Travel and Emissions Impacts of Highway Operations Strategies

March 2014

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This project addressed the short- and long-term impact of highway operations strategies on travel and emissions. Operations strategies are aimed at reducing congestion and improving safety without major physical of highways. Key research questions addressed include: 1) the extent to which highway operations strategies affect throughput, travel delay and travel-time reliability; 2) the extent to which these improved travel conditions result in demand changes, in both the short term and long term; and 3) the system-level traffic flow and emissions impacts of these projects, after accounting for demand changes, including the production of both criteria pollutants and greenhouse gases. A variety of technical analyses was undertaken including: development of an empirical relationship between travel-time reliability and land use patterns; a longitudinal study of the demand effects of operation strategy deployment; and application of regional travel demand and microscopic traffic simulation models to operations deployment scenarios.</td></tr>
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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

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

APPROXIMATE CONVERSIONS FROM SI UNITS

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

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

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EXECUTIVE SUMMARY

PURPOSE AND BACKGROUND

This research project addressed the short- and long-term impact of highway operations strategies on travel and emissions. Operations strategies are aimed at reducing congestion and improving safety without major physical of highways. Key research questions addressed include:

- The extent to which highway operations strategies affect throughput, travel delay, and travel-time reliability.
- The extent to which these improved travel conditions result in demand changes, in both the short term and long term.
- The system-level traffic flow and emissions impacts of these projects, after accounting for demand changes, including the production of both criteria pollutants and greenhouse gases.

Operations strategies provide highly cost-effective solutions to congestion and safety problems. Compared to capacity expansion projects (new highways or additional lanes), their cost is low and the fact that they work within existing rights-of-way means that their environmental footprint is minimal and they can be implemented quickly. Rapid project turnaround is a major benefit of operations strategies because not only do benefits start accruing immediately and lengthy and distressful work zones are avoided, but the public sees that agencies are dealing with current problems. Further, many operations strategies deal with disruptions on the roadway system – incidents, inclement weather, work zones, and special events – which are not only highly visible and a source of frustration to travelers, but contribute substantially to both total congestion and the unreliability of travel.

In the past several years, transportation strategies of all kinds have come under increased scrutiny due to heightened concern for air quality and especially for the climate change potential of greenhouse gasses (GHG), a major by-product of the fossil fuels consumed by the major of on-road vehicles. With regard to operations improvements, two primary issues are at the heart of this scrutiny:

- **Demand Effects –** Does reducing congestion by deploying operations strategies lead to increased traveler use of the improved facility and to more highway trip-making in general?
- **Emissions Impacts –** To what extent do changes in travel behavior reduce short-term emissions gains?

STUDY APPROACH

After dismissing analysis of travel surveys, the approach relied on two types of analysis. First, empirical before/after data analysis was selected because it was felt that roadway surveillance data had matured to the point of being capable of detecting changes in travel conditions (travel times and demand) due to operational improvements. Atlanta, Georgia was selected as the study location.

Second, because travel-time reliability is a major – and often ignored – benefit of operations improvements, original research on the impact of reliability on land use development patterns was undertaken. The results of this research were then added to a special version of the UrbanSim land use model, which was then integrated into a complete modeling framework with the Metropolitan Transportation Commission travel demand model.

Third, the project team proposed to use advanced modeling frameworks both to estimate the emissions impacts of operations strategies and to study demand impacts. For the emissions impacts of operations, the Integrated Corridor Management (ICM) framework previously used in the San Diego, California I-15 corridor was selected. For emissions analysis, we developed a postprocessor that translated individual vehicle trajectories (produced as microsimulation output) into operating mode distributions. The Motor Vehicle Emission Simulator (MOVES) model was then run in project-level mode to develop emission estimates.

Fourth, the choice of an advanced modeling framework to estimate demand changes due to operations was more problematic, confounded by the fact that the ideal framework to study this issue currently does not exist. The final framework for the advanced modeling phase of the approach is shown in Figure 1. It combines the use of the MTC travel demand model with the reliability-enhanced UrbanSim model.

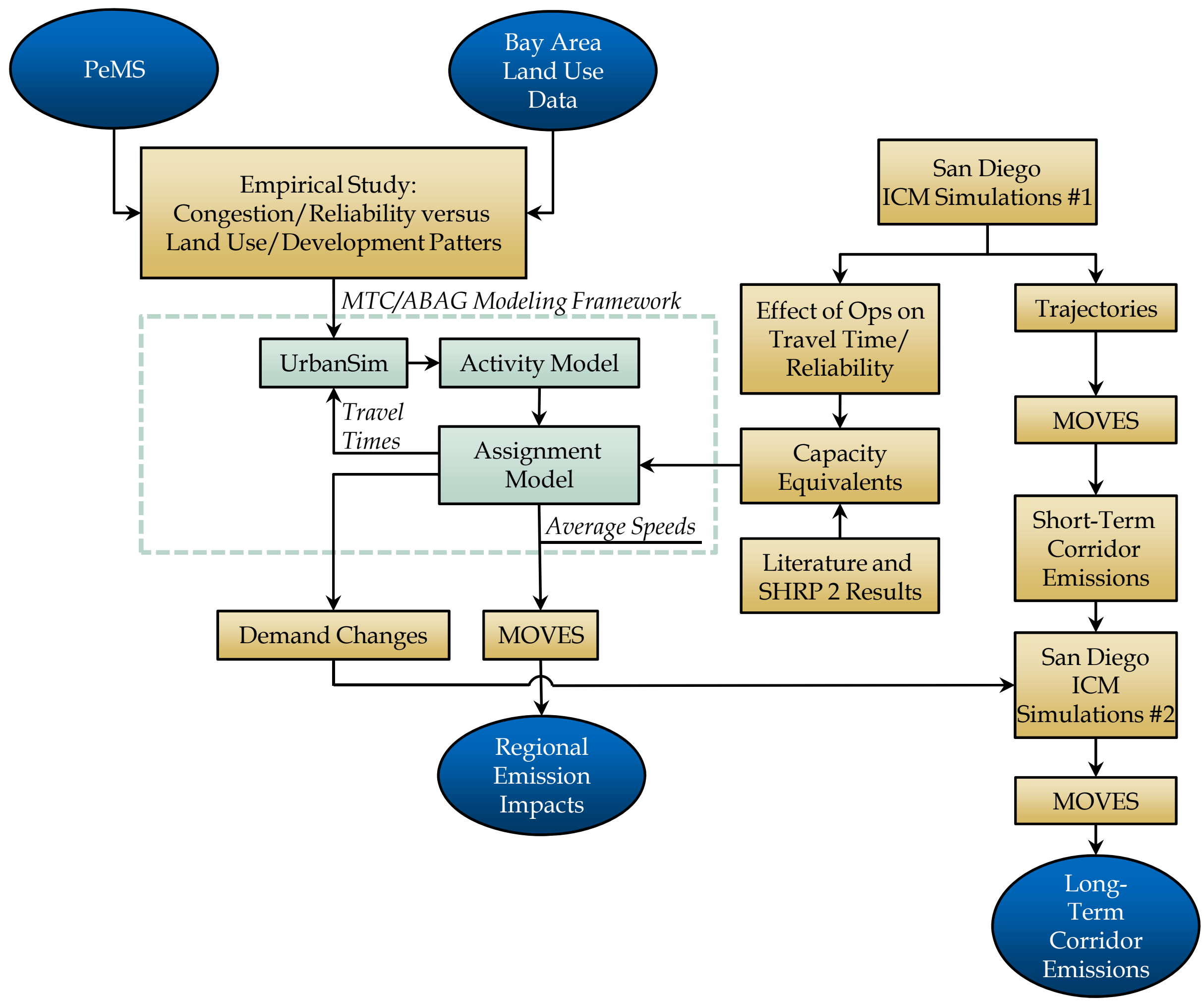

Figure 1. Flowchart. Final study approach, advanced modeling phase.
(Source: Cambridge Systematics, Inc.)

CONCLUSIONS

This study examined the effects that operations strategies have on demand and emissions, especially greenhouse gas emissions, in both the short and long terms. Many past studies have documented the positive effect of operations strategies immediately after implementation – the so-called "opening-day effect" – due to their ability to reduce delay at modest investment costs. The findings of this study reinforce that earlier work. However, a major reason for undertaking the study was to determine the extent to which opening-day emissions would endure potential increases in travel demand resulting from improved travel conditions.

Past studies of induced demand have not specifically addressed the effect of operations strategies. Rather, most have focused on the effect of how changes in a supply variable (e.g., lane-miles) result in changes in travel demand, the idea being that additional highway supply results in lower transportation costs by reducing travel times. However, adding supply (whether it be lane-miles or other form of effective capacity) will only lower travel times for an existing facility during times that the facility is congested, making highway supply a crude indicator of how travel times will change. Because of this indirect linkage, some studies have looked at the direct relationship between travel times and demand.

Past studies distinguish between short-term and long-term effects. Short-term effects include diverted trips (route, temporal, and destination shifts) and new or longer trips resulting from latent demand and mode shift. In the long term, relationship is more complex. Improvements in travel time lead to changes in development patterns, which in turn lead to changes in residential and commercial location choice and car ownership. Many authors have argued that diverted trips are not true induced demand. In general, the size of the long-term effect, in terms of the elasticity of demand with a supply variable, has been found to be higher than the short-term effect.

The applicability of past studies of induced demand to operations strategies is dubious for several reasons:

- Relationships based on areawide lane-mile additions versus vehicle-miles of travel (VMT) changes are too crude for judging operations strategies. Operations strategies are only going to be invoked when congestion is present on specific facilities, most often during peak periods, while it is impossible to tell where and when the areawide lane-miles in the studies were applied. There also is the problem of equating operations strategy effects to lane-miles, but this tractable.

- Relationships based on travel time changes versus VMT are based on travel times for an entire trip. Operations strategies are concentrated on higher order facilities, and therefore a trip will only be partially exposed. This means that the travel time savings on the operations-improved facility is less than the overall trip travel time, and therefore an adjustment would have to be made. This is important because the study is concerned specifically with the long-term effects of a deployed operations strategy.

The issue of operations influence on travel-time reliability also is often cited as a reason that historical induced demand relationships do not apply. While it is true that operations strategies do improve reliability, it also is true that other types of highway improvements do as well. Do travelers respond differently to reliability changes than they do to changes in typical travel times? Recent research from the SHRP 2 program suggests that both typical travel time and reliability are components of total transportation cost (i.e., travelers' utility) and that they respond similarly to changes in them. Accounting for reliability as an extra component of total travel cost would be a desirable feature not just for this project but for any analysis that encompasses traveler behavior.

Traditional four-step travel demand models are ill-equipped to capture induced demand because of the lack of feedback to trip generation (including vehicle ownership) and land use. Much has changed in the past decade with the advent of activity-based models, especially those that are linked to land use models. An exploratory analysis of the induced demand effect of operations was conducted as part of the preparatory work to the analysis work described above. The effect of improved signal timing in a corridor was used to replicate the effect of arterial operations strategies (e.g., traffic adaptive control systems). The performance was worsened with the induced demand but is still better than the baseline conditions. A 3 percent increase in volumes was derived by considering tour-based elasticities, which account for trip generation effects (as well as route and time-of-day shifts) but not longer-term effects, such as land use and car ownership shifts. The 3 percent increase in volumes worsens travel time performance by only 1.2 percent, still much better than the base condition. Even a 10 percent increase in through volumes has a better performance than baseline conditions with existing signal settings.

A second case study was undertaken using empirical data from the Atlanta metro area. The study was based on calculating facility travel times using continuously collected speed data from ITS sensors and automatic traffic recorders, in a before/after operational deployment setting with control sections. The results found that at several locations, ramp metering (one of the operations strategies used) did not have an appreciable effect on travel times. In locations where the operations strategies did improve travel times, no discernible increase in VMT occurred, based on an after period of more than one year. This finding corresponds to several studies of matched facility pair comparisons in the literature.

The MTC travel model was used to examine land use and regional demand effects of operations. The MTC model links an advanced iterative land use simulation model (UrbanSim) with an activity-based travel model, so that a more comprehensive treatment of demand effects is possible. Original research was conducted with the UrbanSim model and data from the Bay Area. The results found that development patterns are affected by changes in reliability in additional to typical travel times. This finding mirrors that of the Strategic Highway Research Program 2 research that found traveler behavior also is influenced by both travel time and reliability. Essentially, reliability is an extra congestion-related cost that heretofore has not been accounted for in traveler behavior analyses. The relationships developed by the research were imbedded in a special version of UrbanSim for use in this project.

The enhanced UrbanSim version of the MTC modeling framework was used to conduct tests of deploying operations strategies. This framework includes feedback loops for travel time to the activity model and for both travel time and reliability to the land use model. Congestion in the network was high. Results show that the deployment of operations strategies increases regional VMT, and the increase is proportional to the travel time savings. For the network that was tested, which was significantly congested, for strategies that represent a reasonably high impact on congestion (e.g., bundles of strategies) the VMT increase does not fully erode the CO_2 emissions benefits of operations; small benefits remain after accounting for both short-term and long-term demand effects at the regional level. Strategies that have a lower congestion impact (e.g., ramp metering deployed alone), a marginal increase in CO_2 emissions was found.

The long-term demand increases observed in the MTC model were used to update the I-15 traffic simulation runs. Results showed that the increased demand runs showed less benefit than the original runs, but for the majority of cases, there was a small net reduction in emissions relative to the base case. The demand adjustment procedure used was crude, but necessary given that an integrated model capable of estimating demand changes and refined speed/delay estimates currently is not available.

All of the review and analysis conducted in this study points to several overall conclusions:

1. Operations strategies have an effect on short-term and long-term demand patterns, based on the regional modeling conducted. Because operations strategies improve travel time, there is no *a priori* reason to expect them to behave any differently than capital expansion projects in this regard. However, the strategies tested in this study were all supply related. Traveler information, which affects demand, was tested using a simulation model, but the results were deemed to be problematic. In the short term, traveler information may reduce demand on congested facilities by allowing travelers to make different choices for destinations, modes, or to forego a trip altogether. (Shifts in routes and departure times effected by traveler information are likely to have a negligible impact on demand.) However, in the long term, to the degree that traveler information has the global effect of reducing travel times, we would expect it to have similar demand characteristics of other strategies.

2. An empirical before/after analysis of operations deployment (ramp metering and incident management) revealed neither significant changes in travel time or demand. This may be due to relatively small decrease in travel times observed (compared to what would be achieved through capacity expansion or bottleneck removal), indicating that travelers require a significant change in travel time before they adjust their short-term behaviors.

3. Travel-time reliability affects land use decisions. Recent SHRP 2 research found that reliability affects traveler behavior and that, along with typical travel time, is part of the overall disutility associated with trip-making. This project has extended that finding to include the behavior household and business land use decisions. Because reliability is affected by many factors – including disruptions, demand, and their interaction with physical capacity – we expect that other improvements beyond operations would have a similar effect.

4. A microsimulation model, TransModeler previously calibrated for the Integrated Corridor Management Analysis in the I-15 corridor in San Diego, was used to gauge the effects of operations strategies. Individual vehicle trajectories were obtained from the model runs and converted to operating mode distributions for input the MOVES model to produce emissions estimates. This approach was deemed to be superior to using average speeds for MOVES input because it captures vehicle modal activity. However, there has been recent skepticism about the ability of microsimulation-based vehicle trajectories to replicate real-world trajectories. The reason is that the models have been internally calibrated to reproduce macrolevel performance, not individual vehicle performance. This discrepancy is a major concern for trying to obtain an absolute number for emissions; it is probably not as important for judging the relative differences in strategies, as done here.

5. Under the assumption that there is no short- or long-term change in demand, operations strategies produce emissions benefits at the ***corridor*** level, including the primary greenhouse gas, CO_2. The reduction in emissions range from two to nine percent, depending on the type of operations strategy deployed. These results are based on using a microscopic simulation model to develop trajectories for the MOVES model.

6. Accounting for demand changes created by the improved travel conditions resulting from operations, the emissions benefits at the ***regional*** level are less than at the corridor level. Regional CO_2 emissions varied from -1.5 to +1.0 percent, depending on the strategy deployed. This result is based on the regional modeling framework used in this study.

7. Accounting for increased demand due to the original deployment of operations at the ***corridor*** level, emissions reductions are still present, although the reductions are not as great as if no demand increase is assumed (one to nine percent emission reductions). This result is based on using the demand shifts determined from the regional travel model and applied to the microscopic simulation/MOVES model framework. Because the simulations were unable to account for all of the additional VMT estimated by the regional modeling, we expect the emissions benefits to be overstated. Had the simulations accounted for all of the additional VMT, we believe that emissions benefits would have been either neutral or slightly positive.

8. Microsimulation models are excellent tools for assessing roadway performance in terms of travel time and delay. Our experience indicated that their handling of demand changes is more problematic. This manifested itself the most in the analyses where traveler information was implemented – some of the results appear to be counterintuitive. Also, trying to match roadway VMT targets by modifying the trip table based on a "select link" analysis is performed is a difficult task. Finally, even for routine scenarios the model's shifting of demand makes it hard to compare the effects of one strategy versus another. VMT is a legitimate effect of network conditions, not a static input, but it is difficult to know if the model's treatment of demand replicates reality.

9. The study stretched the limits of current modeling capability by stitching together results from one model (demand estimates from the MTC travel model) with another (speed estimates from the I-15 microscopic simulation model). The ideal modeling framework to study this problem would have a single model that has the land use and travel activity components of the MTC model with the traffic assignment portion replaced with mesoscopic simulation model. Even then, there is a question whether the vehicle trajectories produced by mesoscopic simulation adequately reflect real-world trajectories. In fact, the accuracy of microscopic simulation produced trajectories have been called into question. Until this issue is resolved, a good deal of uncertainty will remain in **any** modeling framework that is employed to study the long-term effects of operations strategies on emissions.

RECOMMENDATIONS

Based on our experience with this project, the team offers the following recommendations for future work:

- <u>Fully integrated modeling frameworks with advanced features should be promoted in order to understand the supply demand implications for alternative investments</u>. These features should include:

- A land use model that is sensitive to changes in transportation network conditions.
- An activity-based travel demand model.
- Traffic assignment via simulation procedures (e.g., mesoscopic simulation) that employs dynamic traffic assignment.

- Travel-time reliability should be both an output of the modeling process as well as an input. Traditional travel demand and microsimulation models should produce reliability measures as output for assessing system performance. Research should be on alternative methods for doing so, including postprocessing and scenario-based analysis. Further, reliability should be part of the feedback process in the modeling chain, in the same way that typical (average) travel times currently are used. This study showed a method for incorporating reliability in land use projections; a similar effort should be undertaken to incorporate reliability into activity models, both as an adjunct to existing models and in the development of new ones.

- When operations projects are evaluated, demand changes over a short-term horizon should be included. Evaluations of completed projects is an important component of a performance management system. Before/after evaluations have traditionally focused on fairly short time periods. With the inclusion of reliability, the time periods must be at least one-year long. We recommend an even longer time horizon – perhaps two years – so that demand shifts can be observed and correlated with improvements in travel conditions. Challenges exist for conducting these studies, including the impact of diversion on facility traffic volumes and changes in the drivers of ambient demand such as economic fluctuations and fuel prices. These studies will add to the knowledge gained here in the Atlanta case studies.

- Empirical analyses of traveler responses (demand) to changes in system condition should be undertaken. Previous efforts to study demand changes – induced or otherwise – have suffered from objective measurements of travel time changes. Either surrogates such as lane-miles of self-reported travel times have been used. However, new forms of data have allowed the direct measurement of travel times on a regional network. These data can be used in conjunction with either longitudinal or cross-sectional studies of travel demand.

- Emissions estimates derived from simulation model trajectory outputs should be investigated further. Specifically:

  - Comparison of emissions derived from simulated trajectories versus real-world trajectories.
  - Comparison of emissions derived from simulated trajectories versus the use of average speeds.

CHAPTER 1. INTRODUCTION

PURPOSE OF THE STUDY

This research project addressed the short- and long-term impact of highway operations strategies on travel and emissions. Operations strategies are aimed at reducing congestion and improving safety without major physical expansion of highways. Strategies of particular interest to the profession include signal timing, ramp metering, traffic incident management, congestion pricing, and active traffic and demand management strategies such as speed harmonization, queue warning, and lane management. Key research questions addressed include:

- The extent to which highway operations strategies affect throughput, travel delay, and travel-time reliability.
- The extent to which these improved travel conditions result in demand changes, in both the short term and long term.
- The system-level traffic flow and emissions impacts of these projects, after accounting for demand changes, including the production of both criteria pollutants and greenhouse gases.

Assessing the long-term emission impacts of operations strategies is a unique aspect of the project, and much of the effort was devoted to this component.

