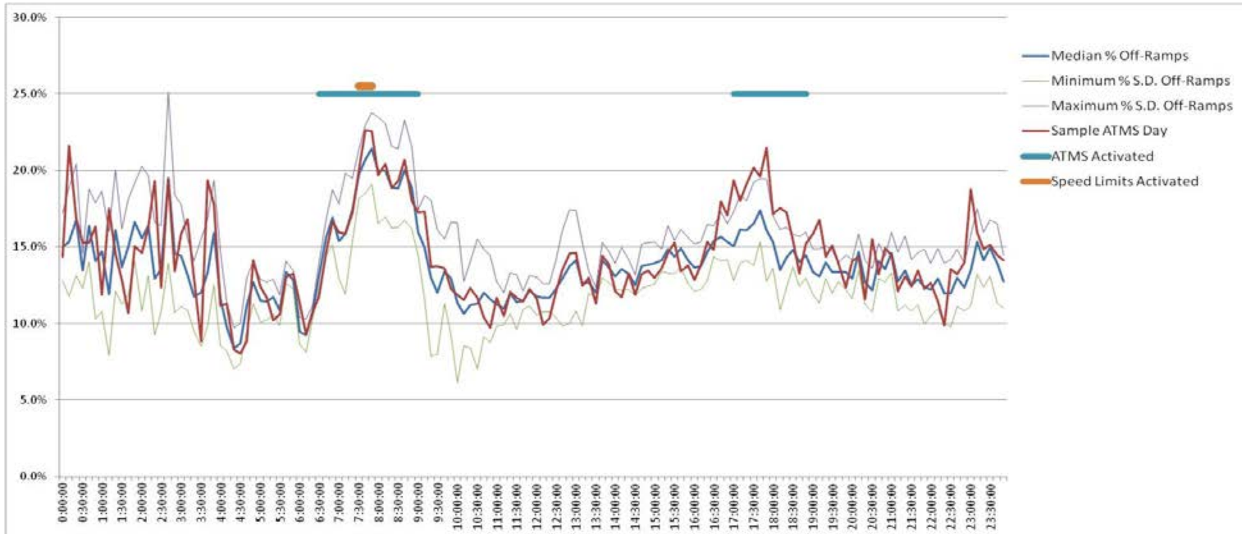
Figure 184. Graph. Median rainy day volumes by time of day—south of Boeing Access Road off-ramp.

Path Choice

As noted earlier, the ATMS activation appears to influence travel behavior. As the system was only visible to the drivers on the roadway, the effects of the ATMS would seem to be most directly related to path choice.

To illustrate how this behavior varies, a comparison of the demand on the Interstate 5 north mainline at the first gantry, located south of the Martin Luther King, Jr. Way and the Boeing Access Road off-ramps (part of a larger complex interchange) were closely examined. This location represents the highest off-ramp activity on the southern portion of the study corridor. Combined, these off-ramps carry between 10 and 20 percent of all the upstream mainline traffic, with especially high proportions during the morning peak hour as it serves workers at Boeing Corporation's Boeing Field facilities.

The findings are graphically depicted in figure 185. November 12, 2012, showed relatively similar demand to the typical median drizzle day at this location. Most of the day, when the ATMS was not activated, the demands were similar between each kind of day. However, when the ATMS was activated in the morning and evening peak periods, the effects of the activation were mixed. In the morning, the activation did not appear to significantly impact the share of exiting traffic. In the afternoon peak period, the mere activation indicated that the message of traffic delays ahead resulted in an increase in off-ramp traffic above the maximum standard deviation and well above the median drizzle day. This is likely a result of morning peak period drivers needing to remain on Interstate 5 to reach destinations farther away or avoidance of high off-ramp activity at the interchange. The afternoon peak period drivers may have had fewer time constraints or were going to destinations where other paths were more reasonable.



Source: DKS Associates

Figure 185. Graph. Percentage of off-ramp traffic comparing median and study drizzle day.

Conclusions

The following conclusions from this research illustrate how variability influences the way that freeway operations strategies work and that variability should be a component of traffic operations research from a behavioral perspective:

- There was an overall reduction in traffic that occurred on rainy days that could not be predicted by travel forecasting models. This reduction could be from a variety of factors, with trip cancellation being the likely major factor. This is important when comparing effects of freeway management strategies, as weather influences on behavior may bias study findings unless the study compares days with similar weather. The data suggest sensitivity during the midday and evening time periods of about 10 to 15 percent for times during the day in each weather type. With this variability, data used in validating traffic volumes should indicate differences due to weather.

- The effects of weather do not seem to influence HOV lane use or transit use in this corridor. The analysis in this case study suggests that weather has only a slight effect on mode choice for users of Interstate 5. This could be important as transit boardings can vary for many reasons, with weather not appearing to be a factor for the longer routes that operate in the corridor. While forecasting may generally need to consider variability, the longer distance mode choice in travel models appears to be less affected by weather than by other influences. Furthermore, drivers' tendency to use the same mode and follow the same route day after day is not well understood. Understanding this traveler inertia could improve implementation of operational interventions.

- This corridor shows lower demand in rainy weather conditions generally across much of the day. When considering the first two conclusions, the reduction in demand seems to be attributable to persons choosing to cancel trips. Cancelled trips are most likely trips being made for purposes other than to work or college, so forecasting that considers variability may be most effective when examining non-work, non-college trips.

- ATMS strategies appear to divert traffic in this corridor, but the effect is significant only at certain times. The success of a path diversion here appears to have greater effect when drivers have the option of leaving the freeway to arrive at their destination. Future intervention strategies similar to ATMS may need to consider the impact of route diversion, but the effect may or may not be important depending on the drivers' ultimate destinations and their awareness of alternate paths.

Limitations

This specific case study provides the ability to intervene in real-time mode choice behavior, so this conclusion is reasonable when applied to this corridor. Its transferability to other corridors will need to be verified before an overall conclusion that mode choice is not a significant behavioral change can be made.

The automated protocols established in an ATMS design are critical to its success, and the success in this corridor may be increased or decreased depending on the signage protocols and placements for ATMS activation. Testing of the automated protocols in this corridor will need to be examined more closely for sensitivity before it is clear what system works most effectively.

Recommended Next Steps and Research in ICM/ATIS

Forecasting methods can be enhanced by incorporating occurrences of variability in the system in some way to reflect variability in influencing factors such as weather rather than relying solely on average behaviors. Travel diaries or GPS travel survey tools for household travel behavior can be expanded to examine the effects on trip generation rates. Furthermore, APC system data can be helpful in examining mode share issues further in corridors. This may be appropriate to focus on the proportions of trips that normally occur at those times, particularly non-work, non-college, and non-home-based trips.

Sensitivity studies on automated protocols yield how successful they are. Research should focus on similar types of days as weather affects demand. Measuring traveler awareness of alternatives is important not only for understanding their choices and experience, but also for capturing the influence of experience travelers in their social networks (see chapter 6).

CHAPTER 9. CONCLUSIONS AND RECOMMENDATIONS

This chapter provides an overall summary of the activities undertaken as part of the study, highlights the principal accomplishments contributed through the work undertaken in conjunction with this effort, extracts the main lessons learned, and provides suggestions for next steps intended to advance the state of the art and practice in modeling traveler choice for the purpose or analysis and evaluation of operational and policy interventions.

SUMMARY AND ACCOMPLISHMENTS

The goal of this study was to address the important gap in modeling capability to support a variety of initiatives that seek to improve traffic conditions, system safety, and sustainability by targeting user choices before and during travel. The main emphasis of this effort was on travelers' higher-level predictive strategic choices because these might be influenced by a range of variables including experienced system performance through the level of service, environmental factors such as weather that affect both system performance as well as activity engagement opportunities, availability and accessibility to alternative modes, quality of the walking environment, as well as measures such as pricing, information supply, dynamic traffic management, etc. A thorough understanding of the determinants of travel choices and behavior and an operational ability to model their dependence on key attributes of the transportation system, network performance, as well as non-network factors, will provide a foundation for designing effective interventions to improve system performance and for evaluating different policies and options by predicting how users will respond to these measures.

This broad goal was first supported through a literature review of network and non-network factors influencing travel behavior in the short, medium, and long terms. In a way, the scope of the present effort covers the entire realm of transportation systems analysis, planning, and operations. A comprehensive conceptual framework was articulated to highlight the principal behavior dimensions and how these interrelate with network performance to determine the impact and effectiveness of a wide range of demand-side and supply-side measures. While the framework provides the structure of a modeling capability to address this wide range of possible questions, no single modeling platform can have both the scale and the appropriate level of detail and focus to address all questions and interventions. In any modeling exercise, some aspects of the system, including traveler decisions, are considered given and fixed, while others are allowed to change and respond to the particular measures under consideration. Physicists have long differentiated between slow-changing and fast-changing dynamics, each requiring different modeling approaches and data observations. Accordingly, this study sought to demonstrate opportunities for improving modeling capabilities with respect to various policy and operational interventions by defining selected case studies. For each case study or scenario, specific modeling tools were elaborated by integrating traveler choice models in system simulation tools and demonstrated to evaluate the effectiveness of the relevant interventions.

The case studies ranged from long-term policy influences of non-network interventions (i.e., walkability and crime) on mode choice to short-term en-route behavior of speed compliance as part of INFLO speed harmonization measures. To cover these different time frames of user behavior adjustments to management and policy strategies, different models were developed, as no single modeling approach fits all purposes. Moreover, all cases model and treat individual behavior in a completely disaggregated manner. However, depending on the focus of the intervention, scale of application and resulting size of the problem, the case study models range from macroscopic to microscopic representation. Where predictive capabilities were needed, well-calibrated statistical models were used. In the case of speed harmonization, the physics of the simulation became of primary importance, and detailed microsimulation tools were used to simulate the user behavior and the associated interactions in the traffic stream. What became clear through all of the case studies is that information and how information is processed is the primary consideration for most of the management strategies. Current statistical models are limited in the way they model the diffusion and processing of information in a connected world. For that purpose, an agent-based model was developed to demonstrate how different processes could be implemented to represent information and attitude diffusion processes. Each of the case studies is summarized in the following subsections.

Urban Policy and Non-Network Interventions Case Study

Early studies of land use and travel behavior focused on hypothesis testing regarding the correlation between built environment and travel. The debate about causality of observed correlations is ongoing. Despite the large number of existing studies, the magnitude of the effects of built environment on travel behavior, specifically mode choice, is unclear. Instead of treating land use in broader categories, this case study analyzed the direct causal relationship of safety perception and walkability on mode choice for the first time. The influence of walkability and safety perception was included in an extensive mode choice model as latent variables to complement all the standard variables such as level of service and demographic variables. In addition, the mode choice model included time-varying level of service attributes.