ORGANIZATION OF THIS REPORT

In the remainder of the Introduction, we discuss the project background, list other reports and technical papers produced from the project, and the overall study approach. The remaining chapters are:

- **Chapter 2: Current Knowledge Base –** a traditional literature review was conducted for the study. Additionally, three white papers also were developed on:

    - The operations versus new capacity impacts of changes in travel-time reliability, average travel time, and monetary travel cost on travel behavior.
    - Implications of induced demand for estimating impacts and social/user benefits (acknowledging geographic and temporal considerations).
    - The effect of accessibility on land use patterns.

- **Chapter 3: Atlanta Case Study: Demand Effects of Operational Improvements –** a before/after study of the effect of ramp metering and incident management in the Atlanta metropolitan area is undertaken.

- **Chapter 4: Impact of Travel-Time Reliability on Real Estate Markets –** original research and testing of the effect of reliability on land use patterns.

- **Chapter 5: Near-Term Emissions Impacts of Operations Strategies –** a microscopic traffic simulation model in a real-world setting is linked to the MOVES emission model to estimate the impacts of operations.

- **Chapter 6: Long-Term Regional Impacts of Operations Strategies –** the Bay Area activity-based travel demand model is linked to a land use model capable of accounting for reliability.

- **Chapter 7: Conclusions and Recommendations.**

BACKGROUND TO THE ISSUES: OPERATIONS STRATEGIES, DEMAND, AND EMISSIONS

This chapter provides an overview of the major issues dealt with by this project. Chapter 2 provides a more thorough discussion of the issues.

Operations strategies are highly cost-effective strategies for addressing congestion and safety problems. Compared to capacity expansion projects (new highways or additional lanes), their cost is low and the fact that they work within existing rights-of-way means that their environmental footprint is minimal and they can be implemented quickly. Rapid project turnaround is a major benefit of operations strategies because not only do benefits start accruing immediately and lengthy and distressful work zones are avoided, but the public sees that agencies are dealing with current problems. Further, many operations strategies deal with disruptions on the roadway system – incidents, inclement weather, work zones, and special events – which are not only highly visible and a source of frustration to travelers, but contribute substantially to both total congestion and the unreliability of travel.

In the past several years, transportation strategies of all kinds have come under increased scrutiny due to heightened concern for air quality and especially for the climate change potential of greenhouse gas (GHG), a major by-product of the fossil fuels consumed by the major of on-road vehicles. With regard to operations improvements, two primary issues are at the heart of this scrutiny:

- **Demand Effects –** Does reducing congestion by deploying operations strategies lead to increased traveler use of the improved facility and to more highway trip-making in general?

- **Emissions Impacts –** How do operations strategies affect vehicular emissions, both with and without considering demand effects (shifts)? Is the demand effect great enough to wipe out short-term emissions gains?

With regard to demand effects, there are several possible reactions that transportation users may have to a change in travel conditions:

1. Change route of travel.
2. Change time of day of travel.
3. Change mode of travel.
4. Change destination of travel.

5. Change amount of travel (new trips by existing and new users that would not have occurred without the change in travel conditions).

The length of trips may be affected by all of these, especially the last two. Only the last one of these reactions is actually a change in the level of demand (induced traffic if the change is an increase in trips, and suppression of travel if the change is a reduction). The other reactions result in diverted trips, but if it is highway trips we seek, diversion from other routes, modes, and times must be considered as induced travel. For example, highway vehicle-miles of travel (VMT) will be increased if trips that formerly took transit now use autos. In theory, then, when a change is made to travel conditions, a range of possible results can occur, in which traffic is diverted away from a facility that has high travel times to a facility that has lower travel times. A combination of diversion and either induced or suppressed travel is what will give rise to changed volumes on the facility that has experienced the change.

In the past decade, increasing attention has been placed by the transportation profession on highway operations strategies as means to reduce congestion and improve safety. However, because these strategies are relatively new and are constantly evolving, little practice experience in determining their impacts has been gained. The *Moving Cooler* report[1] brought the issue of induced demand to the forefront of national attention. For *Moving Cooler*, the short- and long-run elasticities developed for FHWA's Highway Economic Requirements System (HERS) were used for all improvements that were not aimed directly at VMT reduction. For operations strategies, delay reduction was first estimated using technical relationships from a variety of sources, including the ITS Deployment Analysis System (IDAS) and recent literature for newer types of strategies (e.g., Active Traffic Management, ATM).[2]

However, when the HERS elasticities were applied, the savings were drastically reduced because of (estimated) higher induced demand. The *Moving Cooler* analysis used the HERS elasticities for operations strategies so that the results across all non-VMT reduction strategies could be considered and to be consistent with FHWA's Biennial *Condition and Performance Report* to Congress, which uses the HERS model. However, there is a huge amount of uncertainty surrounding the application of elasticities to operations strategies:

- Should short-run elasticities be used at all? If existing trips are diverted to an improved facility, presumably they are coming from already congested facilities or time periods. This means that travelers on the original facilities benefit, but this benefit is not accounted for in the elasticity.

- Should elasticities be applied unadjusted to a project-level analysis? Elasticities are generally developed from systemwide observations on travel changes, and thus are applicable to the entire trip. However, travel on an improved highway chapter only represents a fraction of the entire trip.

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[1] Cambridge Systematics, *Moving Cooler: An Analysis of Transportation Strategies for Reducing Greenhouse Gas Emissions*, Urban Land Institute (publisher), July 2009.

[2] These relationships are the same as used in the HERS Operations Pre-Processor: http://www.fhwa.dot.gov/policy/2010cpr/appa.htm.

Is traveler response to operations improvements the same as for traditional capacity expansion projects? Past studies on induced demand/travel do not distinguish the type of improvements that produced changes in travel time. However, in those data, it is likely that reductions in travel times are primarily due to capacity expansion. The travel-time savings from operations improvements are more modest – do these elicit the same response or is there an "inertia" that has to be overcome before travelers respond? That is, is traveler response truly a continuous function, or is it more stepwise, in which travelers respond to large increments of travel time? Further, is the response to strategies that deal with nonrecurring congestion – which is only present when disruptions take place – different from those that deal with recurring congestion, which occurs every peak period? In other words, does the infrequency of nonrecurring events (relative to recurring ones) cause less of a behavioral shift?

This study was undertaken to address these issues. Specifically, the long-term effects of demand changes caused by implementing operations strategies was a major component of the study. With the exception of NCHRP Project 535, no other previous study has attempted to deal with the long-term effects of operational improvements.[3]

STUDY APPROACH

The project team and FHWA personnel spent a good deal of time refining the study approach. We investigated several options, including: empirical before/after analyses; longitudinal and cross-sectional survey analyses; and running experiments with advanced modeling frameworks. Table 1 shows the options that were considered.

[3] Dowling, Richard et al., "Predicting Air Quality Effects of Traffic-Flow Improvements: Final Report and User's Guide," National Cooperative Highway Research Program Report 535, 2005.

Table 1. Types of analyses and experiments considered for the study.

Type of Analysis	Models or Data to be Used[a]	Priority	Elasticity Estimation: Type of Induced Demand Effect	Elasticity Estimation: Expected Results	Limitations
Facility-Specific: Empirical Before/After					
Time series analysis with control sections	Atlanta: ramp meters, incident management, HOT lanes (L03)	Medium/ High	Short	Short- and long-term elasticities. These also provide travel time and reliability impacts in addition to demand changes.	VMT/demand changes due to a combination of factors in addition to any induced effect (especially economic conditions)
	Atlanta: arterial management (RTOP)		Short		
	Seattle: ATM deployment		Short		
	Seattle: ramp metering (L03)		Short		
	Minneapolis: HOT lanes		Short		
	Minneapolis: capacity expansion (L03)				
	San Diego: ICM		Short		
	San Diego: incident management (L03)		Short		
	Miami: ramp meters and express lanes		Short		
	Orlando: VSL		Short		
	D.C.: hard shoulder running		Short		
Travel Demand Model Experiments					
	San Diego (SANDAG) model	Medium	Short	Demand shifts due to destination change and diversion from other facilities; network-level congestion effect of operations improvements on a facility.	Transferability to other network typologies
Simulation Model Experiments					
	San Diego (I-15); Transmodeler	Medium	Short	Demand shifts due to diversion; effect of traveler information.	Transferability to other network typologies
Disaggregate Analysis: Experimental Economics					
	Berkeley XLAB	High	Both	Increased trip-making; Workplace and residential location.	Essentially a sophisticated form of a stated-preference survey; transferability of results to general population; extra costs involved

Table 1. Types of analyses and experiments considered for the study (continued).

Type of Analysis	Models or Data to be Used[a]	Priority	Elasticity Estimation: Type of Induced Demand Effect	Elasticity Estimation: Expected Results	Limitations
Activity Model Experiments					
	SHRP 2 C10 (B) modeling framework (PECAS → SACSIM → DynusT	High	Both	Full range of induced travel behaviors.	Land use component (PECAS) outside scope of C10 – will require effort by SACOG staff
Traveler Survey Analysis					
Disaggregate Analysis, Longitudinal	ICM Survey (Dallas and San Diego)	High	Short	Traveler behavior changes due to operations strategies (including new and longer trips).	Stated-preferences can be different from real-world activity
	UPA Survey (Atlanta)	High	Short	Traveler behavior changes due to pricing (including new and longer trips).	
Disaggregate Analysis, Cross-Sectional	NHTS (2009)	Low	Both	Update of Barr and Cohen analyses; add simultaneous modeling approach.	Culling out the effect of operations is impossible, but response to small changes in congestion level may act as a surrogate.
Area Studies: Partial elasticities	Minneapolis HH Travel Surveys (2000, 2008)	Low	Long	Control for trip generation factors; note change in trip-making due to system conditions.	Changes in trip-making may be due to societal and socioeconomic factors – pinning it to network conditions may be difficult; culling out the effect of operations is impossible, but response to small changes in congestion level may act as a surrogate.
	PSRC Panel Survey (1999, 2006)		Long		
	Knoxville HH Travel Surveys (2001, 2008)		Long		
	NHTS (2001, 2009)		Long		
Area Study: Proxy Measures					
	Atlanta Detector and ATR data, 2000-2010, Census data	Medium	Short and Long	VMT as a function of lane-miles, congestion level, and area growth.	Lane-miles a poor measurement for traveler behavioral response

[a]"L03" means the data was originally used for SHRP 2 Project L03; additional data for the "after" condition will need to be collected.

The project team and FHWA concluded that pursuing analysis of travel surveys would not be fruitful – most previous studies of induced demand were based on surveys and there was a strong desire to try a more innovative approach. One activity from Table 1 may be of interest in the future, though: the Integrated Corridor Management (ICM) Traveler Panel Survey being conducted by the Volpe Center. The impetus for conducting this survey is that the travel decisions made by individual corridor travelers will significantly influence corridor operations. While much of the investment and complexity of the ICM Initiative will focus on optimizing and coordinating *operations* on the corridor facilities, the ultimate success of the Initiative depends upon the travel choices made by corridor users who will change route, time, or mode of travel in response to their experience with the facilities, coupled with their use of publicly provided real-time traveler information. The survey is being administered to the same panel of respondents before and after ICM implementation, covering both those who travel by car and by transit.

The approach decided upon was to rely on two types of analysis. First, empirical before/after data analysis was selected because it was felt that roadway surveillance data had matured to the point of being capable of detecting changes in travel conditions (travel times and demand) due to operational improvements. Atlanta, Georgia was selected as the study location. The task of monitoring long-term changes in demand from field data is somewhat problematic due to exogenous factors affecting the general demand for highway use, primarily fuel prices and economic conditions. The best way to factor these influences is to establish control sections on similar highways in the same area that have not been improved during the time of interest. Diversion is most likely to occur in the short term while long-term changes in improved versus control sections can be related to true induced demand.

Second, because travel-time reliability is a major – and often ignored – benefit of operations improvements, original research on the impact of reliability on land use development patterns was undertaken. The results of this research were then added to a special version of the UrbanSim land use model,[(4)] which was then integrated into a complete modeling framework with the MTC travel demand model. (See below for details.)

Third, the project team proposed to use advanced modeling frameworks both to estimate the emissions impacts of operations strategies and to study demand impacts. For the emissions impacts of operations, the ICM framework previously used in the San Diego, California I-15 corridor was selected. This framework developed a microsimulation model to study the effect that ICM strategies have on congestion. For this project, we used the framework to conduct experiments of additional operations strategies (see Chapter 3 for details). For emissions analysis, we developed a postprocessor that translated individual vehicle trajectories (produced as microsimulation output) into operating mode distributions (i.e., VSP/speed bins). MOVES was then run in project-level mode to develop emission estimates.

[4] http://www.urbansim.org/Main/WebHome.

Fourth, the choice of an advanced modeling framework to estimate demand changes due to operations was more problematic, confounded by the fact that the ideal framework to study this issue does not currently exist. Table 2 shows the advanced modeling frameworks considered and the desired features for the current study. The ideal framework has an advanced land use model that uses feedback from the network assignments, an activity-based travel model, and a dynamic traffic assignment procedure. The SHRP 2 C10A in Burlington, Vermont came the closest, but it had not yet been fully developed and Burlington was thought to be too small to be representative. The remaining frameworks all had one missing component.

Table 2. Characteristics of existing advanced modeling frameworks considered.

	Desired Features			
Framework	**Land Use Model Linkage?**	**Activity-Based Model?**	**Type of Traffic Assignment**	**Feedback from Assignment?**
SHRP 2 C10A (Burlington)	UrbanSim being linked in by the University of Vermont	Yes	TRANSIMS	To activity and land use models
SHRP 2 C10A (Jacksonville)	No	Yes	TRANSIMS	To activity model only
SHRP 2 C10B (Sacramento)	No	Yes	DynusT	To activity model only
MTC (Bay Area, California)	UrbanSim	Yes	Traditional equilibrium	To activity and land use models

The SHRP 2 C10B framework was originally selected as the primary modeling framework for a number of reasons: CS staff already were developing it so the work could be done efficiently; it could model operations strategies; it is being linked to MOVES to estimate emissions impacts; and a number of operations-oriented tests already were scheduled to be conducted as part of the SHRP 2 project. As shown in Figure 2, a feedback loop exists between DynusT's estimation of network performance (e.g., travel times) and the SACSIM activity model.

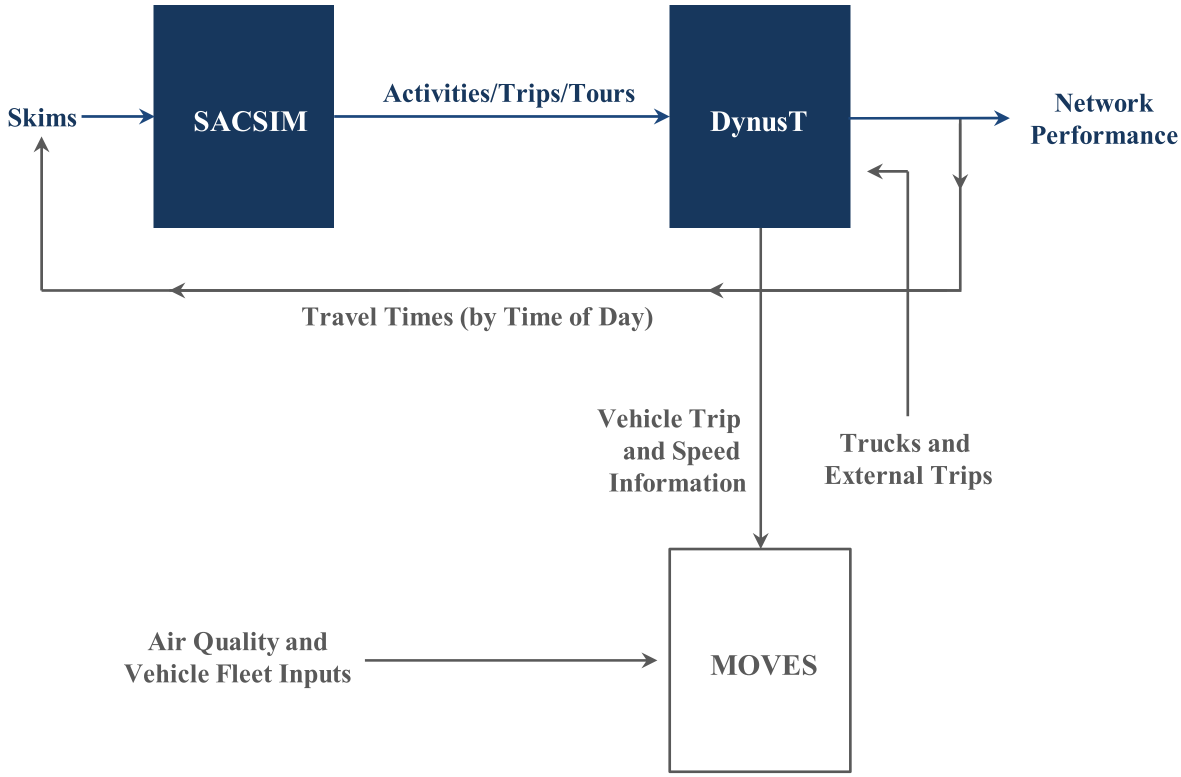

Figure 2. Flowchart. The activity-based modeling framework from SHRP 2 C10B.
(Source: Cambridge Systematics, Inc.)

Unfortunately, the SHRP 2 C10B project experienced significant delays, and these delays necessitated the choice of another advanced framework to assess demand changes. It was decided to use the MTC modeling framework as the alternative. This choice built on the special study of reliability and accessibility/land use patterns as already planned.

The final framework for the advanced modeling phase of the approach is shown in Figure 3. It combines the use of the MTC travel demand model with the reliability-enhanced UrbanSim model. This model combination provides both regional emissions estimates and an estimate of the VMT changes due to replicating the effect of operations strategies in the model. The I-15 simulation runs were run first with the demand patterns originally set during the ICM study, then rerun with the VMT changes from the MTC model.

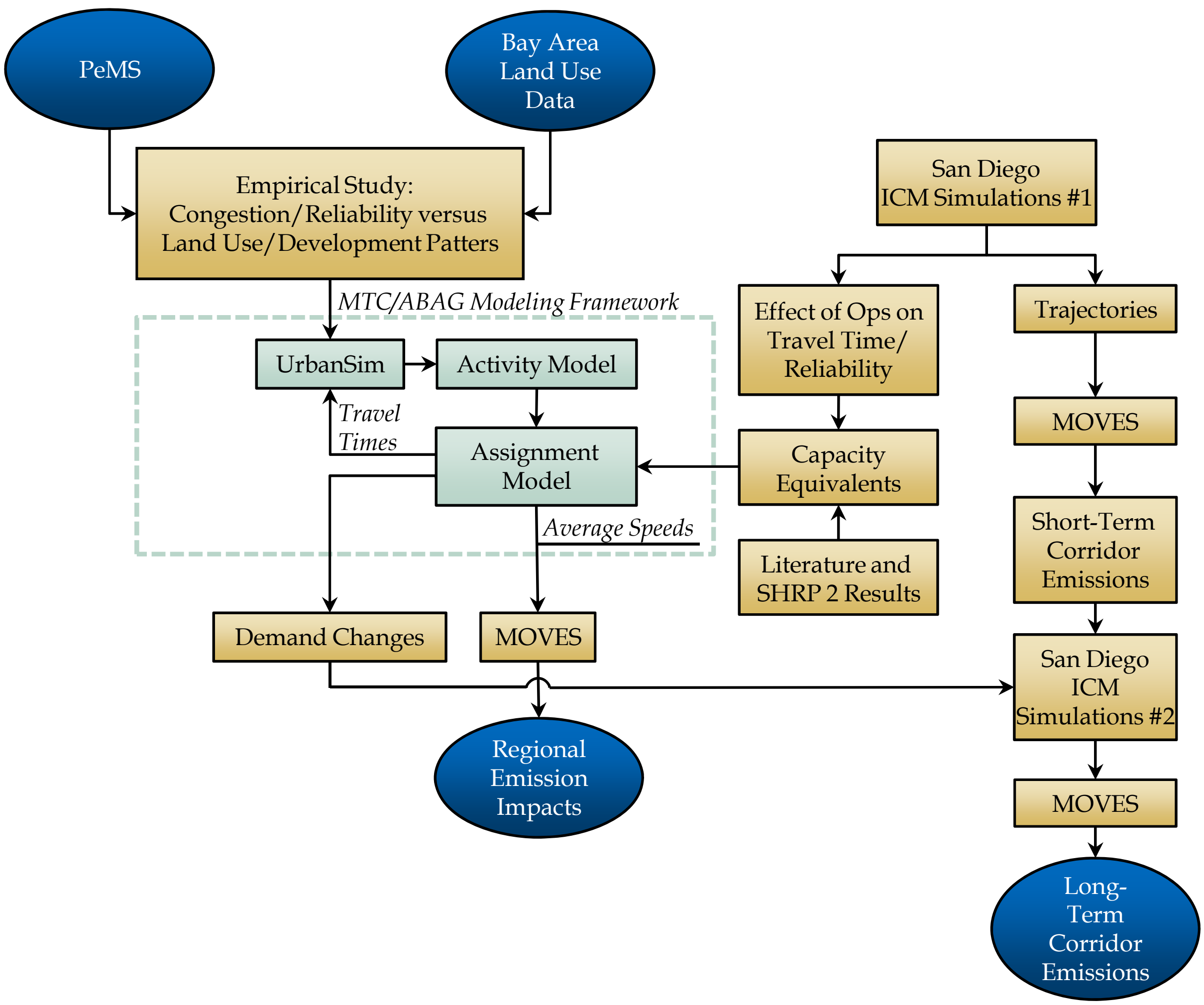

Figure 3. Flowchart. Final study approach, advanced modeling phase.
(Source: Cambridge Systematics, Inc.)