The case study demonstrates how available data sources can be tapped, reconciled, and implemented into available model structures. It also shows the significant influence of disaggregated non-network factors on mode choice.

ATDM Case Study

This case study focused on identifying information and data that can inform understanding of the factors underlying traveler choices to use bicycling as an active transportation mode and the development of models of bicycle mode shift and usage patterns that may be incorporated in regional and operational travel demand forecasting frameworks. The examination included a review of information and data collected by local areas in regional case studies consisting of the following four urban metropolitan regions: Washington, DC, metropolitan region, Southern California metropolitan region (SCAG region), San Francisco Bay area, and the Cleveland, OH, region. Data collected from these regions confirm that bicycle travel is increasing both as an active transportation mode and as a means of travel demand management. However, bicycle travel supply and demand variables collected by local agencies vary considerably in quality and robustness. While leading edge travel demand modeling agencies are beginning to integrate bicycle use data into travel forecasting, significant data gaps limit the ability to fully incorporate bicycling choice and use in activity-based models of travel demand.

Examples from the four metropolitan study areas were presented, focusing on overall bicycle use and limited evidence for potential modal shift in connection with bike on transit service options and bike sharing plans. The importance of factors such as weather in bicycle use decisions is strongly evident through the available data. Recommended data needed to advance the state of the art and the practice were identified and presented.

AERIS Case Study I: Social Networks and Green Behaviors

Attitudes and information can influence individuals' choices on many different levels, but little is known on how information disseminates and attitudes are formed. Management strategies aim to influence user behavior. As a result, attitudes cannot be treated as static and given. This case study developed an agent-based model of information diffusion and attitude formation. The model includes the following three main models:

- **Social network model***:* Lattice neighborhood network, where the home location is modeled as a function of social class and where the initial attitude is also a function of social class.
- **Communication condition***:* The more similar two agents are, the more likely they are to communicate. The similarity attributes are defined on the basis of social class, innovation adopter status, and current attitudes.
- **Opinion revision process***:* This process is based in an impedance function with three trigger mechanisms: class type similarity, opinion leader or follower status, and inertia (status quo mechanism).

Experiments conducted with the developed model demonstrated how the effectiveness of targeted information campaigns to change behavior could be assessed through their impact on opinion and attitude formation and change through agent interaction, word of mouth, and/or social media.

AERIS Case Study II: INFLO and Speed Compliance

Connected vehicle technology enables improvements in flow quality, safety, and sustainability through better driver decisions. Speed harmonization, like ramp metering or VMSs, requires drivers to comply with the advised policy in order to be effective. This case study models speed harmonization and its effect on the system performance and examines its robustness in relation to driver compliance behavior.

The individuals' behavior was simulated with an acceleration and episode duration model. A shockwave detection algorithm was implemented to trigger speed harmonization in real time. By incorporating and calculating emissions based on the motor vehicle emission simulator, the impact of speed harmonization on emissions, in addition to travel time and flow quality, was modeled and demonstrated for a real-world scenario. The study shows that with a compliance level of around 20 percent, nearly the full benefit from speed harmonization can be achieved. The results indicate that even low levels of compliance with the suggested speed limit are sufficient for the near-success of the system. However, the minimum required compliance level varies based on the geometric characteristics of the highway segment and its flow rate.

WRTM Case Study

This case study investigated WRTM strategies in terms of their impact on flows and service levels in the network and how demand management strategies can help maintain acceptable levels of service in the transportation network during bad weather conditions. In order to do so, mode choice, departure time choice, trip cancellation, and trip shifts were studied and included in a simulation of the Chicago, IL, network. Nine combinations of these different choice levels were analyzed to recommend a mix of strategies.

Whereas during bad weather a travel time increase of 27 percent was simulated, it was demonstrated that the level of service during bad weather could be improved to the same level of service as during clear weather conditions by decreasing the demand by around 15 to 20 percent. The study showcased that such a demand decrease could be achieved by promoting alternative modes and policy interventions. A combination of information about expected bad weather travel time reaching 50 percent of travelers, and policies of delayed school openings are able to achieve about 18 percent demand reduction.

These results depict a comprehensive list of demand management and policy strategy scenarios evaluated in this study and the corresponding improvement for network-wide travelers. In general, strategies that target mode choice as well as effective policies that target peak spreading have good potential to improve the cost and reliability of travel by reducing travel time.

ICM Case Study

The last case study analyzed data from the Interstate 5 corridor in Seattle, WA, which is managed by an automated ATMS along the corridor. The case study provides a summary of how information interventions are related to travel behavior variability.

In the corridor, the following phenomena were observed, confirming the importance of understanding behavioral responses of travelers to management interventions:

- This corridor shows lower demand in rainy weather conditions generally across much of the day, which means that cancelled trips are most likely trips being made for purposes other than work or college.
- The effects of weather do not seem to influence HOV lane use or transit use in this corridor.
- ATMS strategies appear to divert traffic in this corridor, but the effect is significant only at certain times. The success of a path diversion appears to have greater effect when drivers have the option of leaving the freeway to arrive at their destination.

LESSONS LEARNED AND NEXT STEPS

Lessons learned from these case studies include the following:

- There is no "one-size fits all" model. This study covered considerable ground in terms of both models and applications. The multidisciplinary domain of travel behavior and travel choice modeling is vast, and its relevance spans the near entirety of the realm of transportation planning, operations, design, policy, and economics. Accordingly, it is challenging to cover the entire territory of travel behavior as an integrated coherent domain. As the state of the art survey and synthesis of practice conducted in the first phase of this study confirmed, models developed for different purposes tend to have different representations of traveler choice processes—from which choice dimensions are included, to how those are specifically modeled, to the widely varying extent of data availability for model development and model application, to the degree to and manner by which these behavior models are integrated or otherwise incorporated in overall model systems of frameworks, to the confidence placed in these models in actual policy applications. There is a plethora of individual models of one or the other aspect of travel behavior that have been captured for one application or academic exercise, but very few examples of comprehensive and convincingly calibrated activity-based model systems or attempts to build these onto integrated and internally consistent network analysis platforms. Fragmentation will likely remain, with different models developed at different resolutions and customized for particular types of applications, although a definitive trend is observed and will continue toward increasing the behavioral content and realism of models applied for operational planning purposes.

- What is common across all these models and applications is that traveler choices and behavioral responses are modeled at the individual level. So long as model platforms allow such representation, the behavioral richness of the models can be improved and enhanced over time as more data becomes available and the state of the art of behavioral modeling itself continues to improve. However, the challenges in handling new behavioral models in existing model platforms arise from the need to incorporate attribute values in the choice models (e.g., in the utility functions or generalized costs) that themselves depend on the collective choices of the users or that require finding certain paths in the network that satisfy properties that require entirely new path-finding algorithms.

- There exists a good range of modeling frameworks and tools to incorporate user choices in the analysis and evaluation of many interventions aimed at improving operations and enhancing the sustainability of our transportation systems. This study successfully illustrated several of these tools in connection with both short-, medium-, and longer-term interventions.

- Not surprisingly, the reliability of the tools is greater for shorter-term and operational planning interventions, as fewer choice dimensions are involved in a primary manner, and base conditions are known. However, as the time horizon increases, the ability of tools to help forecast the impact of different policies diminishes, as many other factors and inputs are changing as well. The dilemma that modelers face in this situation is between seeking to capture the myriad complexities and interactions that exist at the micro level or seeking simpler models and structures that are allow the modeler to better grasp and convey key trade-offs in the contemplated policy choices.

- While powerful modeling and simulation frameworks were demonstrated, the available data and observational bases to calibrate and gain confidence in these tools are inadequate. This is especially true with regard to understanding and modeling the dynamics of individual choices in congested systems that are subject to disruptions, variability, or dynamic control strategies such as pricing and real-time information. No other field of scientific investigation has underinvested to this degree, in relative terms to the costs of the projects, programs and societal costs in observing and measuring how people use the systems that are built and designed. It is imperative that all demonstration projects of connected vehicles, DMAs, advanced system management, etc. include a behavioral study component that is accorded the same level of importance as the technological and engineering features of the projects and is integrated in the very design of the program rather than added as an afterthought.

- There is widespread recognition that new technologies are enabling, and will do so to an even greater degree in the future, new ways to measure and track individual choices. While this goes a long way toward observing actual choices, it is important to recognize that such data would not be sufficient to develop useful behavioral models. The latter require context, and a more complete characterization of the alternatives available to the individual. Therefore, one should not become complacent in this regard and assume that cell phones will capture and convey all the information needed to develop behavioral models. Nonetheless, the transportation domain is seriously lagging other domains when it comes to mining and leveraging the very vast data that are accumulating through such non-traditional sources, such as cell phones, Internet transactions, as well as video images of the transportation system itself (e.g., at train stations and on many highways and intersections).

- New technologies (e.g., smart applications or innovative technologies for collecting traveler behavior) can help, but there are caveats. There is a need to incorporate personal surveys to query respondents on their motivations, intentions, and willingness to change behavior as well as to track actual behavior into management and infrastructure projects. Such surveys can be incorporated together with new technologies that track users anonymous to enhance such data with more behavioral richness.

- New transportation measures and technology-facilitated system operational interventions create new situations that may not yet have real-world counterparts. As a result, there may not be opportunities to observe traveler behavioral responses to such interventions. Furthermore, a real-world demonstration project can generally only implement one particular version among several completing designs. Laboratory experiments have traditionally been proposed as an approach to learn about user behavior in controlled settings, and, in fact, such experiments conducted in the past three decades have provided much of the knowledge gained about the dynamics of route and departure time choice behavior of users. Improvements in simulated worlds and gaming technology provide an entirely new level of possibilities to learn about user behavior in a variety of environments under different types of interventions. This remains a largely untapped and promising arena for travel behavior research aimed at understanding user choices.

- No matter how rich and complete models are, the behavior of users will remain a moving target for many interventions. People by nature adapt and change due to external factors (i.e., the economy, lifestyles, shifting preferences, etc.) as well as factors internal to the transportation system, including the kinds of dynamically changing interventions motivating the present study (e.g., information, prices, controls, etc.). While modeling the mechanisms underlying such behavioral adaptation remains an important part of the research agenda for the travel behavior community, it is important to recognize such adaptation and evolution in the very design of the interventions. This calls for a new paradigm in designing and implementing interventions in which learning about user behavior becomes an integral element of the system, and adapting and fine-tuning the policies are considered by design.

Next Steps

In terms of next steps for advancing the underlying body of knowledge and toolkit available to understand and represent traveler choice behavior in simulation and analysis tools, the priority and opportunity areas identified by the expert panels convened in the first phase of this study provide a blueprint for a research agenda for the field.

In terms of capturing and modeling behavioral phenomena, the following items are important in terms of addressing critical knowledge gaps and are particularly relevant from the standpoint of the interventions of interest while being amenable to significant practical advances:

- Inertia, habit formation, and attitudes.

- Mechanisms, operating at the cognitive level that govern information processing, communication, and other phenomena that affect an individual's propensity for behavior change (e.g., toward more sustainable practices (especially relevant to AERIS)).

- Learning and dynamics, especially in response to information from multiple sources, including social networks as well as experience in a variety of contexts.

- Evolutionary responses from short-term adjustments to long-term patterns.

With regard to methods for studying and modeling behavior, the following items are of importance:

- Available methods for model development and specification have seen considerable advances; however, practice is lagging behind theory and methodological developments.

- Existing methods have not been tested with big data yet. Most methods, especially the more sophisticated ones, are still applied to smaller scale samples and surveys, not massive volumes of transaction data or fine-grained geo- and time-referenced data.

- Other fields (e.g., marketing) have seen a transition toward a new generation of more automated methods (e.g., data mining) aimed at extracting knowledge and prediction from large datasets. As transaction data from fare cards, social media, tracking devices, etc. become commonplace, the travel behavior field needs to broaden its range of tools.

APPENDIX. COMPLETE LIST OF EXAMINED VARIABLES FOR NON-NETWORK MODEL

This appendix provides definitions for all examined variables in the non-network model.

Table 31. Variables and their definitions.

Variable	Definition
Trip ID	Unique ID for each recorded trip
SAMPN	Unique household ID
PERNO	Person ID within a household
PLANO	Trip plan ID for each person
MODE	Chosen trip mode 1. Walk 2. Bike 3. Auto/van/truck driver 4. Auto/van/truck passenger 5. CTA bus 6. CTA train 7. PACE bus 8. Metra train/South Shore Railroad 9. Private shuttle bus 10. Dial a ride/para-transit 11. Taxi 12. Local transit (NIRPC region) 97. Other, specify 98. Don't know 99. Refused
DISTANCE	Trip distance.
auto_cost	Traveling cost by auto.
bus_cost	Traveling cost by bus (CTA and Pace).
cta_rail_cost	Traveling cost by CTA.
metra_cost	Traveling cost by Metra.
walk_cost	Traveling cost by walking (assumed to be zero).
bike_cost	Traveling cost by biking (assumed to be zero).
auto_tt	If auto is the chosen mode, then auto_tt = reported travel time in the survey. Otherwise, auto_tt is obtained from time-dependent origin-destination travel times estimated by a DTA model (DYNASMART).
bus_tt	If bus (either CTA or PACE) is the chosen mode, the bus_tt = reported travel time in the survey. Otherwise, bus_tt is estimated using an average bus speed obtained from the Household Travel Survey.

cta_rail_tt	If CTA train is the chosen mode, the cta_rail_tt = reported travel time in the survey. Otherwise, cta_rail_tt is estimated using an average CTA train speed obtained from the Household Travel Survey.
metra_tt	If Metra is the chosen mode, the metra_tt = reported travel time in the survey. Otherwise, metra_tt is estimated using an average Metra speed obtained from the Household Travel Survey.
walk_tt	If walking is the chosen mode, the walk_tt = reported travel time in the survey. Otherwise, walk_tt is estimated using an average walking speed obtained from the Household Travel Survey.
bike_tt	If biking is the chosen mode, the bike_tt = reported travel time in the survey. Otherwise, bike_tt is estimated using an average biking speed obtained from the Household Travel Survey.
dep_hour	Departure time from origin (hour).
dep_minute	Departure time from origin (minute).
arr_hour	Arrival time at destination (hour).
arr_minute	Arrival time at destination (minute).
act_dur	Activity duration (minute).
or_loc	Origin location ID (approximate).
or_zone07	Origin TAZ (consistent with CMAP and DYNASMART zoning).
des_loc	Destination location ID (approximate).
des_zone07	Destination TAZ (consistent with CMAP and DYNASMART zoning).
OR_GN_PURP	Origin purpose: • Home. • Work. • School. • Other.
DES_GN_PURP	Destination purpose: • Home. • Work. • School. • Other.
purpose	Trip purpose: • HBW. • HBSch. • HBO. • NHB.

Income_level	Household annual income: 1. Less than $20,000. 2. $20,000–$34,999. 3. $35,000–49,999. 4. $50,000–$59,999. 5. $60,000–$74,999. 6. $75,000–$99,999. 7. More than $100,000. 9. Refused.
Income	Household annual income (a value from the associated bin is randomly drawn and assigned).
AGE	Age of the traveler.
DISAB	Dummy variable for disability status of the traveler: 1. Disabled. 2. Not disabled.
HHVEH	Number of vehicles in the household.
HHSIZE	Number of persons in the household.
HHWRK	Number of workers in the household.
O_MixDiversity1Mile	Land use mix diversity index at origin (see figure 17). The mix diversity index is zero if land use is completely homogenous with only one class. The mix diversity index is one if land use is fully mixed with equal proportion of all included land use classes.
O_MixDiversity0.5Mile	Land use mix diversity index at origin (0.5-mi circle)
O_MixDiversity0.25Mile	Land use mix diversity index at origin (0.25-mi circle)
O_ResComm0.25Mile	Dummy variable for mixed use development at origin (residential + commercial) for 0.25-mi circle (1 = mixed use developed, 0 = not mixed use developed).
O_ResCommInst0.25Mile	Dummy variable for mixed use development at origin (residential + commercial + institutional) for 0.25-mi circle (1 = mixed use developed, 0 = not mixed use developed).
O_ResCommInstInds0.25Mile	Dummy variable for mixed use development at origin (residential + commercial + institutional + industrial) for 0.25-mi circle (1 = mixed use developed, 0 = not mixed use developed).
O_ResComm0. 5Mile	Dummy variable for mixed use development at origin (residential + commercial) for 0.5-mi circle (1 = mixed use developed, 0 = not mixed use developed).
O_ResCommInst0.5Mile	Dummy variable for mixed use development at origin (residential + commercial + institutional) for 0. 5-mi circle (1 = mixed use developed, 0 = not mixed use developed).
O_ResCommInstInds0.5Mile	Dummy variable for mixed use development at origin (residential + commercial + institutional + industrial) for 0.5-mi circle (1 = mixed use developed, 0 = not mixed use developed).

O_ResComm1Mile	Dummy variable for mixed use development at origin (residential + commercial) for 1-mi circle (1 = mixed use developed, 0 = not mixed use developed).
O_ResCommInst1Mile	Dummy variable for mixed use development at origin (residential + commercial + institutional) for 1-mi circle (1 = mixed use developed, 0 = not mixed use developed).
O_ResCommInstInds1Mile	Dummy variable for mixed use development at origin (residential + commercial + institutional + industrial) for 1-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_MixDiversity1Mile	Land use mix diversity index at destination (1-mi circle).
O_MixDiversity0.5Mile	Land use mix diversity index at destination (0.5-mi circle).
O_MixDiversity0.25Mile	Land use mix diversity index at destination (0.25-mi circle).
D_ResComm0.25Mile	Dummy variable for mixed use development at destination (residential + commercial) for 0.25-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_ResCommInst0.25Mile	Dummy variable for mixed use development at destination (residential + commercial + institutional) for 0.25-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_ResCommInstInds0.25Mile	Dummy variable for mixed use development at destination (residential + commercial + institutional + industrial) for 0.25-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_ResComm0. 5Mile	Dummy variable for mixed use development at destination (residential + commercial) for 0.5-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_ResCommInst0.5Mile	Dummy variable for mixed use development at destination (residential + commercial + institutional) for 0. 5-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_ResCommInstInds0.5Mile	Dummy variable for mixed use development at destination (residential + commercial + institutional + industrial) for 0.5-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_ResComm1Mile	Dummy variable for mixed use development at destination (residential + commercial) for 1-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_ResCommInst1Mile	Dummy variable for mixed use development at destination (residential + commercial + institutional) for 1-mi circle (1 = mixed use developed, 0 = not mixed use developed).
D_ResCommInstInds1Mile	Dummy variable for mixed use development at destination (residential + commercial + institutional + industrial) for 1-mi circle (1 = mixed use developed, 0 = not mixed use developed).
O_Walk_score	Walk score at origin.
O_Transit_score	Transit score at origin.
D_Walk_score	Walk score at destination.

D_Transit_score	Transit score at destination.
O_CTA_train_0.25	Dummy variable for CTA train accessibility at origin (1 = transit accessible, 0 =not transit accessible) for 0.25-mi circle.
O_CTA_train_0.5	Dummy variable for CTA train accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.5-mi circle.
O_CTA_train_0.75	Dummy variable for CTA train accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.75-mi circle.
O_CTA_train_1	Dummy variable for CTA train accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 1-mi circle.
O_CTA_bus_0.25	Dummy variable for CTA bus accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.25-mi circle.
O_CTA_bus_0.5	Dummy variable for CTA bus accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.5-mi circle.
O_CTA_bus_0.75	Dummy variable for CTA bus accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.75-mi circle.
O_CTA_bus_1	Dummy variable for CTA bus accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 1-mi circle.
O_CTA_Metra_0.25	Dummy variable for Metra accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.25-mi circle.
O_CTA_ Metra _0.5	Dummy variable for Metra accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.5-mi circle.
O_CTA_ Metra _0.75	Dummy variable for Metra accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.75-mi circle.
O_CTA_ Metra _1	Dummy variable for Metra accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 1-mi circle.
O_CTA_Pace_0.25	Dummy variable for Pace accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.25-mi circle.
O_CTA_ Pace _0.5	Dummy variable for Pace accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.5-mi circle.
O_CTA_ Pace _0.75	Dummy variable for Pace accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 0.75-mi circle.
O_CTA_ Pace _1	Dummy variable for Pace accessibility at origin (1 = transit accessible, 0 = not transit accessible) for 1-mi circle.
D_CTA_train_0.25	Dummy variable for CTA train accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.25-mi circle.
D_CTA_train_0.5	Dummy variable for CTA train accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.5-mi circle.
D_CTA_train_0.75	Dummy variable for CTA train accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.75-mi circle.
D_CTA_train_1	Dummy variable for CTA train accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 1-mi circle.