CHAPTER 2. CURRENT KNOWLEDGE BASE

INTRODUCTION

A literature review was conducted for the study. Additionally, three topics were treated in-depth and developed as separate white papers:

- The operations versus new capacity impacts of changes in travel-time reliability, average travel time, and monetary travel cost on travel behavior.
- Implications of induced demand for estimating impacts and social/user benefits (acknowledging geographic and temporal considerations).
- The effect of accessibility and reliability on land use patterns.

Each of these efforts is summarized in this chapter.

LITERATURE REVIEW

Assessing the Impacts of Operations Strategies

Evaluation of Models Used in Analysis of Operations Strategies

Planning and simulation models that have been used for decades to evaluate projects impacts, including air quality, have not accounted for nonrecurring events and congestion. Models generally use data for an average day or average peak or off-peak time period during the day. Since these models are often calibrated against daily traffic volumes they do account for nonrecurring congestion to some extent, but do not fully capture the impacts of incidents, work zones, adverse weather, and special events on performance measures such as travel time, crash rates, fuel consumption, and air quality.

Several recent and well-documented trends in transportation have led to greater interest in modeling nonrecurring congestion and its impacts on system performance:

- For a number of reasons, major increases in roadway capacity are not likely any time in the foreseeable future. Available funds are limited and must be used to primarily to maintain and/or rebuild the existing infrastructure. New capacity is extremely expensive due to the proximity of development and environmental constraints. As a result, transportation agencies are focusing more on operational strategies that are designed to optimize the capacity of the existing system.

- More transportation agencies, particularly State DOTs, are managing based on specific performance measures. There is interest in quantifying these measures wherever possible. Agencies are under increasing pressure to justify funding requests by demonstrating that they are making most efficient use of the dollars being provided. Agencies also are more conscious of the need to communicate their activities to the public. “Dashboard” reports, that show high-level metrics easily understood by laypersons are becoming more popular with

State DOTs and other transportation agencies. These reports increasingly include measures that address agency effort to reduce the impacts of nonrecurring congestion.

- The availability and quality of detailed data that can be used to measure system performance continue to increase. ITS and Transportation Management Centers have continued to expand and mature. These systems are not only monitoring more highways in real time but are producing archives of data on system volumes and speeds that are largely untapped for their research potential. In the past few years, private companies have begun to collect and compile probe data from various sources such as commercial fleets and cell phones. They are selling this information to public agencies, enabling them to monitor speeds on much greater proportions of their highway systems. These data sources allow coverage of rural interstates and major arterials that would not be financially realistic if investment in ITS and communications infrastructure were required. Connected vehicle technology, which is now in its infancy as a planning and research tool, provides much greater potential to monitor movements across the entire system through collection and processing of anonymous data from large numbers of individual vehicles.

- Through the SHRP 2 program and other research efforts, the transportation community is gaining a much better understanding of the impact of nonrecurring events and the concept of reliability. Annual results from the Texas Transportation Institute's annual Urban Mobility Report receive wide attention in the media and used by the public to understand changes in congestion levels. Concepts such travel-time index and buffer index are starting to be used by private and public traffic information services to explain delays to the public and allow changes to be measured. There are many research efforts ongoing to better understand the components and causes of nonrecurring congestion and its impacts.

Measurement of nonrecurring congestion is a focus of much of the research summarized in this chapter. The goal of many of these research efforts is to enable practitioners to predict the impacts of nonrecurring events in real time and communicate that information to the public. A next step would be to provide guidance on whether to use alternative routes and which routes to use. It can also enable system operators to implement mitigating strategies such as dynamic routing of emergency vehicles to incident scenes, retiming of signals or ramp meter rates on alternative routes and implementation of variable speed limits. As data resources and archives are developed over time they can be used to refine these strategies.

Systemwide Congestion and Reliability Analysis

One of the major findings under this category is the increasing use of real-time traffic data by researchers to understand congestion, reliability, and operational strategies. Hainen, Wasson, et al. proposed a technique for assessing route choice and travel time using an anonymous Bluetooth MAC address sampling technique as a surrogate for license plate matching to assess route choice. The authors of this paper concluded that the Bluetooth sampling technique is very cost-effective to deploy and although the results are approximate, the direct measurement of travel times and route choice is potentially very useful for public agencies assessing mobility and travel-time reliability along alternative routes, particularly distribution of traffic between different alternate routes.[5] The benefits of this technique have great potential for better understanding of diversion strategies and could help operators to refine and these strategies make them more effective. Measurement of speeds and travel time using multiple sources of data also was the subject of tried on urban streets in London. The documented technique also has application in performance measurement of freeway management and traveler information strategies.[6] Enhancements to Dynamic Traffic Assignment models for evaluation of operational improvements were reviewed by Kittelson, et al.[7] Model improvements tested included stochastic capacity for freeway and arterials, improved representation of arterial bottlenecks, and use of the findings to represent day-to-day learning capability.

Another effort to model the impacts of ATIS on system performance was developed by Li, Zhou, et al.[8] who modeled two categories of ATIS users using stochastic capacity, travelers with perfect real-time information, and travelers with some knowledge based on historical patterns.

Another advanced technique identified was the multicriterion dynamic user equilibrium (MDUE) traffic assignment model that incorporates travel-time reliability in addition to them more traditional variables of travel time and out-of-pocket cost in the assignment process. The model was tested to look at road pricing schemes in the New York metropolitan region.[9] Another research effort involved development and testing of a stochastic network simulation model that can generate random flow breakdowns at different levels, capture the traffic characteristics at the beginning of the breakdown and evaluate travel time variability.[10]

Incident Management

Several studies were identified that tested analytical techniques for estimating the duration and traffic flow impacts of incidents. The ability to do this is important in making informed operational decisions, including:

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[5] Hainen, Wasson, et al., Purdue University, "Estimating Route Choice and Travel-time reliability Using Field Observations of Bluetooth Probe Vehicles," TRB 2011 Annual Meeting, 11-0462.

[6] Hasan, Choudhury, Ben-Akiva, Emmonds, "Modeling Travel Time Variations on Urban Links in London," TRB 2011 Annual Meeting, 11-0473.

[7] Kittelson, Rouphail, Williams and Zhou, "Analyzing Operational Improvements as an Alternative to Traditional Highway Construction," TRB Annual Meeting, 11-0714.

[8] Li, Zhou, Rouphael, "Planning Level Methodology for Evaluating Traveler Information Provision Strategies under Stochastic Capacity Conditions.

[9] Jiang and Mahmassani, "Congestion Pricing, Heterogenous Users and Travel-time reliability: Multi-Criterion Dynamic User Equilibrium Model and Efficient Implementation for Large Scale Networks."

[10] Jing and Mahmassani, "Predicting Flow Breakdown Probability and Duration in Stochastic Network Models: Impact on Travel-time Reliability."

- Stationing and response routes for service vehicles.
- Implementation of lane closures and/or detours.
- Traveler information messages.
- Allocation of resources to incident management.

With greater geographic coverage through CCTV and larger volumes of traffic and speed data coming back to TMCs, analytical tools are needed to take advantage of these opportunities. One of the reports documents the use of the I-MIT model.[11] Roadway inventory, traffic, and incident data from the Hampton Roads (VA) Traffic Operations Center were used to dynamically predict incident durations, secondary incident occurrence, and associated delays.

Resources – Manuals Guidebooks and Databases

The literature search identified a number of resources that practitioners can use today that document analytical tools, methods, and data for analysis of travel time and reliability. A current major initiative is the Benefit/Cost Desk Reference for Management and Operations that will be issued by FHWA later this year. This reference guide will document techniques for conducting benefit/cost analysis for ITS and operational improvements. Other key references include documentation of the FHWA's Traffic Analysis Tools Program, the U.S. DOT Integrated Corridor Management Program, and a Guidebook on the Congestion Management Process. Tools specific to ITS analysis also are included such as the ITS Deployment Analysis System (IDAS), the Highway Economic Requirements System (HERS) and the Screening for ITS Spreadsheet (SCRITS). There are several manuals designed to help State and MPO planners incorporate ITS, operational, and safety issues into their planning processes.

Emissions Models for Testing Operations Strategies

The following modal emission models were selected for inclusion in the project. A short description of each one and the reason for their selection is provided below. Table 3 presents a summary analysis for modal emission models.

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[11] Khattak, Wang and Zhang, "iMiT: A Tool for Dynamically Predicting Incident Durations, Secondary Incident Occurrence, and Incident Delays.

Table 3. Comparison of modal emissions models.

	Modal Emissions Models								
	MOVES	CMEM (NCHRP 25-11)	MEASURE	CDOH Method	CALINE 4	VT-Micro	TRAQSIM (UCF)	HYROAD (NCHRP 25-6)	NCHRP 25-14
Pollutants Included									
CO	X	X	X	X	X	X	X	X	X
NO_x	X	X	X	X	NO_2	X			X
VOC	X	HC	X	HC		HC			HC
PM_{10}	X				X				X
$PM_{2.5}$	X				X				X
GHG	X	CO_2				CO_2			
Fuel Usage	Energy Consumption					X			
Current Status									
Up to date and supported	Yes.	Yes.	No.	No.	Yes.				No.
Inputs									
Modal activity inputs	Operating Mode Distributions or Vehicle Trajectories.	Second-by-second vehicle speed, acceleration, road-grade, accessory usage (e.g., A/C).			Cruise speed, acceleration time, deceleration time, maximum idle time, minimum idle time.	Second-by-second speed and acceleration.	Second-by-second speed and acceleration.		
Load producing effects included (road-grade, A/C use, etc.)	Yes.	Yes.				No.			
Details on emissions calculation methods	Lookup table of VSP and average-speed bins.	Engine-power demand model.		Modal multipliers convert average-speed emissions factors.	Modal multipliers convert average-speed emissions factors.	Fuel consumption and emission rates predicted directly from empirical models.	Modal multipliers convert average-speed emissions factors.		

Table 3. Comparison of modal emissions models (continued).

	Modal Emissions Models								
	MOVES	**CMEM (NCHRP 25-11)**	**MEASURE**	**CDOH Method**	**CALINE 4**	**VT-Micro**	**TRAQSIM (UCF)**	**HYROAD (NCHRP 25-6)**	**NCHRP 25-14**
Inputs									
Considers vehicle operating history	No (converts vehicle trajectories to operating mode distribution).	Yes, for batch and GUI mode. Not for table mode.							
Strength	General.	General.	GIS applications.	Simple.	Intersection dispersion modeling based on modal emissions factors.		Updated version of CDOH and CALINE models, simpler than CMEM.	CO emissions at intersections.	Heavy-duty for NO_x and HC (does not do CO or PM well). Results used for speed correction factors in other emission rate models.

- **MOVES –** The Motor Vehicle Emissions Simulator (MOVES) is now the EPA's official model for estimating emissions from highway vehicles. It covers all pollutants desired and, when used in project mode, it accepts modal activity inputs. It became available for official SIP and conformity work in January 2010 and is fully supported by the EPA.

- **CMEM –** The Comprehensive Modal Emissions Model (CMEM) was developed by UC Riverside as part of NCHRP Project 25-11. It models emissions by estimating physical properties of engine-power demand using second-by-second data on vehicle speed, acceleration, road-grade, and accessory usage. Therefore, it requires a large amount of data to run, but can be integrated into microsimulation models, such as Paramics, to automate the transfer of this data without intermediate input and output files. It covers all pollutants except for particulate matter.

- **VT-Micro –** Developed by Virginia Tech, VT-Micro predict fuel consumption and emission rates based on empirical models. It covers all pollutants except for particulate matter and has been incorporated into the INTEGRATION microsimulation model.

The following modal emission models were excluded from further consideration. A short description of each one and the reason for their exclusion is provided below.

- **MEASURE –** The Mobile Emissions Assessment System for Urban and Regional Evaluation (MEASURE) was developed by Georgia Tech under a cooperative agreement with the EPA and FHWA. The model contributed to the body of knowledge for modal emissions modeling, but it was folded into the MOVES creation effort and is no longer up to date or supported. It also does not have a greenhouse gas or fuel usage component.

- **CDOH Method –** The Colorado Department of Highways (CDOH) created this method in the early 1980s to develop emission factors that were representative of modal activities. This relatively simple method creates modal multipliers to convert average-speed emission factors to emission factors for each modal activity (accelerations, decelerations, cruise, etc.). This method does not include greenhouse gases or fuel usage and appears to no longer be used as the Colorado DOT recommends using the MOVES model for project-level hot-spot analysis.

- **CALINE4 –** The California Department of Transportation's California Line Source Dispersion Model (CALINE) is mainly for predicting pollutant concentrations for project-level analysis. However, for intersections it contains a method to convert average-speed emission factors to modal emission factors, similar to the CDOH method. It does not include greenhouse gas emissions or fuel usage and is only for light-duty vehicles at intersections.

- **TRAQSIM –** The Transportation Air Quality Simulation Model (TRAQSIM) was developed by the University of Central Florida (UCF) as an updated version of the modal multiplier methods employed by CDOH and CALINE as described above. It is based on more recent vehicle testing conducted in the 1990s. While its simplicity is an advantage it appears to only model carbon monoxide (CO).

- **HYROAD –** The Hybrid Roadway Model (HYROAD) was created under NCHRP 25-6 to integrate a traffic simulation model, emissions model, and a dispersion model into one. However, this model is only for intersections and only covers carbon monoxide (CO) and particulate matter (PM).

- **NCHRP 25-14 Method –** This method of estimating emissions from heavy trucks using second-by-second speed and acceleration data was deemed to provide valid results only for NO_x and HC, but did not provide valid results for CO or PM. The most important results from this study were the identification of the need to update speed correction factors in the MOBILE model for NO_x and HC.

Demand Effects of Transportation Improvements

A summary of the separate literature review that was prepared and how it is useful for the current study is provided below.

- It is extremely important to separate the short- and long-run components of induced travel. It also is critical to identify the independent variable: studies have related induced demand to changes in travel time, lane-miles (a surrogate for roadway capacity), and total travel costs. For operations strategies, the most desirable independent variable is travel time, and the more recent studies use travel time as the independent variable. (However, most studies in the literature use lane-miles.) An advanced modeling framework that incorporates an activity-based model (ABM) uses interzonal travel times to allocate travel activities.

- Short-run elasticities (e.g., diversion of existing trips) have been found to be smaller than long-run elasticities. While additional traffic generated in the short run is appropriate for facility planning, researchers have generally held that, except for modal diversion, long-run changes are more appropriately tagged as induced demand, i.e., new or longer trips that would not have been made without the improvement.

- A variety of analysis strategies have been used to develop induced demand elasticities, and all of the studies suffer from the inability to control various exogenous factors. The most common types of analyses are:

  - Cross-sectional analysis of travel surveys.
  - Facility-specific time series analysis.
  - Macroscopic time series (e.g., relating total VMT to total lane-mile growth).

- Because of the influence of exogenous factors, it is likely that the induced demand effect has been overstated in older studies (see Table 3). A good example is when Cohen reexamined his previous work with additional controls and found that his original elasticities were larger.

- One of the major exogenous factors that is difficult to control is expected growth. Urban transportation improvements (capacity expansion, demand management, and operations) are almost universally made where severe congestion exists, growth is expected to be high, or both. Therefore, depending on the analysis method, at least some of the observed demand growth is incorrectly assigned as “induced” – analysts expected there to be growth. Cross-sectional survey analysis does not suffer from this problem (it has others) but most time series (i.e., longitudinal) analyses do.

- With respect to induced demand as a function of lane-miles, an important distinction not controlled for in macroscopic time series analyses is expansion of existing facilities (e.g., additional lanes) as opposed to totally new capacity (e.g., a new highway or rail line). New capacity will dramatically shift development patterns and create economic opportunities where none previously existed. The effect will be smaller with capacity expansion of existing facilities.

- With regard to operational strategies and demand shifts, most operations strategies are targeted on congestion during peak periods, with the exception of incident management and even there the primary effect will be during peak periods. For example, ramp metering, lane control, and speed harmonization only provide benefits during congested times. The amount of discretionary travel during the peaks is limited, as most of the trips are work-based, especially during the morning peak. (Existing travelers cannot make additional work trips.) Although it is not explicitly stated in the studies reviewed, we do not believe that they are based on peak travel, but rather total travel during the day, when more discretionary trips are present. We postulate that peak travel – the focus of operations – is more inelastic than travel made outside of the peak.

- The long-run elasticity used in the Highway Economic Requirements System (HERS) model (-1.0), is on the high side of the two other studies reviewed where travel time was the independent variable. Further, there is a concern about how elasticities that are developed at the trip level should be applied to a facility-based improvement. This argument says that it is the percent change in travel time for the entire trip – not just that part of the trip on the improved facility – that should be used. Note that this is not an issue for the modeling frameworks with an ABM component as total trip (interzonal) travel times are computed and used.

- One study by work by Toole-Holt et al. demonstrated that in the U.S., the average daily travel time per person increased by 1.9 min per year between 1983 and 2001, and that the majority of this increase came from increased trip-making by travelers. There are two major implications of this finding:

    - Time series studies of induced demand, especially for this period of time, ignore this effect, which is substantial.
    - Increased trip-making occurred even as urban delay quadrupled during this period, suggesting that the induced demand effect is a minimal player in comparison to other exogenous travel factors.

Short-term elasticities of demand with travel time or capacity are routinely observed and included in the traditional travel demand forecasting methods used by transportation planners; it is the long-run effect that is more difficult to ascertain. Nearly all past studies on induced demand have concluded that a long-run induced demand effect exists, yet there is ample evidence that the effect is smaller than previously indicated. Further, operations strategies are targeted at congestion and it is unlikely that they would induce additional discretionary trips outside of peak periods. For example, improving a signalized highway to full access control would provide lower travel times to travels in both peak and nonpeak periods.

Given the problems with past studies, use of an advanced modeling framework will provide insight into the issue of induced demand and operations. Table 4 shows the various components of induced demand (as identified in SHRP 2 Project C04)[(12)] and that with the exception of residential location and land use effects, all of the induced demand components can be modeled.

[12] Parsons Brinckerhoff et al., "Improving Our Understanding of How Highway Congestion and Pricing Affect Travel Demand," SHRP 2 Project C04, Transportation Research Board, 2013, http://www.trb.org/Main/Blurbs/168141.aspx.

Table 4. Ability of activity-based modeling frameworks to accommodate demand shifts.