D_CTA_bus_0.25	Dummy variable for CTA bus accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.25-mi circle.
D_CTA_bus_0.5	Dummy variable for CTA bus accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.5-mi circle.
D_CTA_bus_0.75	Dummy variable for CTA bus accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.75-mi circle.
D_CTA_bus_1	Dummy variable for CTA bus accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 1-mi circle.
D_CTA_Metra_0.25	Dummy variable for Metra accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.25-mi circle.
D_CTA_ Metra _0.5	Dummy variable for Metra accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.5-mi circle.
D_CTA_ Metra _0.75	Dummy variable for Metra accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.75-mi circle.
D_CTA_ Metra _1	Dummy variable for Metra accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 1-mi circle.
D_CTA_Pace_0.25	Dummy variable for Pace accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.25-mi circle.
D_CTA_ Pace _0.5	Dummy variable for Pace accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.5-mi circle.
D_CTA_ Pace _0.75	Dummy variable for Pace accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 0.75-mi circle.
D_CTA_ Pace _1	Dummy variable for Pace accessibility at destination (1 = transit accessible, 0 = not transit accessible) for 1-mi circle.
O_Violent_0_25	Number of violent crimes occurring from 2005–2008 in the 0.25-mi radius of the origin latitude and longitude.
O_Violent_0_50	Number of violent crimes occurring from 2005–2008 in the 0.50-mi radius of the origin latitude and longitude.
O_Violent_0_75	Number of violent crimes occurring from 2005–2008 in the 0.75-mi radius of the origin latitude and longitude.
O_Violent_1	Number of violent crimes occurring from 2005–2008 in the 1-mi radius of the origin latitude and longitude.
O_Index_0_25	Number of index crimes occurring from 2005–2008 in the 0.25-mi radius of the origin latitude and longitude.
O_Index_0_50	Ibid., 0.50-mi radius.
O_Index_0_75	Ibid., 0.75-mi radius.
O_Index_1	Ibid., 1-mi radius.
O_NonIndex_0_25	Number of non-index crimes occurring from 2005–2008 in the 0.25-mi radius of the origin latitude and longitude.
O_NonIndex_0_50	Ibid., 0.50-mi radius.
O_NonIndex_0_75	Ibid., 0.75-mi radius.

O_NonIndex_1	Ibid., 1-mi radius.
O_IndexTransit_0_25	Number of index crimes occurring from 2005–2008 at transit stations/shelters in the 0.25-mi radius of the origin latitude and longitude.
O_IndexTransit_0_5	Ibid., 0.50-mi radius.
O_IndexTransit_0_75	Ibid., 0.75-mi radius.
O_IndexTransit_1	Ibid., 1-mi radius.
O_Prop_0_25	Number of property crimes occurring from 2005–2008 in the 0.25-mi radius of the origin latitude and longitude.
O_Prop_0_5	Ibid., 0.50-mi radius.
O_Prop_0_75	Ibid., 0.75-mi radius.
O_Prop_1	Ibid., 1-mi radius.
D_Violent_0_25	Number of violent crimes occurring from 2005–2008 in the 0.25-mi radius of the destination latitude and longitude.
D_Violent_0_50	Number of violent crimes occurring from 2005–2008 in the 0.50-mi radius of the destination latitude and longitude.
D_Violent_0_75	Number of violent crimes occurring from 2005–2008 in the 0.75-mi radius of the destination latitude and longitude.
D_Violent_1	Number of violent crimes occurring from 2005–2008 in the 1-mi radius of the destination latitude and longitude.
D_Index_0_25	Number of index crimes occurring from 2005–2008 in the 0.25-mi radius of the destination latitude and longitude.
D_Index_0_50	Ibid., 0.50-mi radius.
D_Index_0_75	Ibid., 0.75-mi radius.
D_Index_1	Ibid., 1-mi radius.
D_NonIndex_0_25	Number of non-index crimes occurring from 2005–2008 in the 0.25-mi radius of the destination latitude and longitude.
D_NonIndex_0_50	Ibid., 0.50-mi radius.
D_NonIndex_0_75	Ibid., 0.75-mi radius.
D_NonIndex_1	Ibid., 1-mi radius.
D_IndexTransit_0_25	Number of index crimes occurring from 2005–2008 at transit stations/shelters in the 0.25-mi radius of the destination latitude and longitude.
D_IndexTransit_0_5	Ibid., 0.50-mi radius.
D_IndexTransit_0_75	Ibid., 0.75-mi radius.
D_IndexTransit_1	Ibid., 1-mi radius.
D_Prop_0_25	Number of property crimes occurring from 2005–2008 in the 0.25-mi radius of the destination latitude and longitude
D_Prop_0_5	Ibid., 0.50-mi radius.
D_Prop_0_75	Ibid., 0.75-mi radius.
D_Prop_1	Ibid., 1-mi radius.
OR_Housing_1	Number of housing units at origin (1-mi circle).
OR_Pop_1	Population (head counts) at origin (1-mi circle).
OR_Jobs_1	Number of jobs at origin (1-mi circle).

OR_Area_1	Associated area at origin (1-mi circle). This area is slightly different from the area of a perfect circle because it is the sum of the areas of the census tracts located within the circle.
DES_Housing_1	Number of housing units at destination (1-mi circle).
DES_Pop_1	Population (head counts) at destination (1-mi circle).
DES_Jobs_1	Number of jobs at destination (1-mi circle).
DES_Area_1	Associated area at destination (1-mi circle).
OR_Housing_0.75	Number of housing units at origin (0.75-mi circle).
OR_Pop_0.75	Population (head counts) at origin (0.75-mi circle).
OR_Jobs_0.75	Number of jobs at origin (0.75-mi circle).
OR_Area_0.75	Associated area at origin (0.75-mi circle).
DES_Housing_0.75	Number of housing units at destination (0.75-mi circle).
DES_Pop_0.75	Population (head counts) at destination (0.75-mi circle).
DES_Jobs_0.75	Number of jobs at destination (0.75-mi circle).
DES_Area_0.75	Associated area at destination (0.75-mi circle).
OR_Housing_0.5	Number of housing units at origin (0.5-mi circle).
OR_Pop_0.5	Population (head counts) at origin (0.5-mi circle).
OR_Jobs_0.5	Number of jobs at origin (0.5-mi circle).
OR_Area_0.5	Associated area at origin (0.5-mi circle).
DES_Housing_0.5	Number of housing units at destination (0.5-mi circle).
DES_Pop_0.5	Population (head counts) at destination (0.5-mi circle).
DES_Jobs_0.5	Number of jobs at destination (0.5-mi circle).
DES_Area_0.5	Associated area at destination (0.5-mi circle).
OR_Housing_0.25	Number of housing units at origin (0.25-mi circle).
OR_Pop_0.25	Population (head counts) at origin (0.25-mi circle).
OR_Jobs_0.25	Number of jobs at origin (0.25-mi circle).
OR_Area_0.25	Associated area at origin (0.25-mi circle).
DES_Housing_0.25	Number of housing units at destination (0.25-mi circle).
DES_Pop_0.25	Population (head counts) at destination (0.25-mi circle).
DES_Jobs_0.25	Number of jobs at destination (0.25-mi circle).
DES_Area_0.25	Associated area at destination (0.25-mi circle).
Bike	Number of bicycles in the households.
travel_time_index	Travel time index equals actual travel time divided by free-flow travel time. Free-flow travel times are obtained from a DTA Model (DYNASMART) and actual travel time is the "auto_tt."
DTA_travel_time_index	DTA travel time index equals DTA travel time divided by free-flow travel time. Free-flow travel times and DTA travel times are both obtained from a DTA Model (DYNASMART).
OR_PopDensity_1	Population density at origin (1-mi circle).
OR_JobDensity_1	Job density at origin (1-mi circle).
DES_PopDensity_1	Population density at destination (1-mi circle).
DES_JobDensity_1	Job density at destination (1-mi circle).
OR_PopDensity_0.75	Population density at origin (0.75-mi circle).
OR_JobDensity_0.75	Job density at origin (0.75-mi circle).
DES_PopDensity_0.75	Population density at destination (0.75-mi circle).

DES_JobDensity_0.75	Job density at destination (0.75-mi circle).
OR_PopDensity_0.5	Population density at origin (0.5-mi circle).
OR_JobDensity_0.5	Job density at origin (0.5-mi circle).
DES_PopDensity_0.5	Population density at destination (0.5-mi circle).
DES_JobDensity_0.5	Job density at destination (0.5-mi circle).
OR_PopDensity_0.25	Population density at origin (0.25-mi circle).
OR_JobDensity_0.25	Job density at origin (0.25-mi circle).
DES_PopDensity_0.25	Population density at destination (0.25-mi circle).
DES_JobDensity_0.25	Job density at destination (0.25-mi circle).

ACKNOWLEDGMENTS

The study team would like to acknowledge the many individuals who have enthusiastically supported this study with their time, effort, and comments and substantially contributed to its success. We are especially grateful to Taylor Lochrane and David Yang of USDOT for their leadership in defining and guiding the study and facilitating many contacts with local and State agencies. We are also grateful to all the participants at the traveler behavior workshop held at Northwestern University in November 2011, including the following people:

- Kevin J. Krizek.
- Joan Walker.
- Ram Pendyala.
- Cinzia Cirillo.
- Elisabetta Cherchi.
- Maren Outwater.
- Thomas F. Rossi.
- Bran don Nevers.
- Joe Story.
- Xioaping Zhang.
- Michael Lawrence.
- Lewison Lem.
- Kermit Wies.
- Erik Sabina.
- Becky Knudson.
- David Yang.
- Joe Peters.
- Eric Pihl.
- Supin Yoder.
- Frank Koppelman.
- David Boyce.
- Omer Verbas.

The authors remain solely responsible for all work, findings, conclusions, and recommendations presented in this report.

REFERENCES

1. Raphael, S. and Rice, L. (2002). "Car Ownership, Employment, and Earnings," *Journal of Urban Economics 52*(1), 109–130.

2. Hiscock, R., Macintyre, S., Kearns, A., and Ellaway, A. (2002). "Means of Transport and Ontological Security: Do Cars Provide Psycho-Social Benefits to Their Users?" *Transportation Research Part D: Transport and Environment*, *7*(2), 119–135.

3. Cullinane, S. (2002). "The Relationship Between Car Ownership and Public Transport Provision: A Case Study of Hong Kong," *Transport Policy*, *9*(1), 29–39.

4. Fujii, S. and Kitamura, R. (2000). "Evaluation of Trip-Inducing Effects of New Freeways Using a Structural Equations Model System of Commuters' Time Use and Travel," *Transportation Research Part B*, *34*, 339–354.

5. Handy, S. (2002). "Travel Behaviour-Land Use Interactions: An Overview and Assessment of the Research," in Hani S. Mahmassani (ed.), *In Perpetual Motion: Travel Behavior Research Opportunities and Application Challenges*, Pergamon Press, Oxford, UK.

6. Holtzclaw, J., Clear, R., Dittmar, H., Goldstein, D., and Haas, P. (2002) "Location Efficiency: Neighborhood and Socio-Economic Characteristics Determine Auto Ownership and Use—Studies in Chicago, Los Angeles, and San Francisco," *Transportation Planning and Technology*, *25*(1), 1–27.

7. Lund, H. (2006). "Reasons for Living in a Transit Oriented Development, and Associated Transit Use," *Journal of the American Planning Association*, *72*(3), 357–366.

8. Cao, X., Mokhtarian, P.L., and Handy, S. (2009) "Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings," *Transport Reviews*, *29*(3), 359–395.

9. Mokhtarian, P. and Cao, X. (2008). "Examining the Impacts of Residential Self-Selection on Travel Behavior: A Focus on Methodologies," *Transportation Research Part B*, *42*(3), 204–228.

10. Zhou, B. and Kockelman, K. (2008) "Self-Selection in Home Choice: Use of Treatment Effects in Evaluating the Relationship Between the Built Environment and Travel Behavior," *Transportation Research Record 2077*, 106–112, Transportation Research Board, Washington, DC.

11. Frank, L., Saelens, B., Powell, K.E., and Chapman, J.E. (2007). "Stepping Towards Causation: Do Built Environments or Neighborhood and Travel Preferences Explain Physical Activity, Driving, and Obesity?" *Social Sciences and Medicine*, *65*(9), 1898–1914.

12. Bento, A., Cropper, M., Mobarak, A., and Vinha, K. (2005). "The Effects of Urban Spatial Structure on Travel Demand in the United States," *The Review of Economics and Statistics*, *87*(3), 466–478.

13. Aditjandra, P.T., Cao, X., and Mulley, C. (2012). "Understating Neighbourhood Design Impact on Travel Behavior: An Application of Structural Equations Model to a British Metropolitan Data," *Transportation Research Part A*, *46*, 22–32.

14. Cao, X., Mokhtarian, P.L., and Handy, S. (2007). "Do Changes in Neighborhood Characteristics Lead to Changes in Travel Behavior? A Structural Equations Modeling Approach," *Transportation*, *34*(5), 535–556.

15. Newbold, K.B., Scott, D., Spinney, J.E.L., Kanaroglou, P., and Paez, A. (2005). "Travel Behavior Within Canada's Older Population: A Cohort Analysis," *Journal of Transport Geography*, *13*(4), 340–351.

16. Polk, M. (2003). "Are Women Potentially More Accommodating than Men to a Sustainable Transportation System in Sweden?" *Transportation Research Part D: Transport and Environment*, *8*(2), 75–95.

17. Polk, M. (2004). "The Influence of Gender on Daily Car Use and on Willingness to Reduce Car Use in Sweden," *Journal of Transport Geography*, *12*(3), 185–195.

18. Moriarty, P. and Honnery, D. (2005). "Determinants of Urban Travel in Australia," *Proceedings of the 28th Australasian Transport Research Forum (ATRF)*. Sydney, Australia.

19. Best, H. and Lanzendorf, M. (2005). "Division of Labour and Gender Differences in Metropolitan Car Use: An Empirical Study in Cologne, Germany," *Journal of Transport Geography*, *13*(2), 109–121.

20. Ryley, T. (2005). "Use of Non-Motorised Modes and Life Stage in Edinburgh," *Journal of Transport Geography*, *14*(5), 367–375.

21. Dieleman, F.M., Dijst, M., and Burghouwt, G. (2002). "Urban Form and Travel Behaviour: Micro-level Household Attributes and Residential Context," *Urban Studies*, *39*(3), 507–527.

22. Giuliano, G. (2003). "Travel, Location and Race/Ethnicity," *Transportation Research Part A: Policy and Practice*, *37*(4), 351–372.

23. Giuliano, G. and Narayan, D. (2003). "Another Look at Travel Patterns and Urban Form: The U.S. and Great Britain," *Urban Studies*, *11*(40), 2295–2312.

24. Giuliano, G. and Dargay, J. (2006). "Car Ownership, Travel and Land Use: A Comparison of the U.S. and Great Britain," *Transportation Research Part A: Policy and Practice*, *40*(2), 106–124.

25. Bomberg, M. and Kockelman, K. (2011). "Traveler Response to the 2005 Gas Price Spike," in B. Mendex and J. Pena (eds.), *Household Energy: Economics, Consumption and Efficiency*, NOVA Science Publishers, Inc, Hauppauge, NY.

26. Boarnet, M. and Crane, R. (2001). "The Influence of Land Use on Travel Behavior: Specification and Estimation Strategies," *Transportation Research Part A: Policy and Practice*, *35*(9), 823–845.

27. TCRP. (2004). *Traveler Response to Transportation System Changes, Chapter 13: Parking Pricing and Fees*, Transit Cooperative Research Program. Obtained from: http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rpt_95c13.pdf.

28. TCRP. (2003). *Traveler Response to Transportation System Changes, Chapter 18: Parking Management and Supply*. Obtained from: http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rpt_95c18.pdf.

29. Schlich, R. and Axhausen, K.W. (2003). "Habitual Travel Behaviour: Evidence from a Six-Week Travel Diary," *Transportation*, *30*(1), 13–36.

30. Cherchi, E. and Manca, F. (2011). "Accounting for Inertia in Modal Choices: Some New Evidence Using a RP/SP Dataset," *Transportation*, *38*(4), 679–695.

31. Chorus, C.G., Molin, E.J.E., Van Wee, B., Arentze, T.A., and Timmermans, H.J.P. (2006). "Responses to Transit Information Among Car-Drivers: Regret-Based Models and Simulations," *Transportation Planning and Technology*, *29*(4), 249–271.

32. Srinivasan, K.K. and Mahmassani, H.S. (2000). "Modeling Inertia and Compliance Mechanisms in Route Choice Behavior Under Real-Time Information," *Transportation Research Record 1725*, 45–53, Transportation Research Board, Washington, DC.

33. Jan, O., Horowitz, A.J., and Peng, Z.R. (2000). "Using Global Positioning System Data to Understand Variations in Path Choice," *Transportation Research Record 1725*, 37–44, Transportation Research Board, Washington, DC.

34. Antonisse, R.W., Daly, A.J., and Ben-Akiva, M. (1989). "Highway Assignment Method Based on Behavioral Models of Car Drivers' Route Choice," *Transportation Research Record 1220*, 1–11, Transportation Research Board, Washington, DC.

35. Abdel-Aty, M.A., Jovanis, P.P., and Kitamura, R. (1996). "The Impact of Advanced Transit Information on Commuters' Mode Changing," *Journal of Intelligent Transportation Systems*, *3*(2), 129–146.

36. Mahmassani, H.S. and Stephan, D.G. (1988). "Experimental Investigation of Route and Departure Time Choice Dynamics of Urban Commuters," *Transportation Research Record 1203*, 69–84, Transportation Research Board, Washington, DC.

37. Polydoropoulou, A., Ben-Akiva, M., and Kaysi, I. (1994). "Influence of Traffic Information on Drivers' Route Choice Behavior," *Transportation Research Record 1453*, 56–65, Transportation Research Board, Washington, DC.

38. Khattak, A.J., Schofer, J.L., and Wang, M.H. (1995). "A Simple Time Sequential Procedure for Predicting Freeway Incident Duration," *Journal of Intelligent Transportation Systems*, *2*(2), 113–138.

39. Srinivasan, K.K. and Mahmassani, H.S. (2002). *Dynamic Decision and Adjustment Processes in Commuter Behavior Under Real-Time Information*, Report No. SWUTC/02/167204-1, Southwest University Regional Center, University of Texas, Austin, TX.

40. Mahmassani, H.S. and Herman, R. (1990). "Interactive Experiments for the Study of Trip Maker Behaviour Dynamics in Congested Commuting Systems," *Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, 272–298, Gower, Aldershot, England.

41. Mahmassani, H.S. (1997). "Dynamics of Commuter Behaviour: Recent Research and Continuing Challenges," *Understanding Travel Behaviour in an Era of Change*, 279–313.

42. Avineri, E. and Prashkey, J.N. (2005). "Sensitivity to Travel Time Variability: Travelers' Learning Perspective," *Transportation Research Part C*, *13*, 157–183.

43. Avineri, E. and Prashker, J.N. (2006). "The Impact of Travel Time Information on Travelers' Learning Under Uncertainty," *Transportation*, *33*, 393–408.

44. Kraan, M., Mahmassani, H., and Huynh, N. (2000). "Traveler Responses to Advanced Traveler Information Systems for Shopping Trips: Interactive Survey Approach," *Transportation Research Record 1725*, (1), 116–123, Transportation Research Board, Washington, DC.

45. Hensher, D.A. and King, J. (2001). "Parking Demand and Responsiveness to Supply, Pricing and Location in the Sydney Central Business District," *Transportation Research Part A: Policy and Practice*, *35*(3), 177–196.

46. Handy, S., Weston, L., and Mokhtarian, P.L. (2005). "Driving by Choice or Necessity?" *Transportation Research Part A: Policy and Practice Positive Utility of Travel*, *39*(2–3), 183–203.

47. Puget Sound Regional Council. (2008). *Travel Choices Study: Summary Report*, Seattle, WA. Obtained from: http://www.psrc.org/projects/trafficchoices/summaryreport.pdf.

48. Gupta, S. and Kockelman, K. (2006). "Road Pricing Simulations: Traffic, Land Use, and Welfare Impacts for Austin, Texas," *Transportation Planning & Technology*, *29*(1), 1–23.

49. Gulipalli, S. and Kockelman, K. (2008). "Credit-Based Congestion Pricing: A Dallas-Fort Worth Application," *Transport Policy*," *15*(1), 23–32.

50. Saleh, W. and Farrell, S. (2005). “Implications of Congestion Charging for Departure Time Choice: Work and Non-Work Schedule Flexibility,” *Transportation Research Part A*, *39*, 773–791.

51. TCRP. (2006). *Traveler Response to Transportation System Changes, Chapter 2: HOV Facilities*. Obtained from: http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rpt_95c2.pdf. Site last accessed December 1, 2011.