Choice Dimension	Time Scale for Modeling	Expected Impact	Ability to Model
Network Route Choice	Short term – Trip episode	Stratified response by user group.	Modeled in traffic assignment
Preroute Choice (Toll versus Nontoll)	Short term – Trip episode	Stratified response by user group.	Modeled in ABM portion
Car Occupancy	Short term – Tour/trip episode	Planned and casual carpool.	Modeled in ABM portion
Mode Choice	Short term – Tour/trip episode	Shift to transit, especially to rail and for low/medium-income groups.	Usually modeled in ABM portion
Time of Day/Schedule	Short term – Tour/trip episode	Peak spreading.	Modeled in ABM portion
Destination/Stop Location	Short term – Tour/trip episode	Improved accessibility effect combined with negative pricing effect on trip distribution for nonwork trips.	Modeled in ABM portion
Joint Travel Arrangements	Short term – Within day	Planned carpool/escorting.	Modeled in ABM portion
Tour Frequency, Sequence, and Formation of Trip Chains	Short term – Within day	Lower tour frequency and higher chaining propensity.	Modeled in ABM portion
Daily Pattern Type	Short term – Weekly (day-to-day)	More compressed workdays and work from home.	Modeled in ABM portion
Usual Locations and Schedule for Nonmandatory Activities	Medium term – One month	Compressed/chain patterns; weekly planned shopping in major outlets.	Modeled in ABM portion
Household/Person Mobility Attributes (Transponder, Transit Path, Parking Arrangements at Work)	Medium term – One to six months	Higher percentage of transponder users and parking arrangements for high incomes, higher percentage of transit path holders for low incomes.	Not modeled; likely to have a very small effect
Household Car Ownership Choice	Long term – One year	Stratified response by income group: Higher car ownership for high incomes; Lower car ownership for low incomes.	Usually modeled in ABM portion
School/University Location and Schedule	Long term – One to five years	Choice by transit accessibility; flexible schedules.	Sometimes modeled in ABM portion
Job/Usual Workplace Location and Schedule	Long term – One to five years	Local jobs for low incomes; compressed/ flexible schedules.	Sometimes modeled in ABM portion
Residential Location	Long term – More than five years	Income stratification: High-income suburbs around tolls roads; Low-income clusters around transit.	Need land use model integrated with travel model
Land Use Development	Long term – More than five years	Urban sprawl if no transit; otherwise shift to transit.	Need land use model integrated with travel model

THE IMPACT OF CAPACITY AND OPERATIONS IMPROVEMENTS ON TRAVEL TIME, TRAVEL-TIME RELIABILITY, AND TRAVELER BEHAVIOR

This investigation focused on travel time and travel-time reliability (henceforth, just “reliability”) from two perspectives:

1. How do capacity and operations strategies affect travel time and reliability? What is the mechanism for their effect and what is the scale/magnitude of the effect?

2. How do changes in travel time and reliability affect the behavior of travelers in terms of trip choices? How can these choices be modeled?

Definition of Travel-Time Reliability

Many definitions of reliability have been developed over the years. Most recently, the reliability definitions used by SHRP 2 projects all use the variability in travel times as the fundamental concept behind defining reliability. The common themes in the SHRP 2 definitions can be rolled into the following overarching definition.

Travel-time reliability is the variability in travel times that occur on a facility or a trip over the course of time, and is due to the interaction of the factors that influence travel times: fluctuations in demand, traffic control devices, traffic incidents, inclement weather, work zones, and physical capacity (based on prevailing geometrics and traffic patterns). The reliability of a facility or trip can be reported for different time slices, e.g., weekday-peak hour, weekday-peak period, and weekend.

A corollary to the basic definition of reliability as variability is the concept of failure, or its opposite, on-time (success). The underlying variability in travel times implies that a certain number of trips will be within an acceptable threshold, and thus will have “failed” or “succeeded.”

From a measurement perspective, reliability is defined from the distribution of travel times, for a given facility/trip and time slice, that occurs over a significant span of time; one year is generally long enough to capture nearly all off the variability caused by disruptions. A variety of different metrics can be computed once the travel time distribution has been established, including standard statistical measures (e.g., standard deviation, kurtosis), percentile-based measures (e.g., 95th percentile travel time, Buffer Index), on-time measures (e.g., percent of trips completed within a travel time threshold, and failure measures (e.g., percent of trips that exceed a travel time threshold); see Figure 5.

The basic definition of travel-time reliability (variability in travel times) can be extended to include the notion of predictability, that is, the probability that a travel time for a facility or trip is within acceptable limits for the traveler, given that travel times are affected by interaction of demand fluctuations, traffic control devices, traffic incidents, inclement weather, work zones, and physical capacity. It can also be used to compare current conditions to history: is the travel time today “typical” of what happens or is it better than usual or near-worst case. However, both of these corollaries are based on establishing the variability over time, as defined by the travel time distribution.

In a broader sense, reliability is a dimension or attribute of congestion. Traditionally, the dimensions of congestion have been spatial (how much of the system is congested?), temporal (how long does congestion last?), and severity-related (how much delay is there or how low are travel speeds?). Reliability adds a fourth dimension: how does congestion change from day-to-day?

Relationship Between Travel Time and Reliability

The notion that reliability can be thought of as an attribute of total congestion was verified empirically in SHRP 2 Project L03 and has been observed on a limited basis prior to that.(13) The basic relationship shown in Figure 6 was found to exist for multiple urban areas, multiple measures of reliability (the 95th percentile travel time index is shown, but standard deviation and percent on time trips also exhibit a strong correlation), and for both individual links and travel time over an extended segment. What this means is that an estimate of the mean level of congestion is known, reliability metrics can be predicted. Project L03 developed a set of predictive equations for doing this; one example is:

$$95th\ \%ile\ TTI = 1 + 3.6700 * \ln(MeanTTI)$$

Figure 4. Equation. 95th percentile.
(Source: Cambridge Systematics et al., *Analytic Procedures for Determining the Impacts of Reliability Mitigation Strategies*, SHRP 2 Project L03, Transportation Research Board, 2013, http://onlinepubs.trb.org/onlinepubs/shrp2/SHRP2_S2-L03-RR-1.pdf.)

Where: TTI is the travel time index.

[13] Jones, E.G., (1988), *Characterizing Travel Time Variability in a Commuting Corridor*. MS Thesis, Department of Civil Engineering, University of Texas at Austin. Also, more recently in: *Improving Reliability on Surface Transport Networks*, OECD, ISBN 978-92-82-10242-8, 2010.

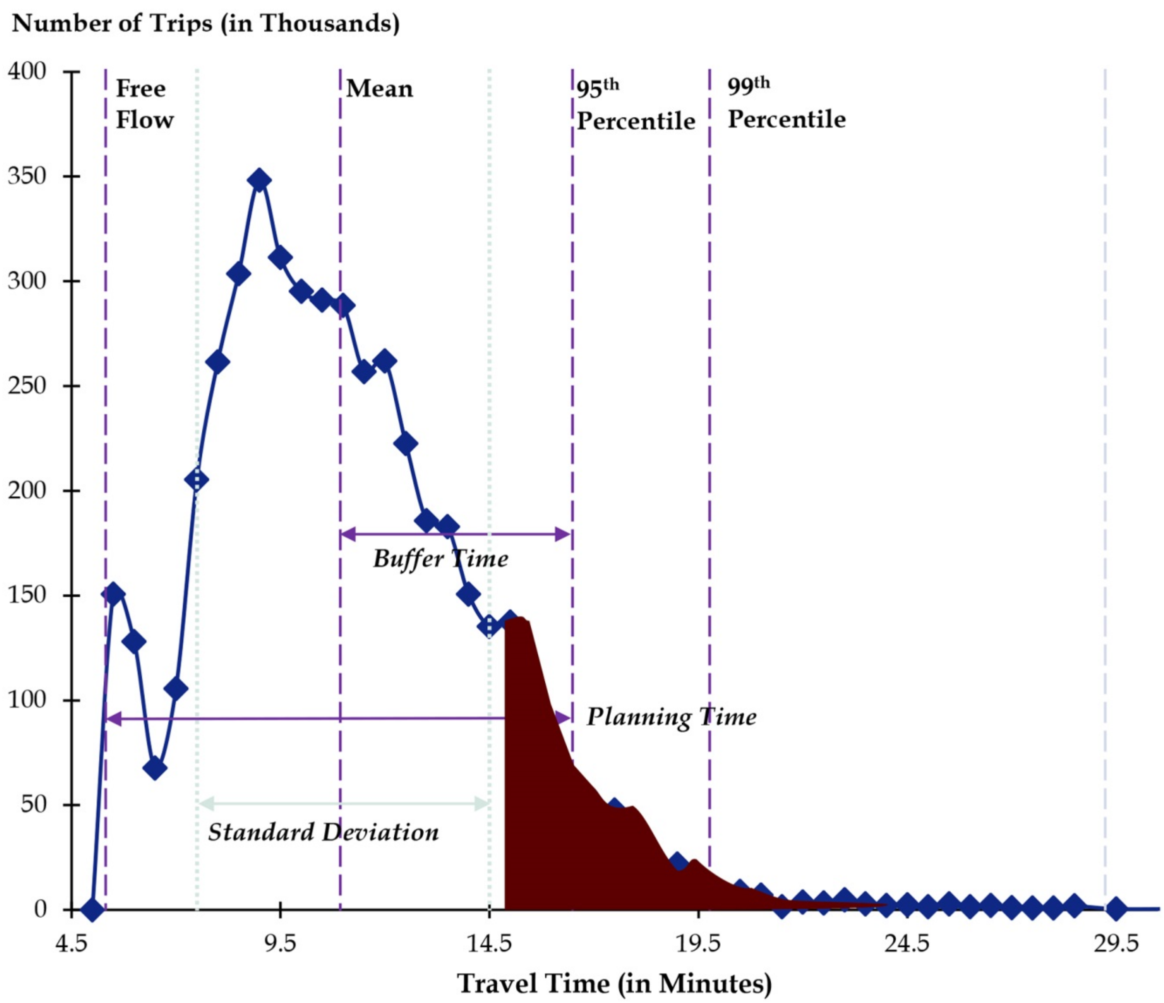

Figure 5. Graph. The travel time distribution is the basis for defining reliability metrics. (Source: Kittelson Associates et al., *Incorporation of Travel-time reliability into the Highway Capacity Manual*, Transportation Research Board, 2014, http://apps.trb.org/cmsfeed/TRBNetProjectDisplay.asp?ProjectID=2197.)

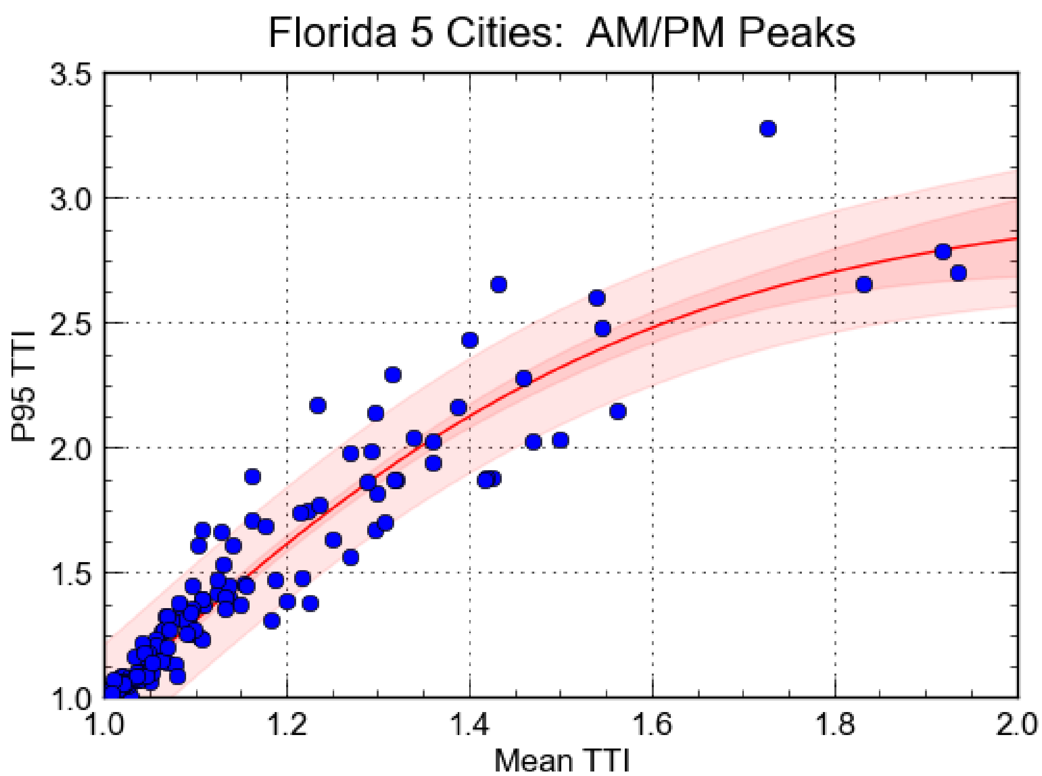

Figure 6. Scatter graph. Correlation between 95th percentile TTI and mean TTI. (Source: Cambridge Systematics, Inc.)

Mechanisms for Affecting Travel Time and Reliability

There are three basic mechanisms for changing both travel time and reliability:

1. Demand – can be reduced overall or shifted to less traveled routes and/or times of travel.
2. Capacity – additional highway space can be added or traffic control systems can be improved to provide an "effective" increase in capacity.
3. Disruptions – can decrease capacity and negatively influence traffic flow. These include:

    a. Incidents – lane and shoulder blockages drop the effective capacity significantly. "Rubbernecking" affects driver behavior and also impacts capacity.
    b. Work Zones – lane/shoulder closures and lane shifts drop the effective capacity significantly.
    c. Weather – affects driver behavior, sometimes drastically, leading to a drop in effective capacity.

Effect of Travel Time and Reliability on Traveler Behavior

The concept of "extra impedance due to unreliable travel" is probably the best way to incorporate reliability into the modeling structure as an input. SHRP 2 Project C04, *Improving Our Under standing of How Highway Congestion and Pricing Affect Travel Demand*, used this approach where the impedance on a link can be captured as a generalized cost function that includes both the average travel time and its standard deviation (which is used as the indictor of reliability; Figure 7).

$$U = a + b \times MedianTime + c \times \frac{Cost}{Inc_e \times Occ_f} + d \times \frac{SDevTime}{Dist} + \cdots$$

Where:
a is a an alternative-specific "bias" constant for tolled facilities.
b is the travel time coefficient, ideally estimated as a random coefficient to capture residual heterogeneity.
MedianTime is the median, typical expected, travel time by auto.
c is the monetary cost coefficient.
$Cost/(Inc_e \times Occ_f)$ is the monetary cost, scaled by power functions of both income and vehicle occupancy.
d is the reliability coefficient.
SDevTime/Dist is a measure of travel-time reliability, specified as the day-to-day standard deviation of the travel time by auto, divided by distance.
And:
Value of Time, VOT = b/c.
Value of Reliability, VOR = d/c.
Reliability Ratio, VOR/VOT = d/b, ranges from 0.5 to 1.5.
VOR range:

Trip purpose	Distance	VOR
Work	5 miles	$54.9/hour
	10 miles	$27.5/hour
	20 miles	$13.8/hour
Non-work	5 miles	$40.8/hour
	10 miles	$20.4/hour
	20 miles	$10.2/hour

Figure 7. Equation. SHRP 2 Project C04's generalized highway utility function.
(Source: PB Americas et al., *Improving Our Understanding of How Highway Congestion and Pricing Affect Travel Demand*, SHRP 2 Project C04, Transportation research Board, 2013, http://www.trb.org/Main/Blurbs/168141.aspx.)

An alternative but conceptually similar approach can be based on the recent work of Small, Winston, and Yan.[14] They adopted the quantitative measure of variability as the upper tail of the distribution of travel times, specifically, the difference between the 80th and 50th percentile travel times. The authors argue that this measure is better than a symmetric standard deviation, since in most situations, being "late" is more crucial than being "early," and many regular travelers will tend to build a "safety margin" into their departure times that will leave them an acceptably small chance of arriving late (i.e., planning for the 80th percentile travel time would mean arriving late for only 20 percent of the trips).

Based on this work, the notion of "travel time equivalents" can be used, where reliability is equilibrated to average travel time. The calculation of travel time equivalents can then be constructed as:

$$TTE = MTT + a * (80\%TT - 50\%TT)$$

Figure 8. Equation. TTE.
(Source: Dowling, Richard and Margiotta, Richard, *Guide for Highway Capacity and Operations Analysis of Active Transportation and Demand Management Strategies*, prepared for FHWA Office of Operations, June 2013, http://www.ops.fhwa.dot.gov/publications/fhwahop13042/fhwahop13042.pdf.)

Where:

TTE is the travel time equivalent on the link.
MTT is the mean travel time (min).
a is the Reliability Ratio (VOR/VOT).
80%TT is the 80th percentile travel time (min).
50%TT is the 50th percentile travel time (min).

To be successful, further work is needed to more tightly define the Reliability Ratio. SHRP 2 Project C04 suggests a range of 0.5 to 1.5, but a review of past studies suggests that the range is more in the 0.9 to 1.2 range. Therefore, a value of 1.0 seems to be very reasonable as a for composite trips. However, previous research indicates that the value of reliability varies by trip purpose. For example, NCHRP Report 431 found the following values, using standard deviation as the measure of reliability:[15]

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[14] Small, K.A., C. Winston, and J. Yan. (2005) Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability, Econometrica, 73(4), 1367-1382.

[15] Small, K. A., R. Noland, X. Chu, and D. Lewis. (1999) Valuation of Travel-Time Savings and Predictability in Congested Conditions for Highway User-Cost Estimation, National Cooperative Highway Research Program Report 431, National Academy Press.

Table 5. Value of travel time variability.

Trip Type	Dollars per Minute of Standard Deviation
Work, high income	0.258
Work, low income	0.215
Nonwork, high income	0.210
Nonwork, low income	0.167

Source: Small, Noland, Chu, and Lewis (1999).

IMPLICATIONS OF INDUCED DEMAND FOR ESTIMATING IMPACTS AND SOCIAL/USER BENEFITS

Overview of Induced Demand

This investigation addressed the following question: what are the implications of induced demand for estimating effects on traffic and social benefits?

One novel concept (novel to highway planners, not novel to economists) introduced in this paper is that induced demand is a measure of the user benefits of implementing the operational improvement (e.g., the improvement makes it easier to get work and increases the range of possible job opportunities for a worker). The less induced demand, the less beneficial is the operational improvement to the new users of the facility.

The problem is illustrated in the conceptual diagram in Figure 9:

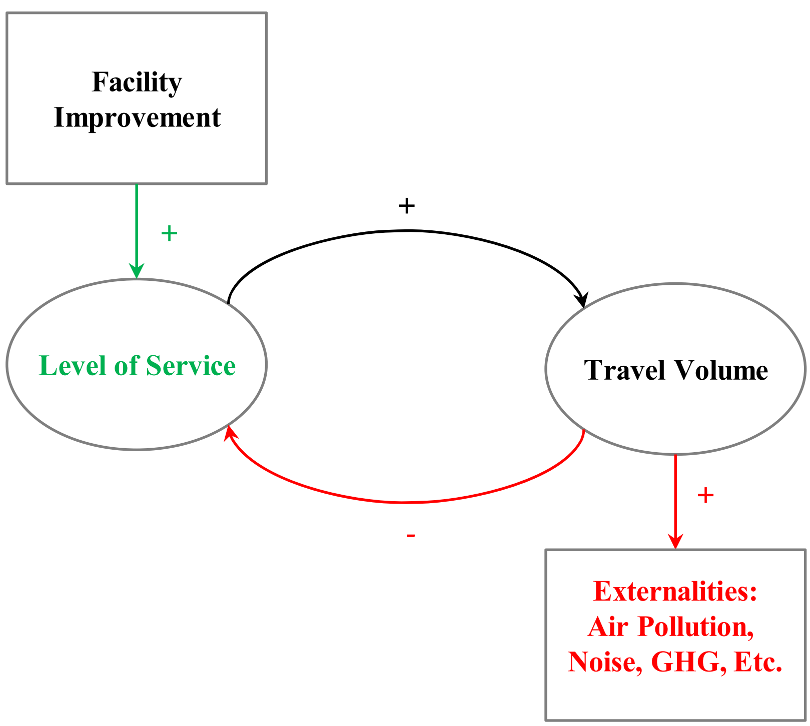

Figure 9. Flowchart. Effects of a facility improvement on level of service, travel volume, and externalities.
(Source: Cambridge Systematics, Inc.)

- A change is made to a facility that improves level of service (inverse of travel cost) on the facility.
- Improved level of service on the facility encourages higher travel volume on the facility.
- Higher travel volume on the facility in turn reduces level of service on the facility.
- Higher travel volume also results in higher externality costs such as air pollution, noise, and greenhouse gas emissions.

Most transportation analyses today are based on forecasts from traditional four-step travel models, which presume fixed trip-rates regardless of the cost of travel. Hence, changes in demand due to changes in travel costs are not accounted for in the estimation of social benefits and costs. This raises the following issues for analyzing the impacts and social benefits and costs of facility improvements:

- What is the magnitude of induced demand due to a facility improvement?
- How can induced demand – i.e., new trip making due to reduced travel costs – be distinguished from estimated changes in travel volumes due to shifts in route, mode, destination, and time of travel?
- Will induced demand affect facility operations and thereby reduce level of service below that which was originally forecast?
- What are the secondary effects of a facility improvement other transportation facilities in the area, and how can these be accounted for?
- Are current analysis tools capable of accounting for induced demand? If not, are there any quick fixes that could be put in place without substantially changing the regional travel model?

For purposes of this discussion we define *induced demand* as additional travel due to improvements on a facility that lower the total cost of travel: i.e., additional travel that would not have taken place in absence of the improvements. This is to be distinguished from *observed volumes* on the facility where the improvements are made, which may be due to one or more of the following:

- **Route choice:** additional traffic diverted from alternate routes.
- **Mode choice:** traffic diverted from alternate modes.
- **Travel time choice:** traffic diverted from alternate time periods.
- **Additional travel:** new trips made because the total cost of travel is lower.