52. Cervero, R. and Kockelman, K. (1998). “Travel Demand and the 3Ds: Density, Diversity, and Design,” *Transportation Research Part D*, *2*(3), 199–219.

53. Soltani, A. and Primerano, F. (2005). “The Effects of Community Design,” *Proceedings of the 28th Australasian Transport Research Forum (ATRF)*, Sydney, Australia.

54. Naess, P. (2003). “Urban Structures and Travel Behaviour—Experiences from Empirical Research in Norway and Denmark,” *European Journal of Transport and Infrastructure Research*, *3*(2), 155–178.

55. Naess, P. and Jensen, O. (2004). “Urban Structure Matters, Even in a Small Town,” *Journal of Environmental Planning and Management*, *47*(1), 35–57.

56. Cervero, R. (2002). “Built Environments and Mode Choice: Toward a Normative Framework,” *Transportation Research Part D: Transport and Environment*, *7*(4), 265–284.

57. Gärling, T. and Axhausen, K.W. (2003). “Introduction: Habitual Travel Choice,” *Transportation*, *30*(1), 1–11.

58. Mahmassani, H.S. and Chang, G.L. (1986). “Experiments with Departure Time Choice Dynamics of Urban Commuters,” *Transportation Research Part B: Methodological*, *4*(20), 297–320.

59. Bayarma, A., Kitamura, R., and Susilo, Y.O. (2007). “Recurrence of Daily Travel Patterns: Stochastic Process Approach to Multiday Travel Behavior,” *Transportation Research Record 2021*, 55–63, Transportation Research Board, Washington, DC.

60. Charles River Associates. (1978). *On the Development of a Theory of Traveler Attitude-Behavior Interrelationships, Vol III: Executive Summary: Overview of Methods, Results, and Conclusions*, U.S. Department of Transportation, Washington, DC.

61. Bamberg, S. (2000). “The Promotion of New Behavior by Forming an Implementation Intention: Results of a Field Experiment in the Domain of Travel Mode Choice,” *Journal of Applied Social Psychology*, *30*(9), 1903–1922.

62. Schönfelder, S. and Axhausen, K.W. (2003). “Activity Spaces: Measures of Social Exclusion?” *Transport Policy*, *10*(4), 273–286.

63. Ortuzar, J. de D. and Willumsen, L.G. (2001). *Modelling Transport*, Wiley, Chichester, United Kingdom.

64. Simon, H. (1959). “A Behavioral Model of Rational Choice,” *Quarterly Journal of Economics*, *69*, 99–118.

65. Mahmassani, H.S. and Chang, G.L. (1987). “On Boundedly Rational User Equilibrium in Transportation Systems,” *Transportation Science*, *21*(2), 89–99.

66. Sheehan, R. (2010). *The Future of Transportation: Smart Cars/Smart Roads*, Presentation at the 2010 APWA Annual Congress and Exposition, Boston, MA.

67. Ewing, R. and Cervero, R. (2010). “Travel and the Built Environment: A Meta-Analysis,” *Journal of the American Planning Association*, *76*(3), 265–294.

68. Zhang, M. (2004). “The Role of Land Use in Travel Mode Choice: Evidence from Boston and Hong Kong,” *Journal of the American Planning Association*, *70*(3), 344–360.

69. Litman, T.A. (2005). *Land Use Impacts on Transport: How Land Use Factors Affect Travel Behavior*, Victoria Transport Institute, Victoria, Canada. Obtained from: http://www.vtpi.org/landtravel.pdf. Site last accessed March 5, 2014.

70. Levinson, D. (2012) *Directions for Research in Transport and Land Use*. Obtained from: http://blog.lib.umn.edu/levin031/transportationist/2012/04/directions-for-research-in-tra.html. Site last accessed March 5, 2014.

71. Boarnet, M.G. (2011). “A Broader Context for Land Use and Travel Behavior, and a Research Agenda,” *Journal of the American Planning Association*, *77*(3), 197–213.

72. Cervero, R. (1994). “Transit-Based Housing in California: Evidence on Ridership Impacts,” *Transport Policy*, *1*(3), 174–183.

73. Salon, D. (2006). *Cars and the City: An Investigation of Transportation and Residential Location Choices in New York City*, Ph.D. dissertation, Department of Agricultural and Resource Economics, University of California, Davis, Davis, CA.

74. Bhat, C.R. and Guo, J.Y. (2007). “A Comprehensive Analysis of Built Environment Characteristics on Household Residential Choice and Auto Ownership Levels,” *Transportation Research Part B*, *41*(5), 506–526.

75. Brownstone, D. and Golob, T. (2009). “The Impact of Residential Density on Vehicle Usage and Energy Consumption,” *Journal of Urban Economics*, *65*(1), 91–98.

76. Levine, J. (2006). *Zoned Out: Regulation, Markets, and Choices in Transportation and Metropolitan Land Use*, RFF Press, Washington, DC.

77. Kozuki, A.T.C.Y. and Mahmassani, H.S. (2009). *Information Acquisition and Social Interaction Mechanisms in Opinion Formation and Market Adoption of Transportation Services*, Presented at the 88th Annual Meeting of the Transportation Research Board, Washington, DC.

78. Abt SRBI. (2009). *Rider/Non-Rider Behavior and Attitudes Survey*, Final Draft Report, Chicago, IL.

79. Loukaitou-Sideris, A., Ligget, R., and Hiseki, H. (2002). *The Geography of Transit Crime: Documetation and Evaluation of Crime Incidence on and Around the Green Line Stations in Los Angeles*, Working Paper, University of California Transportation Center, Berkeley, CA.

80. Ingalls, G.L., Hartgen, D.T., and Owners, T.W. (1994). "Public Fear of Crime and its Role in Bus Transit Use," *Transportation Research Record 1433*, Transportation Research Board, Washington, DC.

81. Needle, J.A. and Cobb, R.M. (1997). "Improving Transit Security," *Transportation Research Board TCRP Synthesis 21*, Transportation Research Board, Washington, DC.

82. Painter, K. (1996). "The Influence of Street Lighting Improvements on Crime, Fear and Pedestrian Street Use, After Dark," *Landscape and Urban Planning*, *35*(2–3), 193–201.

83. (2012). *Crime Prevention through Environmental Design.* Obtained from: http://www.cpted.net/. Site last accessed March 5, 2014.

84. Loukaitou-Sideris, A. (1999). "Hot Spots of Bus Stop Crime: The Importance of Environmental Attributes," *Journal of the American Planning Association*, *65*(4), 395–411.

85. Ferrell, C.E., Mathur, S., and Mendoza, E. (2008). "Neighborhood Crime and Non-Auto Mode Choice," *Mineta Transportation Institute Report*, *7*(2), 1–119.

86. Ferrell, C.E., Mathur, S., Meek, J., and Piven, M. (2012). "Neighborhood Crime and Travel Behavior: An Investigation of the Influence of Neighborhood Crime Rates on Mode Choice—Phase 2," *Mineta Transportation Institute Report*, *11*(4), 1–114.

87. Humpel, N., Owen, N., and Leslie, E. (2002). "Environmental Factors Associated with Adults' Participation in Physical Activity: A Review," *American Journal of Preventive Medicine*, *22*(3), 188–199.

88. Kim, S., Ulfarsson, G.F., and Hennessy, J.T. (2007). "Analysis of Light Rail Rider Travel Behavior: Impacts of Individual, Built Environment, and Crime Characteristics on Transit Access," *Transportation Research Part A*, *41*(6), 511–522.

89. Smith, R., Reed, S., and Baker, S. (2010). "Street Design: Part 1—Complete Streets," *Public Roads*, *74*(1).

90. Bento, A.M., Cropper, M.L., Mobarak, A.M., and Vinha, K. (2003). "The Impact of Urban Spatial Structure on Travel Demand in the United States," *Working Paper 3007*, The World Bank, Washington, DC.

91. Ewing, R., Greenwald, M.J., Zhang, M., Walters, J., Feldman, M., Cervero, R., and Thomas, J. (2009). *Measuring the Impact of Urban Form and Transit Access on Mixed Use*

Site Trip Generation Rates—Portland Pilot Study, U.S. Environmental Protection Agency, Washington, DC.

92. Frank, L.D., Kavage, S., Greenwald, M., Chapman, J., and Bradley, M. (2009). *I-PLACE3S Health & Climate Enhancements and Their Application in King County*, King County HealthScape, Seattle, WA.

93. Kitamura, R., Mokhtarian, P.L., and Laidet, L. (1997). "A Micro-Analysis of Land Use and Travel in Five Neighborhoods in San Francisco Bay Area," *Transportation*, *24*(2), 125–158.

94. Rajamani, J., Bhat, C., Handy, S., Knaap, G., and Song, Y. (2003). "Assessing Impact of Urban Form Measures on Nonwork Trip Mode Choice After Controlling for Demographic and Level-of-Service Effects," *Transportation Research Record 1831*, 158–165, Transportation Research Board, Washington, DC.

95. Frank, L.D. and Engelke, P. (2005). "Multiple Impacts of the Built Environment on Public Health: Walkable Places and the Exposure to Air Pollution," *International Regional Science Review*, *28*(2), 193–216.

96. Hedel, R. and Vance, C. (2007). *Impact of Urban Form on Automobile Travel: Disentangling Causation from Correlation*, Presented at the 86th Annual Meeting of the Transportation Research Board, Washington, DC.

97. Naess, P. (2005). "Residential Location Affects Travel Behavior—But How and Why? The Case of Copenhagen Metropolitan Area," *Progress in Planning*, *63*(1), 167–257.

98. Pushkar, A.O., Hollingworth, B.J., and Miller, E.J. (2000). *A Multivariate Regression Model for Estimating Greenhouse Gas Emissions from Alternative Neighborhood Designs*, Presented at the 79th Annual Meeting of the Transportation Research Board, Washington, DC.

99. Cervero, R. and Murakami, J. (2010). "Effects of Built Environments on Vehicle Miles Traveled: Evidence from 370 US Urbanized Areas," *Environment and Planning A*, *42*(2), 400–418.

100. Chatman, D.G. (2009). "Residential Self-Selection, the Built-Environment, and Nonwork Travel: Evidence Using New Data and Methods," *Environment and Planning A*, *41*(5), 1072–1089.

101. Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., and Polydoropoulou, A. (2002). "Integration of Choice and Latent Variable Models," *In Perpetual Motion: Travel Behavior Opportunities and Application Challenges*, 431–470, International Association for Travel Behavior Research, Washington, DC.

102. Walk Score. (2012). W*alk Score APIs Overview*. Obtained from: http://www.WalkScore.com/professional/walk-score-apis.php. Site last accessed May 12, 2012.