Of these, the first three could justifiably called *apparent* (as opposed to real) induced demand; only the last is truly induced demand. As discussed below, the estimation of benefits requires a broader perspective than the particular facility in question. Otherwise, the calculation of user benefits may be biased upward by including apparent induced demand. That is, an improvement on a facility may attract trips that were formerly using more congested routes. Regardless of how demand shifts are characterized, the most important aspect is how systemwide VMT and system operating conditions change as a result of an improvement.

The limited analysis presented here of additional trip making due solely to a reduction in the cost of travel. There are a number of potential effects that can lead to additional induced demand; the most important effect is demand added by increased land development in response to lower travel costs. But it is still common practice in regional travel demand forecasting to use a fixed future land use scenario regardless of changes to the transportation network. Accounting for indirect effects on demand due to changes in land development, though potentially important, is beyond the scope of this project.

Induced Demand in the Context of User Benefits

Real-world estimation of user benefits can be confounded by the following.

Failure to account for systemwide effects. Improvements to a facility can lead to shifts in travelers' routes, modes, destinations, and time of day of travel. This will show up in travel modeling as increased travel volume on the facility where the improvement is made. But this increase includes effects of travelers who change route and travel mode in response to the reduced travel time. If the increase in volume is attributed solely to new travelers, the benefits to these new travelers will be undervalued by the extent to which the "new" travel volumes on the facility include existing travelers who formerly used other routes or modes, or traveled to other destinations.

Limitations of existing travel models. In economic theory, the demand curve is shown as sloping downward and to the right: i.e., as the price decreases, the quantity demanded increases. But most travel models in use today are four-step models that assume fixed trip generation rates for each purpose; total trip making is insensitive to changes in travel cost. In other words, the demand curve is assumed to be vertical (zero elasticity). While this may be a reasonably close approximation to work trip making in the short run, it is highly implausible for nonwork trips. New generation tour-based travel models that explicitly take into account the dependence of trip generation on travel cost show a that trip making has a significant nonzero elasticity.

There are two ways to address this problem: 1) use a tour-based model that explicitly models dependence of trip making on travel time, or 2) use an independent set of travel demand elasticities to approximate the change in total travel in response to the change in travel time. Table 6 shows a set of travel time elasticities and cross-elasticities derived from simulations using a tour-based travel demand model (Dowling Associates, 2005). Short-run elasticities for truck travel are probably quite small, as these are dependent primarily on economic activity at the trip ends; hence, induced demand for truck travel can probably be ignored for the short run.

Table 6. Travel time elasticities from a tour-based travel demand model.

Demand		Travel Time: AM Peak Drive Alone	AM Peak Shared Ride	AM Peak Transit	PM Peak Drive Alone	PM Peak Shared Ride	PM Peak Transit
AM Peak	Drive Alone	-0.225	0.030	0.010	-0.024		
	Shared Ride	0.037	-0.303	0.032		-0.028	
	Transit	0.036	0.030	-0.129			-0.007
PM Peak	Drive Alone	-0.124			-0.151	0.015	0.005
	Shared Ride		-0.109		0.019	-0.166	0.016
	Transit			-0.051	0.018	0.015	-0.040
Off Peak	Drive Alone	-0.170			-0.069		
	Shared Ride		-0.189			-0.082	
	Transit			-0.074			-0.014

Source: Portland Tour-Based Model applied to Puget Sound region (Dowling Associates, 2005).
Note: Blank entries indicate where cross-elasticities were set a priori to zero.

Single set of land use and demographic forecasts. In practice, most regional travel model forecasts are carried out using a single set of land use and demographic forecasts. But land use in particular is sensitive to travel costs.

Other Societal Costs Due to Induced Demand

Externalities due to induced demand include noise, air pollution, and greenhouse gas emissions. Noise effects are still debated, although available studies indicate that a reasonable figure for noise costs are between 0.1 cents and 0.3 cents per mile for freeway traffic (Victoria Transportation Policy Institute). Small and Kazimi (1995) estimated the cost of automotive air pollution at $0.20 per mile in urban areas.[16] For greenhouse gases, the U.S. Government in 2010 adopted a figure of $21 per ton of CO_2 equivalent, which equates to about 0.8 cents per mile for a fleet average MPG of 25. This has been criticized by some economists as too low (Ackerman and Stanton, 2010); the UK government has estimated short-to-medium term costs of CO_2 at about $87 per ton, or about 3.3 cents per mile (United Kingdom Department of Energy and Climate Change, 2010). In 2013, the U.S. figure was updated to $37 per ton.[17]

Taking the Small and Kazimi estimate for air pollution, the average estimate for noise, the and adding in the official U.S. Government number, this works out to about 20.8 cents per mile for combined externality effects. If these values are used to estimate the externality costs of induced demand, then the externality costs for induced demand for the add-a-lane alternative are about 9 percent to -12 percent of the estimated user benefits, and more than an order of magnitude greater than the additional user benefits due to induced demand.

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[16] Original estimate converted to 2011 dollars.

[17] http://www.whitehouse.gov/sites/default/files/omb/inforeg/social_cost_of_carbon_for_ria_2013_update.pdf and http://www.whitehouse.gov/blog/2013/11/01/refining-estimates-social-cost-carbon.

Case Study: Signal Timing Improvements on an Arterial

Setting

We selected a section of El Camino Real (CA State Highway 82) a major arterial in the Bay Area to investigate the induced demand implications for estimating the impacts of common traffic operations improvements. The study section parallels the U.S.-101 study corridor and is often used as an alternative route by commuters. The study section includes 15 signalized intersections for a total length of 3.24 miles. There are three through lanes plus exclusive left turn lanes on all intersection approaches. All signals are coordinated actuated and most of them have protected left turn phases.

We used the SYNCHRO software to evaluate existing conditions and optimize the signal settings (cycle length, splits, and offsets). We checked the baseline conditions and made adjustments to the existing signal settings to eliminate severely oversaturated movements. This is because SYNCHRO (as well as any other signal timing optimization software) cannot accurate model the delays and other impacts in oversaturated conditions, which results in unrealistic improvements during the signal optimization process.

We applied SYNCHRO first to optimize the signal settings under baseline conditions. Next we kept the signal settings fixed and simulated the effects of increased through traffic volume on the arterial by 3 percent, 5 percent, and 10 percent. The results are shown in Table 7 and Figure 10.

Table 7. Estimated performance measures for base case and alternatives.

Performance Measure	Baseline	Baseline Optimal Settings	Induced Demand[a]		
			3%	5%	10%
Arterial Through Traffic					
Travel time (sec)	691	589	596	601	617
Delay (sec/veh)	223	122	128	133	149
Vehicle miles of travel	7,579	7,579	7,807	7,958	8,337
Vehicle hours of travel	444	378	395	405	435
Mean vehicle speed (mph)	17.1	20.0	19.8	19.6	19.2
Person miles of travel[b]	9,095	9,095	9,368	9,550	10,005
Person hours of travel	532	454	473	486	522
Total System					
Vehicle miles of travel	8,879	8,879	9,105	9,257	9,635
Vehicle hours of travel	515	456	471	481	509
Person miles of travel	10,655	10,655	10,926	11,108	11,562
Person hours of travel	618	547	565	13,330	611
Fuel consumption (gal)	699	614	632	644	677
CO emissions (kg)	48.9	42.9	44.2	45.0	47.4
NOx emissions (kg)	9.5	8.4	8.6	8.8	9.2
VOC emissions (kg)	11.3	10.0	10.2	10.4	11.0

[a] Percent increase of through volume.
[b] Vehicle occupancy of 1.2 person/vehicle was assumed.

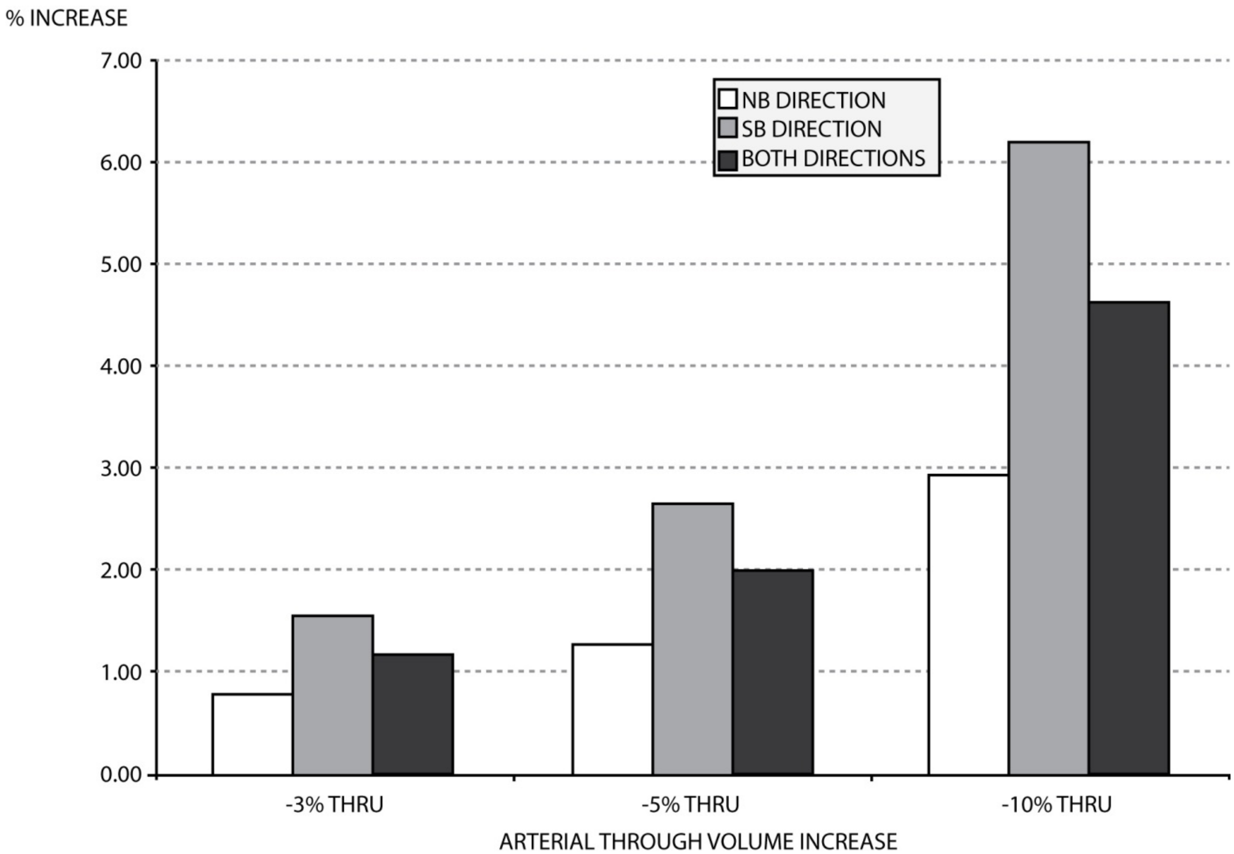

Figure 10. Bar graph. Change in arterial through traffic travel times.
(Source: Cambridge Systematics, Inc.)

The assumed volume increase of 3 percent is consistent with the reported elasticities in Table 6. Signal timing optimization resulted in 15 percent travel time improvement which could result in induced demand of about 3 percent. We also tested 5 percent and 10 percent volume increases to test the sensitivity of the results.

Analysis Results

Table 7 shows that signal timing optimization with baseline volumes improved travel time on the arterial by 15 percent (from 691 sec to 589 sec). The performance was worsened with the induced demand but is still better than the baseline conditions. As Figure 10 shows a 3 percent increase in volumes worsens performance by only 1.2 percent; even a 10 percent increase in through volumes has a better performance than baseline conditions with existing signal settings (Table 7). Note that this type of analysis could be also used to evaluate how much additional traffic can be absorbed by arterial parallel to freeways.

User Benefit Calculations

We used the a value of time ($13.94/hour) for these calculations. We estimated the benefits for a) the baseline conditions with optimal signal settings, and b) induced demand of three percent for through traffic on the arterial. The results are shown in Table 8. Note that these benefits apply only for the AM peak hour. The annual benefits for the AM peak period would be $493,500 for the baseline and $477,500 for the induced demand case assuming 250 weekdays and two hour AM peak period.

Table 8. User benefits.

Performance Measure Total System	Baseline	Baseline Optimal Settings	Induced Demand 3%
Person miles of travel	10,655	10,655	10,926
Person hours of travel	618	547	565
Mean person speed (mph)	17.2	1.5	19.3
Travel cost ($/person mile)	$0.81	$0.72	$0.72
User benefits		$987	$955

Note that the benefits gained by new users of the facility (induced demand) are not included in the above performance table. However, as pointed out earlier, the benefits to new users (3 percent of all future users) would be approximately one-half of those experienced by current users (97 percent of the future users). Thus, accounting for the benefits experienced by new users (induced demand) would increase the computed benefits (after induced demand) by about 1.5 percent, from $955 to $970. The difference between the computed induced demand benefits and the baseline benefits is $17, less than 2 percent of the computed baseline benefits.

Summary and Conclusions

Several conclusions can be drawn from this analysis:

- The major conclusion is that user benefit calculations must be done at as broad a scale as possible. Estimating user benefits at a facility level only will distort user benefit calculations because the estimates will be confounded mainly by route shifts. *The issue of using an appropriately broad scale of analysis appears to be much more significant than whether or not to include induced demand in the analysis.*

- There is a benefit to induced travel due to lower travel costs, namely the value of travel to persons who would not have otherwise traveled but are now traveling because of reduced travel costs.

- Induced travel can be estimated at a systemwide level by applying elasticities derived from other studies. While this approximation may not be as good as travel demand estimates derived from a model that specifically incorporates travel cost in trip generation, travel demand elasticities are low enough so that there is little distortion using elasticities alone.

- The case studies estimated that induced demand contributes less than one percent to total demand. Hence, it is unlikely that estimated travel times would change very much if induced demand were included in the operations analysis, even after accounting for the fact that under congested conditions travel times rise nonlinearly with volume increases.

- From the case studies shown here it is clear that benefits to new users are *de minimis* compared to benefits to current users. This is because: 1) demand elasticities are low to begin with, and 2) the average value of time for new users is about half that of current users. Using the travel time elasticity measures derived in the NCHRP study,[(18)] it is clear that even a 10 percent reduction in travel times from the base case would result in at maximum a 3 percent change in demand; such large changes in travel time are not likely in absence of massive capacity increases.

- Externality costs due to induced demand can be significant, and appear to be much higher than benefits due to induced demand. But these still appear to be relatively small (on the order of 10 percent) compared to user benefit estimates.

- The findings from the signal retiming study indicate that induced demand does not significantly affect the system performance under the optimized timings. Also, although we assumed a range of additional traffic (up to 10 percent) in most cases the additional induced demand would be small. Signal timing optimization results in significant 15 percent reduction in travel times, which translates to only about 1.7 min savings per traveler at the study corridor.

EFFECT OF ACCESSIBILITY ON LAND USE PATTERNS

Overview

For over 15 years the transportation land use literature has attempted to relate the demand for travel to aggregate measures of the built environment. Models of travel behavior regress an outcome variable – often trip generation, mode choice, or vehicle miles traveled (VMT) – on demographics and measurements of land use. Land use variables are typified by the 3Ds (Kockelman and Cervero, 1997)[(19)] which capture in turn the density, diversity, and design of a geographic area.[(20)] Variables commonly include residential density, diversity of land uses, and

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[18] Dowling, Richard et al., "Predicting Air Quality Effects of Traffic-Flow Improvements: Final Report and User's Guide," National Cooperative Highway Research Program Report 535, 2005.

[19] Kockelman, Kara, and Robert Cervero. "Travel Demand and the 3Ds: Density, Diversity, and Design." *Transportation Research Part D: Transport and Environment* 2, no. 3 (1997): 199-219.

[20] Other "Ds" have since been added including destinations, distance to transit, demographics, and travel demand management, e.g., parking. An updated version of the Ds is described in Cervero and Ewing (2010) and a review of the impact of demographics is provided in Pucher and Renne (2003).

design of the street grid, and counts of destinations within a constant time distance (an isochrone). Most studies compute land use variables at a fairly coarse geographic scale such as transportation analysis zones (TAZ) or census tracts, despite the fact that the built environment often changes on a block-by-block basis.

This paper added to previous research by proposing and implementing a concept of land uses located in space relative to a multimodal transportation graph, which enables the following contributions to the travel literature. First and foremost, the framework described here is designed to accurately represent pedestrian-scale accessibility, which continues to be a secondary consideration in current travel modeling practice. Second, it has been theorized (Crane, 1996;[21] Krizek, 2003[22]) that pedestrian demand cannot be measured accurately without also measuring the relative accessibility of auto travel – indeed some have said that reducing level of service on roads is necessary to induce pedestrian travel (Chatman 2008).[23] Finally, 3Ds variables are criticized on the grounds that they do not propose a behavioral explanation for travel (Boarnet and Crane, 2001).[24] This paper takes the position that travel is a derived demand most heavily influenced by access to destinations, traits of the routes to those destinations, and modified by attributes of the decision-maker (e.g., Cervero, 2002;[25] Guo et al., 2007[26]).

A number of methodological advances enable this research, which allows representation of the full set of local streets for pedestrian-scale accessibility, a hierarchical graph to capture the tradeoff between modes, and integration of microscale land use data to measure the full population of alternative destinations in the city. A fully estimated destination choice model is beyond the scope of this project due to length requirements, but future research will address this question fully.

We examined the question of whether and to what degree policies which encourage compact development can reduce VMT and the concomitant greenhouse gas (GHG) emissions (Boarnet,

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21 Crane, R. "The Influence of Urban Form on Travel: An Interpretive Review." *Journal of Planning Literature* 15, no. 1 (2000): 3–23.

22 Krizek, K. J. "Neighborhood Services, Trip Purpose, and Tour-based Travel." *Transportation* 30, no. 4 (2003): 387–410.

23 Chatman, D. G. "Deconstructing Development Density: Quality, Quantity and Price Effects on Household Non-work Travel." *Transportation Research Part A: Policy and Practice* 42, no. 7 (2008): 1008–1030.

24 Boarnet, M., and R. Crane. *Travel by Design: The Influence of Urban Form on Travel*. Oxford University Press, USA, 2001.

25 Cervero, R. "Built Environments and Mode Choice: Toward a Normative Framework." *Transportation Research Part D: Transport and Environment* 7, no. 4 (2002): 265–284.

26 Guo, Jessica Y., Chandra R. Bhat, and Rachel B. Copperman. "Effect of the Built Environment on Motorized and Nonmotorized Trip Making: Substitutive, Complementary, or Synergistic?" *Transportation Research Record: Journal of the Transportation Research Board* 2010, no. -1 (2007): 1–11.

2011[(27)]; Brownstone, 2008[(28)]). This topic is of particular relevance in the State of California, which has passed Senate bill 375 (SB375) which mandates that each of its MPOs creates a sustainable community strategy (SCS). Each SCS must analyze potential GHG reduction through coordinated land use and transportation (Barbour and Deakin, 2012),[(29)] and must model the impact of policies which increase residential density on reductions in automobile use and increases in travel by sustainable modes such as walking, bicycling, and public transit. This research is performed as part of the UrbanSim (Waddell, 2002)[(30)] analysis performed by the Urban Analytics Lab at UC Berkeley for the San Francisco Bay Area SCS funded by the Metropolitan Transportation Commission (MTC).

Previous Research

For over 15 years the transportation land use literature has attempted to relate the demand for travel to aggregate measures of the built environment. Models of travel behavior regress an outcome variable – often trip generation, mode choice, or vehicle miles traveled (VMT) – on demographics and measurements of land use. Land use variables are typified by the 3Ds (Kockelman and Cervero, 1997)[(31)] which capture in turn the density, diversity, and design of a geographic area. Variables commonly include residential density, diversity of land uses, and design of the street grid, and counts of destinations within a constant time distance (an isochrone). Most studies compute land use variables at a fairly coarse geographic scale such as transportation analysis zones (TAZ) or census tracts, despite the fact that the built environment often changes on a block-by-block basis.

Despite limited microdata available at the time, Ewing and Cervero (2001) are able to draw broad conclusions based on a wide breadth of empirical literature that trip generation is largely based on demographics, trip distance varies largely with the built environment, and mode choice depends on both demographics and the built environment, but predominantly on demographics. Although these early studies were a major contribution to our understanding of the influence of land use on the demand for travel, this type of study was quickly criticized for its lack of behavioral foundation (Crane, 2000; Boarnet and Crane, 2001). Boarnet (2011) identifies 3Ds-style studies as "reduced form" models and argues for the move to "structural models," which explain *why* residential density, for instance, might influence travel.