103. Mahmassani, H.S., Hu, T., Peeta, S., and Ziliaskopoulos, A. (1994). *Development and Testing of Dynamic Traffic Assignment and Simulation Procedures for ATIS/ATMS Applications*, Technical Report No. DTFH61-90-R-00074-FG, Center for Transportation Research, University of Texas at Austin, Austin, TX.

104. CMAP. (2008). *Traveler Tracker Survey*, Chicago, IL. Obtained from: http://www.cmap.illinois.gov/travel-tracker-survey. Site last accessed April 1, 2013.

105. METRA. (2007). *2007 Metra Program and Budget*. Obtained from: http://metrarail.com/metra/en/home/about_metra/planning_records_reports/finance_budget.html. Site last accessed April 29, 2014.

106. Bhat, C.R. and Gossen, R. (2002). *A Mixed Multinomial Logit Model Analysis of Weekend Recreational Episode Type Choice*, Technical Report, Department of Civil Engineering, University of Texas at Austin, Austin, TX.

107. Handy, S.L., Boarnet, M.G., Ewing, R., and Killingsworth, R.E. (2002). "How the Built Environment Affects Physical Activity: Views from Urban Planning," *American Journal of Preventive Medicine*, *23*(2S), 64–73.

108. Sallis, J.R., Frank, L.D., Saelens, B.E., and Kraft, M.K. (2004). "Active Transportation and Physical Activity: Opportunities for Collaboration on Transportation and Public Health Research," *Transportation Research Part A*, *38*(4), 349–268.

109. Vautin, D. and Walker, J.L. (2011). *Transportation Impacts of Information Provision & Data Collection via Smartphones*, Presented at the 90th Annual Meeting of the Transportation Research Board, Washington, DC.

110. Taylor, T.L. (2006). *Play Between Worlds: Exploring Online Game Culture*, MIT Press, Cambridge, MA.

111. Mahmassani, H.S., Chen, R.B., Huang, Y., Williams, D., and Contractor, N. (2010). "Time to Play? Activity Engagement in Multiplayer Online Role Playing Games," *Transportation Research Record 2157*, 129–137, Transportation Research Board, Washington, DC.

112. Giuliano, G. (1998). "Information Technology, Work Pattern and Intra-Metropolitan Location: A Case Study," *Urban Studies*, *35*(7), 1077–1095.

113. Golob, T.F. and Regan, A.C. (2001). "Impact of Information Technology on Personal Travel and Commercial Vehicle Operations: Research Challenges and Opportunities," *Transportation Research C*, *9*(2), 87–121.

114. Mahmassani, H.S., Yen, J-R., Herman, R., and Sullivan, M. (1993). "Employee Attitudes and Stated Preferences Towards Telecommuting: An Exploratory Analysis," *Transportation Research Record 1413*, 31–41, Transportation Research Board, Washington, DC.

115. Mokhtarian, P.L. (2003). “Telecommunications and Travel: the Case for Complementarity,” *Journal of Industrial Ecology*, *6*(2), 43–57.

116. Mokhtarian, P.L., Collantes, G.O., and Carsten, G. (2004). “Telecommuting, Residential Location, and Commute Distance Traveled: Evidence from State of California Employees,” *Environment and Planning A*, *36*, 1879–1897.

117. DC Capital Bikeshare. (2013). Obtained from: http://www.capitalbikeshare.com/. Site last accessed April 26, 2013.

118. Department of Environmental Services. (2012). *Arlington Transportation Demand Management Strategic Plan, FY 2013–FY 2040*, Arlington, VA.

119. Co, S. (2011) *Regional Bicycle Working Group and Regional Pedestrian Committee*, San Francisco, CA. Obtained from: http://apps.mtc.ca.gov/events/agendaView.akt?p=1769. Site last accessed March 5, 2014.

120. Southern California Association of Governments. (2009). *Maximizing Mobility in Los Angeles—First and Last Mile Strategies*, Final Report, Los Angeles, CA.

121. Doyle, G.L., Liban, E.C., Goldsmith, L., Ledbetter, L., Marcelo, M., and Cooper, K.B. (2012). *Bicycle-Rail Trip Analysis and Greenhouse Gas Emissions Reduction Focused Study*, Presented at the 91st Annual Meeting of the Transportation Research Board, Washington DC.

122. Metropolitan Washington, Council of Governments. (2010). *MWCOG Bikesharing Analysis of the DC Region*. Obtained from: http://www.mwcog.org/uploads/committee-documents/bV5YWlxe20100820155649.pdf. Site last accessed March 25, 2013.

123. Bay Area Rapid Transit. (2012). *BART Bicycle Plan: Modeling Access to Transit*, Eisen/Letunic in association with Fehr and Peers and Nelson/Nygaard, San Francisco, CA.

124. Bay Area Rapid Transit. (2012). *BART Bicycle Investment Tool*, San Francisco, CA. Obtained from: http://bart.gov/guide/bikes/investment.aspx. Site last accessed March 5, 2014.

125. Flamm, B.J. (2012). “Determinants of Bicycle-on-Bus Boardings: A Case Study of the Greater Cleveland RTA,” *Journal of Public Transportation*, *16*(2).

126. Koppelman, F.S. and Pas, E.I. (1980). “Travel-Choice Behavior: Models of Perceptions, Feelings, Preference, and Choice,” *Transportation Research Record 765*, 26–33, Transportation Research Board, Washington, DC.

127. McFadden, D. (1986). “The Choice Theory Approach to Market Research,” *Marketing Science*, *5*(4), 275–297.

128. Golob, T. (2003). “Structural Equation Modeling for Travel Behavior Research,” *Transportation Research Part B: Methodological*, *37*(1), 1–25.

129. Ben-Akiva, M., McFadden, D., Garling, T., Gopinath, D., Walker, J., Bolduc, D., Boersch-Supan, A., Delquie, P., Larichev, O., Morikawa, T., Polydoropoulou, A., and Rao, V. (1999). "Extended Framework for Modeling Choice Behavior," *Marketing Letters*, *10*(3), 187–203.

130. Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D., Daly, A., de Palma, A., Gopinath, D., Karlstrom, A., and Munizaga, M.A. (2002). "Hybrid Choice Models: Progress and Challenges," *Marketing Letters*, *13*(3), 163–175.

131. Scheiner, J. and Holz-Rau, C. (2007) "Travel Mode Choice: Affected by Objective or Subjective Determinants?" *Transportation*, *34*, 487–511.

132. Van Acker, V. and Witlox, F. (2010) "Car Ownership as a Mediating Variable in Car Travel Behaviour Research Using a Structural Equation Modelling Approach to Identify its Dual Relationship," *Journal of Transport Geography*, *18*(1), 65–74.

133. Van Acker, V., Mokhtarian, P.L., and Witlox, F. (2011) "Going Soft: On How Subjective Variables Explain Modal Choices for Leisure Travel," *European Journal of Transport and Infrastructure Research*, *11*, 115–146.

134. Vredin Johansson, M., Heldt, T., and Johansson, P. (2006). "The Effects of Attitudes and Personality Traits on Mode Choice," *Transportation Research Part A: Policy and Practice*, *40*(6), 507–525.

135. Espino, R., Roman, C., and Ortuzar, J. (2006). "Analyzing Demand for Suburban Trips: A Mixed RP/SP Model with Latent Variables and Interaction Effects," *Transportation*, *33*(3), 241–261.

136. Abou-Zeid, M., Ben-Akiva, M., Bierlaire, M., Choudhury, C., and Hess, S. (2010). "Attitudes and Value of Time Heterogeneity," *Applied Transport Economics: A Management and Policy Perspective*, 523–545.

137. Rogers, E.M. (2003). *Diffusion of Innovations*, 5th Ed., Free Press, New York, NY.

138. Tversky, A. and Kahneman, D. (1974). "Judgment Under Uncertainty: Heuristics and Biases," *Science*, *185*, 1124–1131.

139. Ebbinghaus. (1913). *Memory: A Contribution to Experimental Psychology*, Columbia Univeristy, New York City, NY.

140. Talebpour, A., Mahmassani, H.S., and Hamdar, S.H. (2013). *Speed Harmonization: Effectiveness Evaluation under Congested Conditions*, Proceedings of the 92nd Annual Meeting of the Transportation Research Board, Washington, DC.

141. Wilensky, U. (1999). *NetLogo*, Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

142. Federal Highway Administration. (2012). *Concept Development and Needs Identification for Intelligent Network Flow Optimization (INFLO)—Concept of Operations Walkthrough Workbook*, U.S. Department of Transportation, Washington, DC.

143. Waller, S.T., Ng, M.W., Ferguson, E., Nezamuddin, N., and Sun, D. (2009). *Speed Harmonization and Peak-Period Shoulder Use to Manage Urban Freeway Congestion*, Report No. FHWA/TX-10/0-5913-1, Federal Highway Administration, Washington, DC.

144. Federal Highway Administration. (2012). *AERIS Transformative Concepts and Applications Descriptions*, U.S. Department of Transportation, Washington, DC.

145. Chang, G.L, Park, S.Y., and Paracha, J. (2011) "Intelligent Transportation System Field Demonstration: Integration of Variable Speed Limit Control and Travel Time Estimation for a Recurrently Congested Highway," *Transportation Research Record 2243*, 55–66, Transportation Research Board, Washington, DC.

146. Austroads. (2010). *Best Practice for Variable Speed Limits: Literature Review*, AP-R342/09, Austroads Incorporated, Sydney, Australia.

147. Fuhs, C. (2010) *Synthesis of Active Traffic Management Experiences in Europe and the United States*, Report No. FHWA-HOP-10-031, Federal Highway Administration, Washington, DC.

148. Kwon, E., Brannan, D., Shouman, K., Isackson, C., and Arseneau, B. (2007). *Field Evaluation of a Variable Advisory Speed Limit System for Reducing Traffic Conflicts at Work Zones*, Presented at the 84th Annual Meeting of the Transportation Research Board, Washington, DC.

149. Bham, G.H., Long, S., Baik, H., Ryan, T., Gentry, L., Lall, K., Arezoumandi, M., Liu, D., and Schaeffer, B. (2010). *Evaluation of Variable Speed Limits on I-270/I-255 in St. Louis*, Missouri Department of Transportation, Jefferson City, MO.

150. The United Kingdom Highway Agency. (2007). *M25 Controlled Motorway Summary Report*, Department for Transport, London, UK.

151. Talebpour, A., Mahmassani, H.S., and Kim, J. (2013) *Toward Capturing Sources of Travel Time Unreliability in Microscopic Traffic Models: Driver Heterogeneity, Flow Breakdown, and Crash Occurrence*, Proceedings of the 92nd Annual Meeting of the Transportation Research Board, Washington, DC.