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[27] Boarnet, M. G. "A Broader Context for Land Use and Travel Behavior, and a Research Agenda." *Journal of the American Planning Association* 77, no. 3 (2011): 197–213.

[28] Brownstone, D. "Key Relationships Between the Built Environment and VMT." *Transportation Research Board* (2008): 7.

[29] Barbour, Elisa, and Elizabeth A. Deakin. "Smart Growth Planning for Climate Protection." *Journal of the American Planning Association* 78, no. 1 (2012): 70-86.

[30] Waddell, P. "UrbanSim: Modeling Urban Development for Land Use, Transportation, and Environmental Planning." *Journal-American Planning Association* 68, no. 3 (2002): 297-314.

[31] Ewing, R., and R. Cervero. "Travel and the Built Environment: a Synthesis." *Transportation Research Record: Journal of the Transportation Research Board* 1780, no. -1 (2001): 87-114.

Pedestrian Models

Data has become increasingly available at the pedestrian-scale, and a large body of literature in the demand for pedestrian travel has resulted. The commercial success of Walkscore, which now services almost six million queries a day, is well established. Walkscore is a weighted combination of the fine-grained location of nine types of nearby destinations (Walkscore, 2011);[(32)] its *raison d'etre* at this time as a commercial application is in selling real estate and the correlation with real estate values has been established (Copyright 2009).[(33)]

Recently, Walkscore has been confirmed as predictive of walking trip generation (Weinberger and Sweet, 2012),[(34)] but this study relates Walkscore to modeled pedestrian outcomes derived from travel models, which themselves misrepresent the walking environment. The theoretical framework established for Walkscore in Frank et al. (2008)[(35)] and Moudon et al. (2006)[(36)] is likely valid, but the set of destinations, the weights applied to the destinations, and the distance decay function are empirical questions that merit more investigation. Additionally the relationship of pedestrian travel to meso- and macroscale accessibility is largely missing from this line of research.

Econometric Frameworks

Econometric frameworks have long been the workhorse of travel modeling. Discrete choice modeling (McFadden, 1980)[(37)] allows the estimation of indirect utility among a discrete number of alternatives subject to a linear in parameters utility function and a given distribution for a random error term. Discrete choice was first widely applied to travel demand models by Ben-Akiva and Lerman. A framework for mode choice is provided in Cervero (2002), which allows for both discrete choice estimation of utility among travel modes as well as using 3Ds measurements as explanatory variables. This approach is used in Guo et al. (2007), which studies

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[32] "Walk Score Methodology."" Front Seat, Inc., July 15, 2011. http://www2.walkscore.com/pdf/WalkScoreMethodology.pdf.

[33] Copyright, Joe. "Walking the Walk: How Walkability Raises Home Values in U.S. Cities" (2009). Crane, R. "On Form Versus Function: Will the New Urbanism Reduce Traffic, or Increase It?" *Journal of Planning Education and Research* 15, no. 2 (1996): 117-126.

[34] Weinberger, Rachel, and Matthias N. Sweet. "Integrating Walkability Into Planning Practice." In *Transportation Research Board 91st Annual Meeting*, 2012.

[35] Frank, L. D, J. Kerr, J. F Sallis, R. Miles, and J. Chapman. "A Hierarchy of Sociodemographic and Environmental Correlates of Walking and Obesity." *Preventive Medicine* 47, no. 2 (2008): 172-178.

[36] Moudon, A. V, C. Lee, A. D Cheadle, C. Garvin, D. Johnson, T. L Schmid, R. D Weathers, and L. Lin. "Operational Definitions of Walkable Neighborhood: Theoretical and Empirical Insights." *Journal of Physical Activity & Health* 3 (2006): 99.

[37] McFadden, D. "Econometric Models for Probabilistic Choice Among Products." *Journal of Business* (1980): 13-29.

the substitution of pedestrian and auto modes, finding that pedestrian travel is largely complimentary to automobile travel (in other words, pedestrian access generates additional walking trips that do not tend to substitute for automobile travel).

The City in a Network

First and foremost, it is presumed that travel is a derived demand such that there is an "attractor" at the destination which is counteracted by an "impedance" in the network as is typical of the gravity model (Hansen 1959).[38] Unlike the gravity model, this network-based model estimates the relative importance of attributes which can include 1) the amount or quality of activity at the destination; 2) aspects of the route; and 3) attributes of the decision-maker, which modify the elasticities of the first two sets of traits.

The simplest version of the conception proposed here places land use in the context of the local street network, using network distances that are equivalent to the length of the streets traversed. Most urban spatial data is either georeferenced with a latitude and longitude or is assigned to a parcel and thus has a spatial position through the location of parcels in a region.[39] A typical schema of urban data relationships is shown in Figure 11, which depicts data frequently used in urban modeling (e.g., Waddell 2002): households and businesses are assigned to buildings which are assigned to parcels which are placed within the context of the local street network. Alternatively, any spatial data can be assigned to the network by latitude or longitude or any other geometry representable in a geographic information system (GIS). Figure 11 describes the land use and transportation datasets used in this research. Each box is a dataset with the type of data above and the possible sources listed inside the box. Relationships between land use and the transportation network are mediated either through a latitude/longitude pair or a parcel shape which defines a location in the city.

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[38] Hansen, W. G. "How Accessibility Shapes Land Use." *Journal of the American Institute of Planners* 25, no. 2 (1959): 73-76. Measurements include "isochrones" which sum opportunities within a distance or travel time, "gravity model" measures which discount the opportunities by some measure of the distance to each destination, and logsum measures which estimate coefficients on attractors and impedances using a statistical framework, typically using a discrete choice model.

[39] There are currently around 150 million non-government owned parcels in the United States (another 10 million are owned by the government). The primary purpose of parcels is two-fold: preventing/resolving private property disputes between land owners and efficient collection of property taxes.

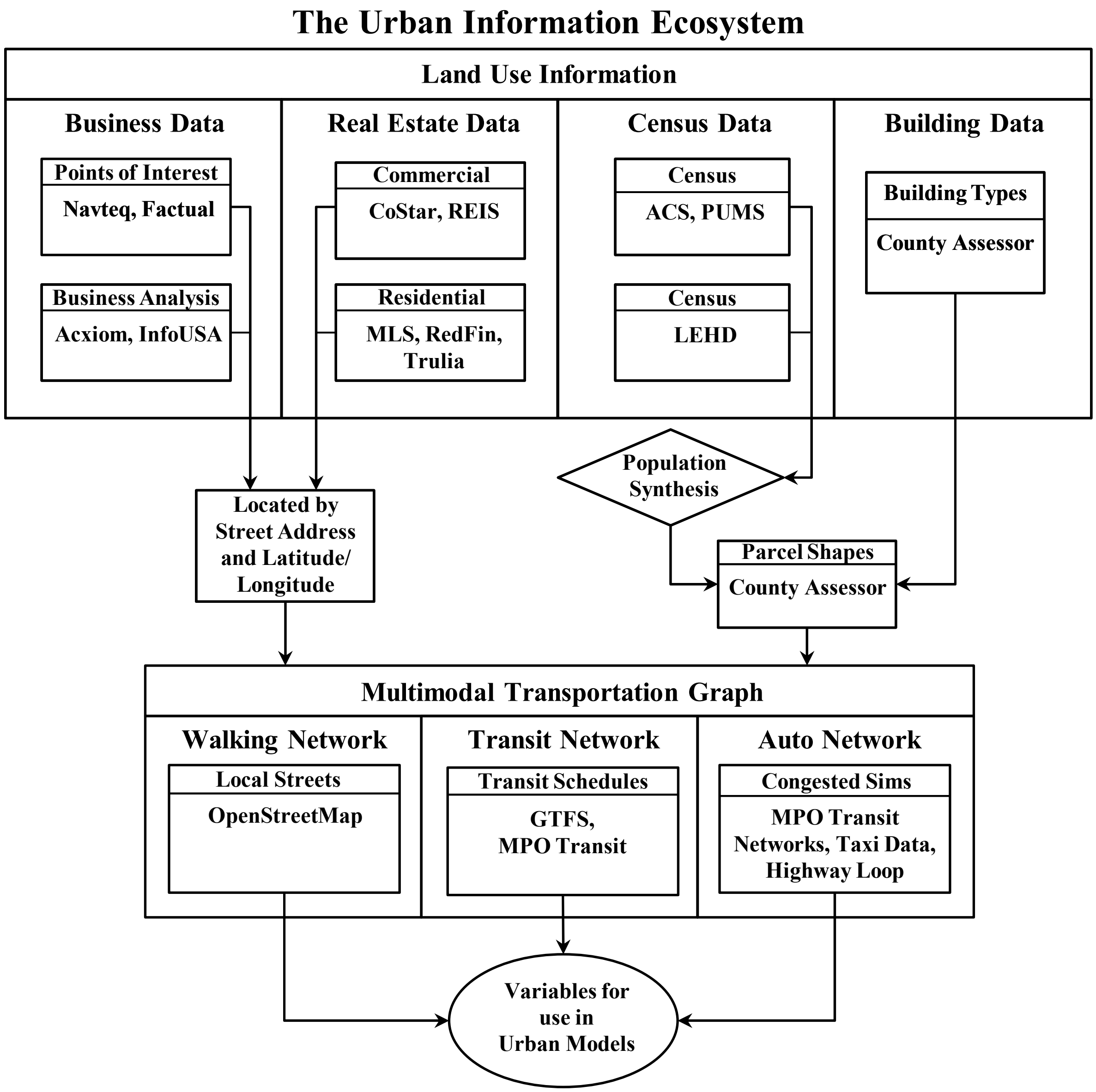

Figure 11. Flowchart. Interaction of information in an urban system.
(Source: Waddell, P. "UrbanSim: Modeling Urban Development for Land Use, Transportation, and Environmental Planning." *Journal of the American Planning Association* 68, no. 3 (2002): 297-314.)

Assignment of Land Use

Land use data must be efficiently connected to the transportation network. Datasets are large, and the number of objects of each type for the Bay Area implementation is shown in Table 9. In an ideal case, the synthesized population and dataset of firms are assigned to the parcel map, and the parcel map gives addresses that define the means of access and egress from that parcel to the local street network. Every person has access to every firm and vice versa via these access and egress points. This complete graph of parcel connections is here called the Parcel Graph.

In practice, data currently are subject to a complicated set of messy interrelationships. Although population might be accurate at higher-level census geographies, the assignment to buildings is typically performed by iterative fitting to observed marginals (Beckman et al., 1996)[40] which introduces error. Firm data is yet more problematic: establishments are tracked in a number of datasets, but businesses with multiple locations are often assigned to a single building, and geographic knowledge is often no more specific than assignment to the nearest tract or block group centroid. Building data are maintained by county assessors and contain myriad errors in spatial encoding, including repeated stacked or overlapping parcels, misrepresentation of buildings types, unrecorded informal units, etc.

Table 9. Number of objects per dataset used in the Bay Area SCS implementation.

	Count of Objects
Parcels	2,023,915
Single Family Houses	1,479,511
Non-SF Buildings	456,749
Establishments	464,302
Jobs	3,395,967
Households	2,608,023
People	6,996,929

Street Node Geography

An extremely useful simplifying assumption has been made in this research to adopt “street node geography.” In this case, each land use is mapped to its nearest street intersection and thus all land use is assumed to exist at point locations coincident with the vertices of the network being used, here called the Node Graph. Thus, the city can be conceived as a Voronoi diagram of the local street network intersections. Spatial data is assigned first to parcels, parcel centroids are mapped the nearest street node, and the relationship between parcels and nodes is used to map land use to the network.[41] Since walking distances are typically significantly larger than the distance from each parcel to its nearest street intersection, this reduces accuracy of models very little.

Additionally, street networks are an immanent and varying property of cities which are naturally denser in the dense areas of the city and sparser in less dense areas of the city. Thus, the street network is an important cue that there is less information present in areas which have large distances between nodes, and the street network “compresses” the city appropriately. Space is

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[40] Beckman, R. J, K. A Baggerly, and M. D McKay. “Creating Synthetic Baseline Populations.” *Transportation Research Part A: Policy and Practice* 30, no. 6 (1996): 415-429.

[41] A dual conception exists here where land use is mapped to the nearest edge as opposed to the nearest vertex. This is “block face” geography (Clifton et al. 2008) and can be represented by using the “line graph” of the local street network in which every edge is replaces by a vertex and vice versa. Block face geography can be more accurate than street node geography in some situations: for instance, real estate value and demand might vary by block face rather than street intersection.

thus represented more accurately where it matters most.[42] This reduces the number of land use elements by almost a factor of 10 which relieves computational burden while maintaining spatial resolution appropriately. The assignment of land use can be applied to any network, including networks for other transportation modes discussed next.

[42] This assumption fails for large parcels like urban parks, university campuses, and corporate office parks. Generally speaking, where location of actual buildings is known, assignment of building to street node directly should be done. Unfortunately, this information is often unavailable and large parcels must be allocated proportionally to all adjacent street nodes.

CHAPTER 3. ATLANTA CASE STUDY: DEMAND EFFECTS OF OPERATIONAL IMPROVEMENTS

PURPOSE OF THE CASE STUDY ANALYSIS

Several previous studies of the effect of transportation improvements on induced demand undertook an empirical approach that considered time series data on facilities or on an areawide basis; Cervero provides a summary of these and other types of study designs used to examine induced demand.(43) Facility-based studies most commonly track changes in demand over time in relation to the physical expansion of the facility, as measured in lane-miles. The concept is that increasing capacity (lane-miles) leads to a decrease in travel time, which in turn effects both short- and long-term demand changes. However, due to do data limitations in the past, the size of the actual travel time change is not monitored over time, and lane-miles is used as a surrogate (indicator) variable. Further, no previous studies have considered the effect of operational strategies on induced demand, with the exception of NCHRP Report 535, but the strategies covered there were land additions (general purpose and high-occupancy vehicle), access management, intersection channelization, and signal timing. Clearly, the state of the operations practice has advanced to include other forms of operations that need to be addressed.

This analysis was undertaken to address both of these issues using the Atlanta, Georgia region as a case study. It is based on using demand measurements from several sources (mostly continuous) and continuous travel time measurements. It considers three types of operational strategies limited to urban interstates in the Atlanta region:

1. Ramp metering.
2. Routine incident management and dynamic message signs (DMS).
3. Travel times posted on DMSs.
4. Quick clearance incentive program for large truck incidents.

BACKGROUND

Operations in the Atlanta Region

Operations on Atlanta freeways is controlled by the Georgia Department of Transportation (GDOT) under its NaviGAtor program. It was first activated in April 1996, just before the 1996 Summer Olympics in Atlanta. It includes traffic cameras, dynamic message signs, ramp meters, and a traffic speed sensor system. A highly structured incident management program, HERO, has evolved as well and is coordinated with other NaviGAtor activities. As of early 2011, 508 directional miles (approximately 254 centerline miles) of freeways in the Atlanta region were covered by cameras and traffic sensors. Figure 12 shows this coverage.

[43] Cervero, Robert, Induced Travel Demand: Research Design, Empirical Evidence, and Normative Policies, Journal of Planning Literature, Vol. 17, No. 1, August 2002.

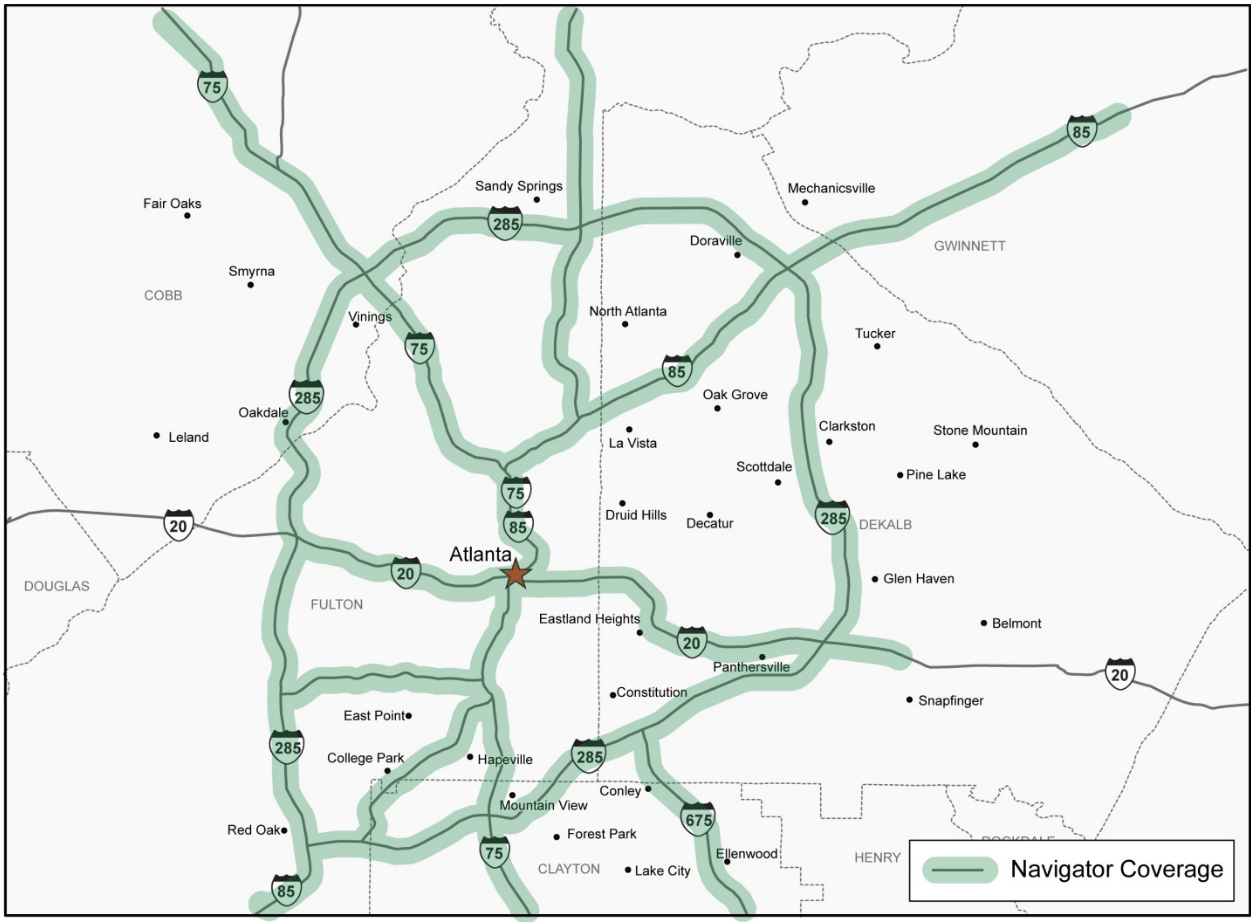

Figure 12. Map. Atlanta NaviGAtor coverage, 2011.
(Source: http://www.511ga.org/.)

Study Period and Study Sections

The study period is from 2001 (the first year for which archived data from the NaviGAtor system is available) to 2010. Only nonholiday weekdays were analyzed. Study periods were defined to represent "extended peak periods" in order to capture queuing and trips that may have been diverted in time. The AM period was 6:00 to 11:00 a.m. and the PM period was 3:00 to 8:00 p.m. The analysis was done for each direction individually, so directions of travel were defined as peaking in either the AM or PM periods.

A wide array of study sections was defined to include both study and control/regional sections. A study section is defined as a unidirectional highway segment approximately 4-6 miles long, except the I-85 study sections which are 9.8 miles long. The exact length depends on the network typology and local travel patterns. For example, a major freeway-to-freeway interchange should be located at the terminus of a segment, not in the middle. The treatment sections used in the analysis are defined as following:

- 1 = I-75 NB from I-285 to Roswell Rd (5.19 miles).
- 2 = I-75 SB from I-285 to Roswell Rd (5.19 miles).
- 5 = I-285 EB from GA-400 to I-75 (6.50 miles).
- 6 = I-285 WB from GA-400 to I-75 (6.50 miles).
- 7 = I-285 EB from GA-400 to I-85 (6.03 miles).
- 8 = I-285 WB from GA-400 to I-85 (6.03 miles).
- 9 = I-75 NB from Roswell Rd to Barrett Pkwy (5.18 miles).
- 10 = I-75 SB from Roswell Rd to Barrett Pkwy (5.18 miles).
- 11 = I-85 NB after Brookwood Split to I-285 (9.80 miles).
- 12 = I-85 SB after Brookwood Split to I-285 (9.80 miles).

Two comparison groups were formed: a control group, which included locations where ramp metering had not been installed as of mid-2010, and a regional group which included all of the control sites plus other locations around the area which did receive ramp metering prior to 2010.

Highway Improvements During the Study Period

- **Freeway Ramp Metering Project.** GDOT began a regional freeway ramp metering program in early 2008. The goal of the program is to provide ramp meters on most all freeway entrance ramps in the 10 county Atlanta Region, freeway-to-freeway ramps are not planned to be metered. Currently there are 169 interchanges metered. GDOT is continuing to add meters to the program. Since mid-2009, the ramp meters have been upgraded and are running as traffic responsive devices, allowing each meter to respond to local traffic conditions on the ramp and interstate based on ramp and mainline detection. The meters are still operating in an isolated manner and have no coordination with other ramps in the system. Future planned upgrades will deploy the SWARM software that will allow the ramp meters to be operated in groups, allowing for a systemwide response to traffic conditions. ***On all study sections, ramp meter installation was completed by September 2008.***

- **Towing Recovery and Incentive Program (TRIP).** GDOT introduced TRIP in early 2008 to provide monetary incentives to qualified towing operators for the quick clearance of large commercial vehicle incidents. This program is a critical component of the metropolitan Atlanta traffic incident management quick clearance program. TRIP incidents involve large vehicles and complicated debris or hazardous material (HAZMAT) spills, which would normally take a significant amount of time to clear from a roadway. TRIP can only be activated by designated personnel, such as a GDOT Highway Emergency Response Operator (HERO) supervisor or a police officer on-scene, based upon specific criteria and procedures. Once declared a TRIP incident, the designated TRIP company for that area is notified. The TRIP company supervisor must arrive on scene within 30 minutes of notification and all basic equipment must arrive within 45 minutes if called between 5:30 a.m. and 7:00 p.m., Monday through Friday; at other times, the equipment is allowed 60 minutes to arrive. The TRIP company remains on scene until they receive an official notice to proceed to clear the incident from the roadway. Upon receiving the notice to proceed, the TRIP company must have the roadway cleared and open to traffic within 90 minutes. When the program began in 2008 it covered I-285 and all interstates inside I-285. The coverage boundaries were expanded in June 2009 and again in April 2010.

- **Expected Travel Times on DMS Displays.** Beginning in 2008, GDOT began posting expected travel times to recognizable destinations on their DMSs.

- **Capital Expansion.** A limited amount of lane additions were conducted on the study and control sections during the study period. The major project was a redesign of the "Downtown Connector" from 2007 to 2009 (Chapters 3 and 4) and for his reason they have been excluded from this analysis. The other noteworthy capital expansion project was the addition of auxiliary lanes on I-75 north of its interchange with I-285 in 2004 (Chapters 1 and 2).

Table 10 shows the deployment of operations strategies on the sections by year. Note that the study sections have had multiple treatments, making it impossible to break out the effect of individual strategies. However, as operations strategies usually have much smaller congestion relief impacts than capital expansion, having multiple treatments makes it more likely that the effect can be observed. The deployment of operations strategies on the control segments is less than ideal – it would be best if they had received no operational treatment. As discussed in the next section, for this and other reasons, additional control sections for demand were selected using the automatic traffic recorder (ATR) data.

Table 10. Deployment of operational strategies on Atlanta study sections.

Section Nos.	Ramp Meters	Towing Recovery and Incentive Program (TRIP)	Travel Times on DMSs	Routine Incident Management
Treatment – 1/2	mid-2008	2009	2008	2000
Treatment – 5/6	mid-2008	early 2008	2008	2000
Treatment – 7/8	mid-2008	early 2008	2008	2000
Treatment – 9/10	mid-2008	2009	2008	2000
Treatment – I-85 Study Sections				
Control/Regional – 21	2011	2010	2008	2000
Control/Regional – 23/24	2011	2010	2008	2000
Control/Regional – 31	(none)	2010	2008	2000
Control/Regional – 32/33	2010	2010	2008	2000
Control/Regional – 34/35	2010	2010	2008	2000

DATA SOURCES

NaviGAtor Data

The Atlanta Region has been collecting detector data, including speed and volumes, since the Summer Olympics in 1996. The original archiving was at 15-minute intervals, and during the summer of 2007, the archiving interval was changed to 5-minute. The data are speed, volume, and lane occupancy measurements taken at very closely spaced (1/3- to ½-mile) intervals. From the speed measurements, travel times are computed for the entire section, and from there a variety of travel time-based performance metrics can be computed, including reliability metrics because the data are continuously collected.

ATR Data

State DOTs maintain continuously operating traffic count devices at fixed locations around their states for a variety of purposes. These data are reported to FHWA monthly and serve as the basis for the *Traffic Volume Trends* report. Data are reported as hourly volumes by lane at the ATR locations. Data for Georgia was obtained from FHWA for this study. ATR data are available for the 2000-2010 period, but there is inconsistency in the years present at different stations. Only a few stations have data for all 11 years, and there are many more stations for the 2007-2010 period as GDOT increased their traffic counting activity. Figure 13 shows the location of the urban interstate ATRs that were used in the Atlanta analysis.

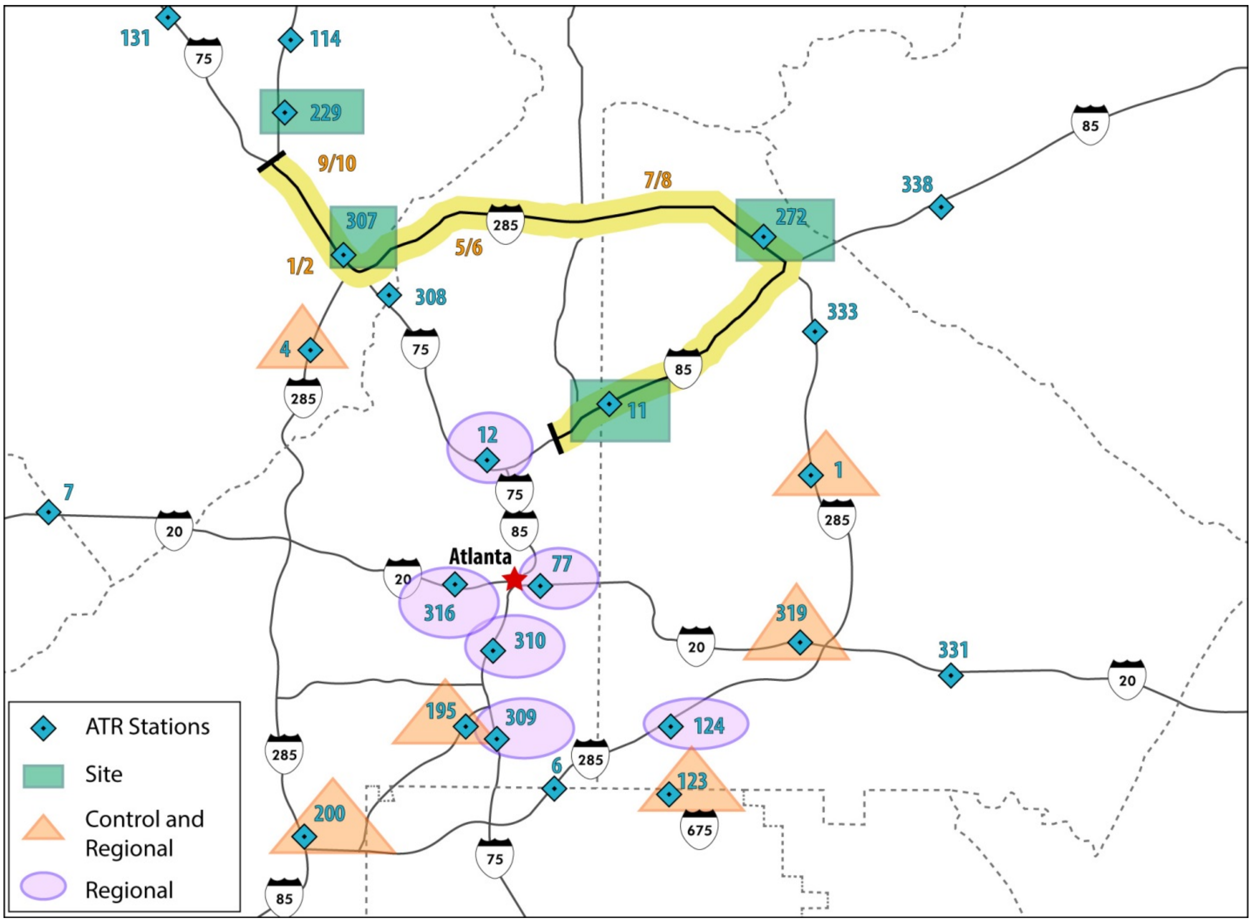

Figure 13. Map. Urban Interstate ATRs in the Atlanta region.
(Source: Cambridge Systematics, Inc.)

RESULTS

Table 11 shows the growth in congestion level, as measured by the TTI, and demand, as measured by the peak period AADT; the first two quarters of 2008 and 2010 are averaged for this comparison to smooth the data. Table 12 shows a summary of the quarterly volume trend results, Figure 14 through Figure 23 show the quarterly volume (demand) patterns, and Figure 14 through Figure 23 show the congestion trends. Note that the plots show the ***growth in demand from the previous quarter.*** Therefore, all comparisons must be made relative to the zero percent line. For example, if growth in one quarter is negative, a rising trend from this quarter to the next may still represent negative growth if it does not cross the zero percent line. Table 13 through 17 show the net growths in demand over the entire before and after periods. Figure 14 through Figure 23 show monthly congestion and volume statistics for each site.

For context, regional VMT for freeways and arterials fluctuated over the period for the before/after studies, based on data from Texas A&M's Urban Mobility Study:(44)

- 2006 – 92,685
- 2007 – 92,630
- 2008 – 88,500
- 2009 – 89,373
- 2010 – 91,511

The effect of the economic downturn can be seen in the 4.7 percent decrease from 2006 to 2008. Then, VMT in the subsequent recovery increased by 3.4 percent from 2008 to 2010.

The two types of operations treatments studied – ramp metering and towing incentives – were implemented at various times during 2008; these are indicated on the plots. Table 11 provides a synopsis of the volume and congestion plots. Several observations can be made about these results:

- As measured on a quarterly basis (Table 11 and Figure 14 through Figure 23), ramp metering and the large truck towing incentive program have only a small effect on congestion levels at best, and in many instances, no discernible impact was detected, especially when factoring in changes in demand over the same period. It should be pointed out that the treatment sites are all on highway sections that are routinely moderately to severely congested, and this may be limiting the ramp meters' effectiveness. (Once traffic flow has broken down, ramp meters become largely ineffective.)

- When the before/after treatment conditions are measured on a monthly basis (Figure 14 through Figure 23), in most cases, the effect of ramp metering on congestion is positive over the first few months after implementation, i.e., congestion was reduced slightly.

- Demand at the treatment sites appears to be most heavily influenced by regional trends, rather than anything specific to the site. The fact that demand patterns at the treatment sites follow the same pattern as for the region in all but a few cases is evidence of this.

- In cases where ramp metering and towing incentives appear to have a discernible impact on congestion trends, the effect is small and demand does not appear to respond to the small change in congestion.

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[44] http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/ums/congestion-data/atlan.pdf; daily VMT in thousands.

Table 11. Change in Congestion Level and Demand on Study Sections

	Percent Change, 1st Two Quarters 2008 versus 1st Two Quarters 2010 – TTI	Percent Change, 1st Two Quarters 2008 versus 1st Two Quarters 2010 – Peak AADT
AM Peak		
Regional	-2.6%	+0.2%
I-85 between GA-400 and I-285 (towing incentive program) ATR Site 11	+7.7%	+2.0%
I-75 between Roswell Road and Barrett Parkway ATR Site 229/SHRP Section 10	-5.0%	-3.8%
I-285 between GA-400 and I-285 ATR Site 272/SHRP Section 8	-4.5%	-0.5%
I-75 from I-285 to Roswell Road ATR Site 307/SHRP Section 2	+2.0%	-3.0%
I-285 between I-75 and GA-400 ATR Site 272/SHRP Section 5	+3.5%	-1.7%
PM Peak		
Regional	+4.4%	+1.4%
I-85 between GA-400 and I-285 (towing incentive program) ATR Site 11	+5.9%	-3.4%
I-75 between Roswell Road and Barrett Parkway ATR Site 229/SHRP Section 9	0.0%	+0.4%
I-285 between GA-400 and I-285 ATR Site 272/SHRP Section 7	0.2%	-1.7%
I-75 from I-285 to Roswell Road ATR Site 307/SHRP Section 1	-1.9%	+2.4%
I-285 between I-75 and GA-400 ATR Site 272/SHRP Section 6	+1.7%	-0.5%

Table 12. Summary of quarterly trends.

	Short-Term Effects (12 months)	Long-Term Effects (see also Table 13)
AM Peak		
I-85 between GA-400 and I-285 (towing incentive program) ATR Site 11	Congestion Impacts: 10 percent drop in first quarter then slight increases, mirror control, and regional growths. Demand Changes: Demand growth was slightly negative in first two quarters, then slightly positive, generally follows control and regional trends. Minimal effect on congestion; no effect on demand.	Congestion Impacts: Little distinction from control and regional trends. Demand Changes: Change in generally flat over the period; mirrors control and regional patterns but shows less quarter to quarter volatility. Minimal effect on congestion; no effect on demand.
I-75 between Roswell Road and Barrett Parkway ATR Site 229/SHRP Section 10	Congestion Impacts: Small increase in congestion in the first quarter, then a decrease which follows control and regional trends. Demand Changes: First quarter data unavailable; second quarter slightly positive, third quarter slightly negative, mirrors control, and regional patterns. Minimal effect on congestion; no effect on demand.	Congestion Impacts: Erratic quarter-to-quarter growth rates; fourth-quarter of every year shows positive congestion growth; pattern similar to control and regional growths. Demand Changes: Relatively flat (some small positive, some small negative growths); control and regional growths much higher. Minimal effect on congestion; no effect on demand.
I-285 between GA-400 and I-285 ATR Site 272/SHRP Section 8	Congestion Impacts: Small increase in first quarter followed by small decreases in second and third quarters follow control and regional patterns. Demand Changes: Change in demand slightly positive over the three quarters while control and regional growths are slightly negative. Minimal effect on congestion; no effect on demand.	Congestion Impacts: Not assessed; likely data problems. Demand Changes: Growth is positive but not as high and control and regional growths.
I-75 from I-285 to Roswell Road ATR Site 307/SHRP Section 2	Congestion Impacts: Small increase in first quarter, then moderate decreases in second and third quarters; second and third quarter mirror control and regional growths. Demand Changes: Flat growth mirrors control and regional growths. Small positive effect on congestion; no effect on demand	Congestion Impacts: Small net increase versus flat growth for control and regional sites. Demand Changes: Relatively flat growth is less than either he control or regional growths. Minimal effect on congestion; no effect on demand.
I-285 between I-75 and GA-400 ATR Site 272/SHRP Section 5	Congestion Impacts: Sharp increase in first quarter, sharp decreases in second and third quarters; patterns mirrors control and regional growths, but decreases are higher. Demand Changes: Change in demand slightly positive over the three quarters while control and regional growths are slightly negative. Small positive effect on congestion; small increase in demand.	Congestion Impacts: Small net growth is similar to control and regional growths. Demand Changes: Growth is positive but not as high and control and regional growths. Minimal effect on congestion; no effect on demand.

Table 12. Summary of quarterly trends (continued).

	Short-Term Effects (12 months)	Long-Term Effects (see also Table 13)
PM Peak		
I-85 between GA-400 and I-285 (towing incentive program) ATR Site 11	Congestion Impacts: Congestion decreased in first quarter (same for control and regional), then was flat while control and regional were positive. Demand Changes: Decrease in first two quarters; slight increase in third quarter; closely mirrors control and regional growths. Small impact on congestion; no impact on demand.	Congestion Impacts: Congestion growth is mostly flat, but there appears to be a sharp increase everywhere in the third quarter of 2011. Demand Changes: Small net decrease in demand, while control and regional sections showed an increase. Minimal Effect on congestion; no increase in demand.
I-75 between Roswell Road and Barrett Parkway ATR Site 229/SHRP Section 9	Congestion Impacts: Increase in first quarter then large decreases in second and third quarters, roughly follows control and regional patterns. Demand Changes: Slight increase in second quarter, slight decrease in third quarter, follows control and regional patterns. Minimal effect on congestion; no effect on demand.	Congestion Impacts: Not assessed; likely data problems. Demand Changes: Relatively flat growth over the period roughly the same as for control and regional sites.
I-285 between GA-400 and I-285 ATR Site 272/SHRP Section 7	Congestion Impacts: Large increase in first quarter followed by flat growth follows regional pattern exactly. Demand Changes: Growth is flat, which is less than either control or regional patterns. Minimal effect on congestion; no effect on demand.	Congestion Impacts: Very volatile; possible data problems in late 2010; prior to that, growth is positive and higher than control and regional sites. Demand Changes: Demand growth is slightly negative, roughly the same as regional sites. Minimal effect on congestion; no effect on demand.
I-75 from I-285 to Roswell Road ATR Site 307/SHRP Section 1	Congestion Impacts: Decrease in first two quarters, then sharp increase in third quarter (may be data error); does not follow control or regional patterns. Demand Changes: Small decrease in second quarter, small increase in third quarter. Assuming third quarter congestion value is an error, small positive effect on congestion, no effect on demand.	Congestion Impacts: Erratic growth is highly positive until last quarter of 2010 and does not follow control or regional trends. Demand Changes: Relatively flat growth over the period mirrors control and regional growths. No apparent impact of ramp meters over the period. High levels of congestion appear to be suppressing volume growth.
I-285 between I-75 and GA-400 ATR Site 272/SHRP Section 6	Congestion Impacts: Erratic congestion growth, may indicate data problems. Demand Changes: Growth is flat, which is less than either control or regional patterns.	Congestion Impacts: Erratic congestion growth, may indicate data problems. Demand Changes: Demand growth is slightly negative, roughly the same as regional sites.