152. Hegyi, A., Schutter, B.D., and Hellendoorn, J. (2005). "Optimal Coordination of Variable Speed Limits to Suppress Shock Waves," *IEEE Transactions on Intelligent Transportation Systems*, *6*(1), 167–174.

153. Hegyi, A., Hoogendoorn, S.P., Schreuder, M., Stoelhorst, H., and Viti, F. (2010). *SPECIALIST: A Dynamic Speed Limit Control Algorithm Based on Shock Wave Theory*, Proceedings of the 11th International IEEE Conference on Intelligent Transportation Systems, Madeira Island, Portugal.

154. Carlson, R.C., Papamichail, I., and Papageorgiou, M. (2011) "Local Feedback-Based Mainstream Traffic Flow Control on Motorways Using Variable Speed Limits," *IEEE Transactions of Intelligent Transportation Systems*, *12*(4), 1261–1276.

155. Carlson, R.C., Papamichail, I., and Papageorgiou, M. (2011). *Comparison of Local Feedback Controllers for the Mainstream Traffic Flow on Freeways Using Variable Speed Limits*, Proceedings of the 14th International IEEE Conference on Intelligent Transportation Systems, Washington, DC.

156. Hegyi, A. and Hoogendoorn, S.P. (2008). *Dynamic Speed Limit Control to Resolve Shock Waves on Freeways—Field Test Results of the SPECIALIST Algorithm*, Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems, Beijing, China.

157. Lin, P.W., Kang, K.P., and Chang, G.L. (2004) "Exploring the Effectiveness of Variable Speed Limit Controls on Highway Work-Zone Operations," *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *8*(3), 155–168.

158. Zheng, Z., Ahn, S., Chen, D., and Laval, J. (2011). "Applications of Wavelettransform for Analysis of Freeway Traffic: Bottlenecks, Transient Traffic, and Traffic Oscillations," *Transportation Research Part B: Methodological*, *45*(2), 372–384.

159. Allaby, P., Hellinga, B., and Bullock, M. (2007). "Variable Speed Limits: Safety and Operational Impacts of a Candidate Control Strategy for Freeway Applications," *IEEE Transactions on Intelligent Transportation Systems*, *8*(4), 671–680.

160. Hamdar, S.H., Treiber, M., Mahmassani, H.S., and Kesting, A. (2008). "Modeling Driver Behavior as Sequential Risk-Taking Task," *Transportation Research Record 2088*, 208–217, Transportation Research Board, Washington, DC.

161. Google Maps. (2012). *Geographic characterization of the selected segment in Chicago, IL*. Data date: 2012. Data date: 2012. Generated via Google Maps online, obtained from: http://maps.google.com/. Generated January 31, 2012.

162. Hamdar, S.H. (2009). *Modeling Driver Behavior As a Stochastic Hazard-Based Risk Taking Process*, PhD Thesis, Northwestern University, Evanston, IL.

163. Hamdar, S.H. and Mahmassani, H.S. (2009). "Life in the Fast Lane: Duration-Based Investigation of Driver Behavior Differences Across Freeway Lanes," *Transportation Research Record 2124*, 89–102, Transportation Research Board, Washington, DC.

164. Kahneman, D. and Tversky, A. (1979). "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica*, *47*(2), 263–291.

165. Chaudhary, N.A., Zongzhong T., Messer, C.J., and Chu, C. (2004). *Ramp Metering Algorithms and Approaches for Texas*, Report No. FHWA/TX-05/0-4629-1, Federal Highway Administration, Washington, DC.

166. Talebpour, A., Mahmassani, H.S., and Hamdar, S.H. (2012). “Safety First: Assessing Congestion Effects on Experienced Driver Risk Using a Microsimulation Approach,” *Transportation Research Record 2316*, 106–113, Transportation Research Board, Washington, DC.

167. Kim, J. and Mahmassani, H.S. (2011). “Correlated Parameters in Driving Behavior Models: Car-Following Example and Implications for Traffic Simulation,” *Transportation Research Record 2249*, 62–77, Transportation Research Board, Washington, DC.

168. Pisano, P. and Goodwin, L. (2002). *Surface Transportation Weather Applications*, Presented at the 2002 Institute of Transportation Engineers Annual Meeting, Washington, DC.

169. Mixon-Hill Inc., et al. (2005). *Clarus Weather System Design: Detailed System Requirements Specification*. Obtained from: http://www.clarusinitiative.org/documents/Final_Clarus_System_Detailed_Requirements.pdf.

170. Pisano, P., Alfelor, R.M., Pol, J.S., Goodwin, L.C., and Stern, A.D. (2005). *Clarus—The Nationwide Surface Transportation Weather Observing and Forecasting System*, Presented at the 21st International Conference on Interactive Information Processing Systems (IIPS) for Meteorology, Oceanography, and Hydrology. Obtained from: http://ams.confex.com/ams/pdfpapers/83961.pdf. Site last accessed March 5, 2014.

171. Mahmassani, H.S., Dong, J., Kim, J., Chen, R.B., and Park, B. (2009). *Incorporating Weather Impacts in Traffic Estimation and Prediction Systems*, Report No. FHWA-JPO-09-065, Federal Highway Administration, Washington, DC.

172. Mahmassani, H.S., Kim, J., Hou, T., Zockaie, A., Saberi, M., Jiang, L., Verbas, Ö., Cheng, S., Chen, Y., and Haas, R. (2012). *Implementation and Evaluation of Weather Responsive Traffic Estimation and Prediction System*, Report No. FHWA-JPO-12-055, Federal Highway Administration, Washington, DC.

173. Mahmassani, H.S. (1998). “Dynamic Traffic Simulation and Assignment: Models, Algorithms, and Applications to ATIS/ATMS Evaluation and Operation,” *Operations Research and DecisionAid Methodologies in Traffic and Transportation Management*, NATO ASI Series, 104–132.

174. Zhou, X., Qin, X., and Mahmassani, H.S. (2002). “Dynamic Origin-Destination Demand Estimation with Multiday Link Traffic Counts for Planning Applications,” *Transportation Research Record 1831*, 30–38, Transportation Research Board, Washington, DC.

175. Dong, J., Mahmassani, H.S., and Lu, C.C. (2006). “How Reliable is this Route?: Predictive Travel Time and Reliability for Anticipatory Traveler Information Systems,” *Transportation Research Record 1980*, 117–125, Transportation Research Board, Washington, DC.

176. Luoma, J., Rämä, P., Penttinen, M., and Anttila, V. (2000). "Effects of Variable Message Signs for Slippery Road Conditions on Reported Driver Behaviour," *Transportation Research Part F*, *3*, 75–84.

177. Rämä, P. (2001). "Effects of Weather-Controlled Message Signing on Driver Behavior," PhD Thesis, *VTT Publications*, *447*.

178. Hogema, J.H. and van der Horst, R. (1997). "Evaluation of A16 Motorway Fog-Signaling System with Respect to Driving Behaviour," *Transportation Research Record 1573*, 63–67, Transportation Research Board, Washington, DC.

179. Cooper, B.R. and Sawyer, H. (1993). *Assessment of M25 Automatic Fog-Warning System*, Final Report, Report No. TRL-PR-93-16, Transport Research Laboratory, Crowthorne, South Africa.

180. Gopalakrishna, D., Cluett, C., Kitchener, F., and Balke, K. (2011). *Developments in Weather Responsive Traffic Management Strategies*, Report No. FHWA-JPO-11-086, Federal Highway Administration, Washington, DC.

181. Abdel-Aty, M. (2003). "Analysis of Driver Injury Severity Levels at Multiple Locations Using Ordered Probit Models," *Journal of Safety Research*, *34*(5), 597–603.

182. Srinivasan, K.K. and Mahmassani, H.S. (1999). "Role of Congestion and Information in Trip-Makers' Dynamic Decision Processes: Experimental Investigation," *Transportation Research Record 1676*, 44–52, Transportation Research Board, Washington, DC.

183. Bowman, J.L. and Ben-Akiva, M.E. (2011). "Activity-Based Disaggregate Travel Demand Model System with Activity Schedules," *Transportation Research Part A: Policy and Practice*, *35*(1), 1–28.

184. Google Maps. (2012). *Chicago, IL, study area and adjacent ASOS stations*. Data date: 2012. Generated by: Hani Mahmassani via Google Maps online, obtained from http://maps.google.com/. Generated October 1, 2012.

185. Google Maps. (2012). *Selected detector locations in Chicago, IL*. Data date: 2012. Generated by: Hani Mahmassani via Google Maps online, obtained from http://maps.google.com/. Generated October 1, 2012.

186. *Travel Tracker Survey*. Chicago Metropolitan Agency for Planning, Chicago, IL. Obtained from: http://www.cmap.illinois.gov/data/transportation/travel-tracker-survey.

187. *National Transit Database*. Federal Transit Administration, Charlottesville, VA. Obtained from: http://www.ntdprogram.gov/ntdprogram/.

188. Domencich, T. and McFadden, D. (1975). *Urban Travel Demand: A Behavioral Analysis*, North-Holland, Amsterdam.

189. Ben-Akiva, M. and Lerman, S. (1985). *Discrete Choice Analysis*, MIT Press, Cambridge, MA.

190. Noland, R.B. and Small, K.A. (1995). "Travel-Time Uncertainty, Departure Time Choice, and the Cost of Morning Commutes," *Transportation Research Record 1493*, 150–158, Transportation Research Board, Washington, DC.

191. Schrank, D.L., Turner, S.M., and Lomax, T.J. (1993). *Estimates of Urban Roadway Congestion—1990*, Report No. FHWA/TX-90/1131-5, Texas Transportation Institute, Texas A&M University, College Station, TX.

192. Knapp, K.K. (2000). *Investigation of Volume, Safety, and Vehicle Speeds During Winter Storm Events*, 57–64, Ninth AASHTO/TRB Maintenance Management Conference, Juneau, AK.

193. McBride, J.C., Benlangie, M.C., Kennedy, W.J., McCornkie, F.R., Steward, R.M., Sy, C.C., and Thuet, J.H. (1977). *Economic Impacts of Highway Snow and Ice Control*, Report No. FHWA-RD-77-95, Federal Highway Administration, Washington, DC.

194. Hanbali, R.M. (1994). "Economic Impact of Winter Road Maintenance on Road Users," *Transportation Research Record 1442*, 151–161, Transportation Research Board, Washington, DC.

Recycled
Recyclable

HRDO-20/09-14(10)E