Table 13. Summary of before/after volume trends at ATR Site 11

Site	AM/PM	Net Volume Growth – Before (Q1/2007 to Q4/2007)	Net Volume Growth – Growth Percent	Net Volume Growth – After (Q1/2008 to Q4/2010)	Net Volume Growth – Growth Percent
11	a.m.	41496 to 39752	-4.20%	40924 to 39612	-3.21%
Control	a.m.	25256 to 21472	-14.98%	20552 to 21314	3.71%
Regional	a.m.	28457 to 25928	-8.89%	24929 to 25764	3.35%
11	p.m.	43876 to 41816	-4.70%	43012 to 42098	-2.12%
Control	p.m.	28106 to 23642	-15.88%	22944 to 23876	4.06%
Regional	p.m.	32874 to 29107	-11.46%	27928 to 28952	3.66%

Table 14. Summary of before/after volume trends at ATR Site 229

Site	AM/PM	Net Volume Growth – Before (No Data)	Net Volume Growth – Growth Percent	Net Volume Growth – After (Q3/2009 to Q4/2010)	Net Volume Growth – Growth Percent
229	a.m.			39771 to 39612	-0.40%
Control	a.m.			19371 to 21314	10.03%
Regional	a.m.			24648 to 25764	4.53%
229	p.m.			42949 to 42098	-1.98%
Control	p.m.			23150 to 23876	3.14%
Regional	p.m.			28266 to 28952	2.43%

Table 15. Summary of before/after volume trends at ATR Site 272

Site	AM/PM	Net Volume Growth – Before (Q4/2007 to Q2/2008)	Net Volume Growth – Growth Percent	Net Volume Growth – After (Q3/2008 to Q4/2010)	Net Volume Growth – Growth Percent
272	a.m.	49005 to 48932	-0.15%	47280 to 48093	1.72%
Control	a.m.	21472 to 20383	-5.07%	19568 to 21314	8.93%
Regional	a.m.	25928 to 24648	-4.94%	24382 to 25764	5.67%
272	p.m.	39435 to 41261	4.63%	41463 to 40461	-2.42%
Control	p.m.	23642 to 22919	-3.06%	22350 to 23876	6.83%
Regional	p.m.	29107 to 27331	-6.10%	26928 to 28952	7.52%

Table 16. Summary of before/after volume trends at ATR Site 307

Site	AM/PM	Net Volume Growth – Before (No data)	Net Volume Growth – Growth Percent	Net Volume Growth – After (Q1/2009 to Q4/2010)	Net Volume Growth – Growth Percent
307	a.m.			55772 to 56211	0.79%
Control	a.m.			19762 to 21314	7.85%
Regional	a.m.			24696 to 25764	4.33%
307	p.m.			55245 to 52292	-5.35%
Control	p.m.			23196 to 23876	2.93%
Regional	p.m.			28419 to 28952	1.87%

Table 17. Summary of before/after volume trends at ATR Site 308

Site	AM/PM	Net Volume Growth – Before (No Data)	Net Volume Growth – Growth Percent	Net Volume Growth – After (Q1/2009 to Q4/2010)	Net Volume Growth – Growth Percent
308	a.m.			34903 to 35378	1.36%
Control	a.m.			19762 to 21314	7.85%
Regional	a.m.			24696 to 25764	4.33%
308	p.m.			35841 to 34139	-4.75%
Control	p.m.			23196 to 23876	2.93%
Regional	p.m.			28419 to 28952	1.87%

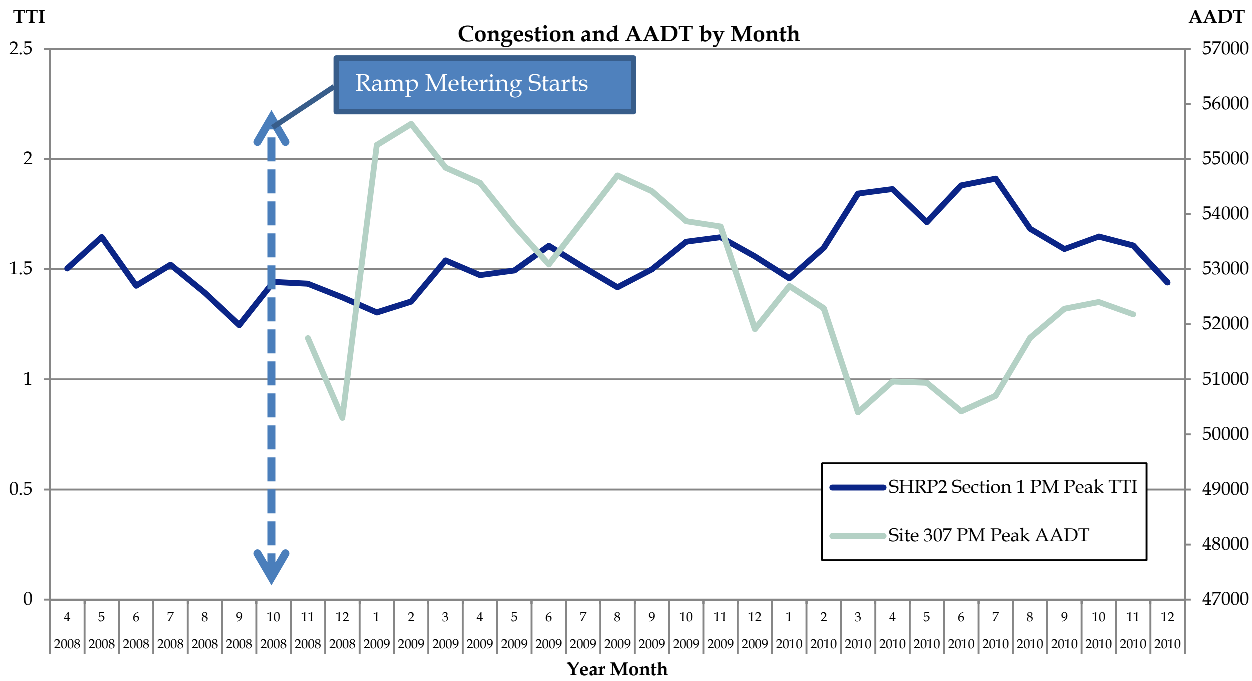

Figure 14. Graph. SHRP Section 1.0, PM peak.
(Source: Cambridge Systematics, Inc.)

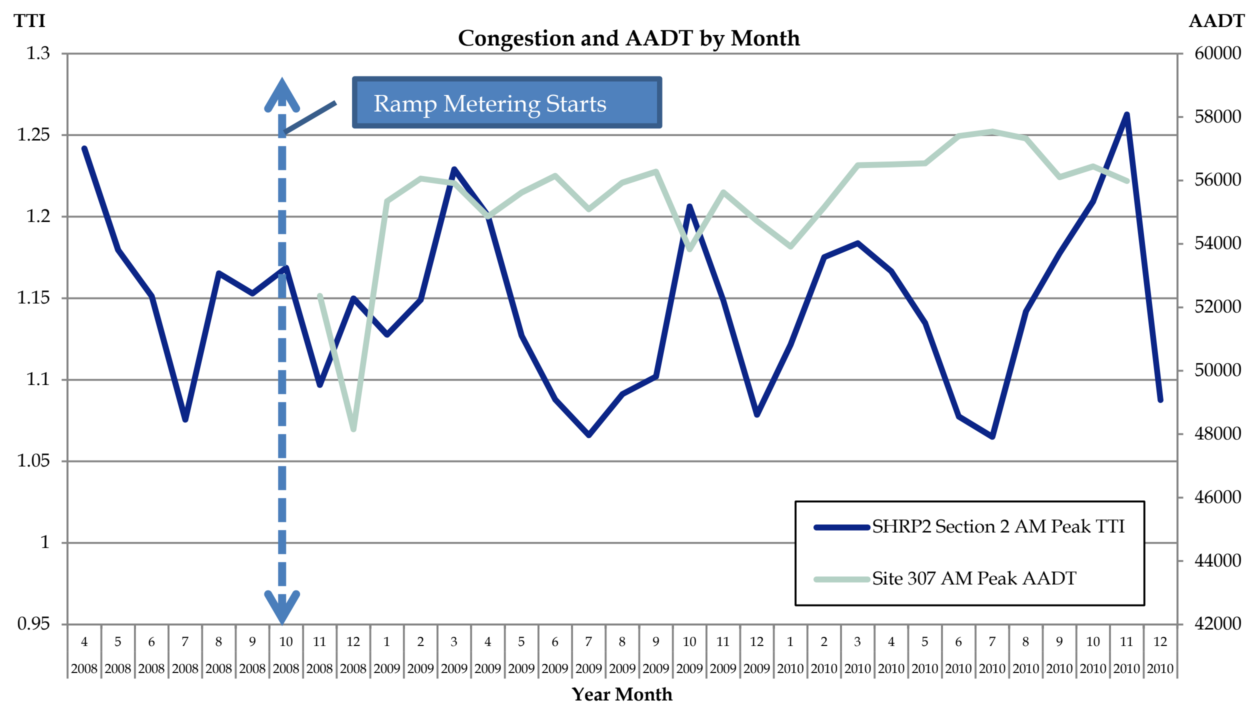

Figure 15. Graph. SHRP Section 2.0, AM peak.
(Source: Cambridge Systematics, Inc.)

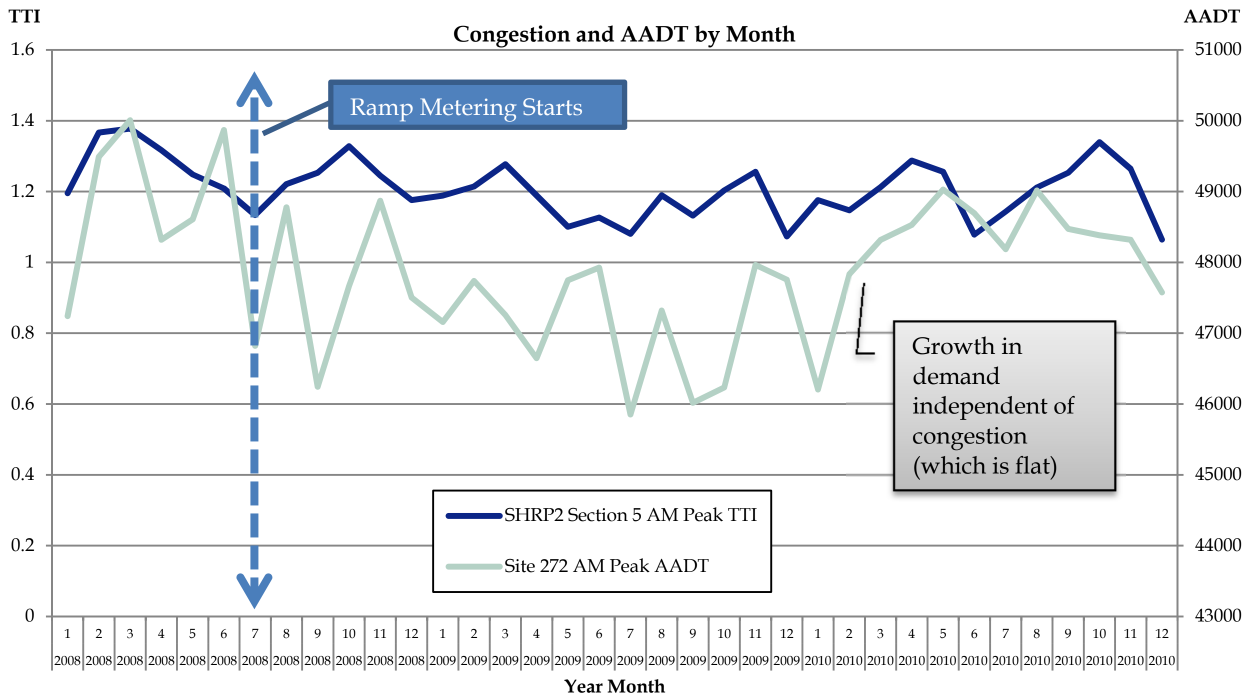

Figure 16. Graph. SHRP Section 5.0, AM peak.
(Source: Cambridge Systematics, Inc.)

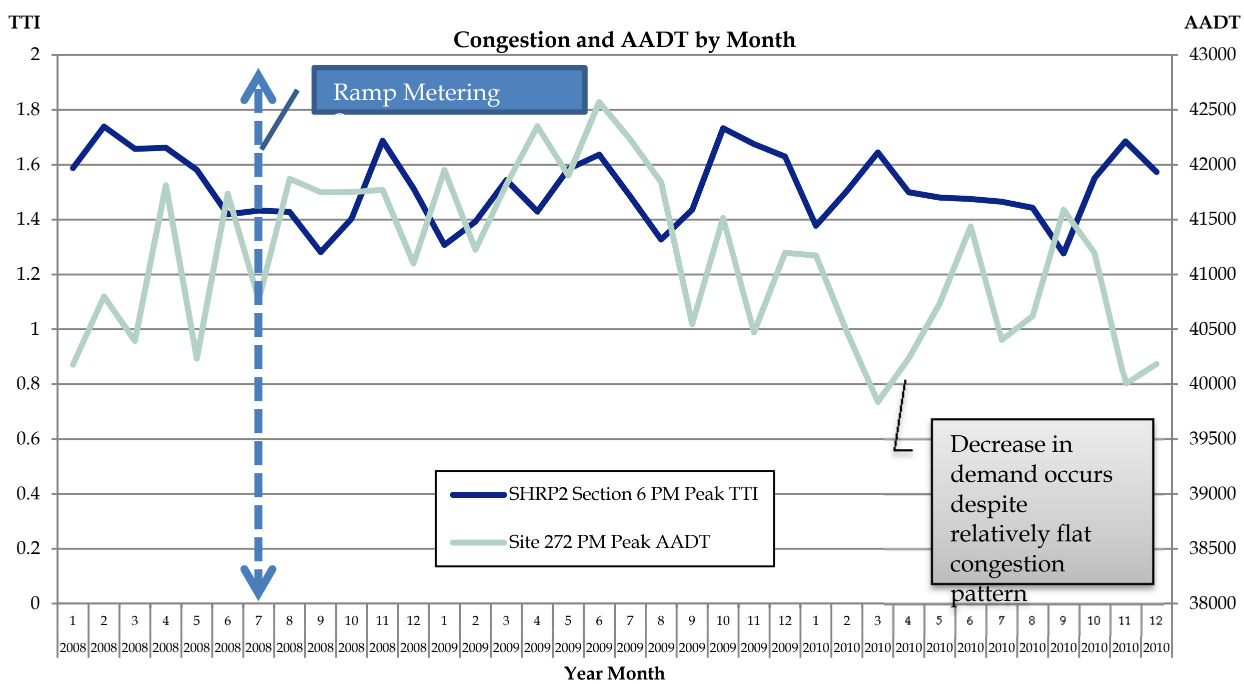

Figure 17. Graph. SHRP Section 6.0, PM peak.
(Source: Cambridge Systematics, Inc.)

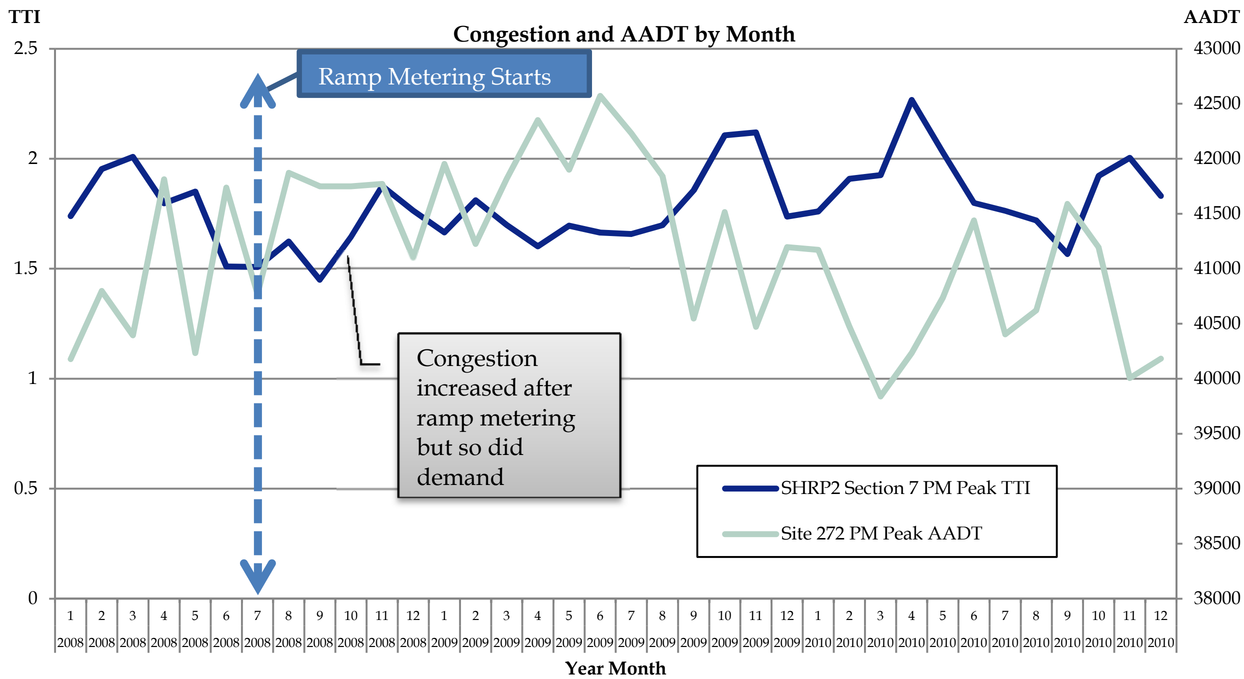

Figure 18. Graph. SHRP Section 7.0, PM peak.
(Source: Cambridge Systematics, Inc.)

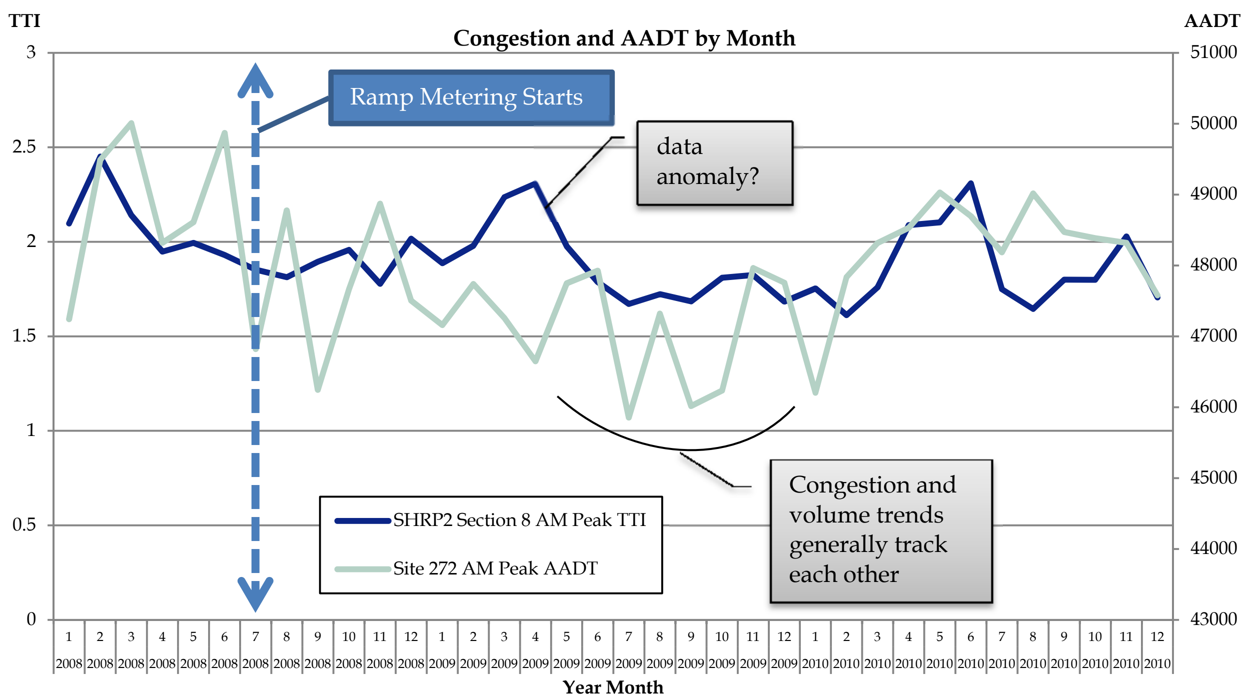

Figure 19. Graph. SHRP Section 8.0, AM peak.
(Source: Cambridge Systematics, Inc.)

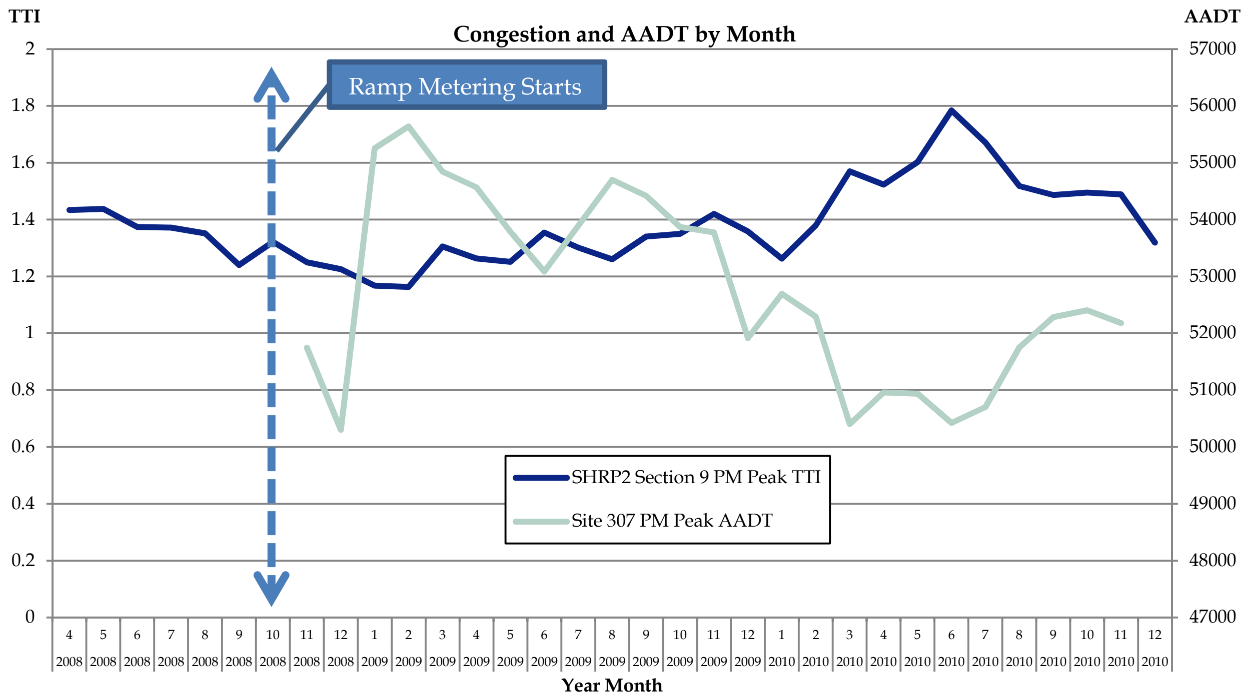

Figure 20. Graph. SHRP Section 9.0, PM peak.
(Source: Cambridge Systematics, Inc.)

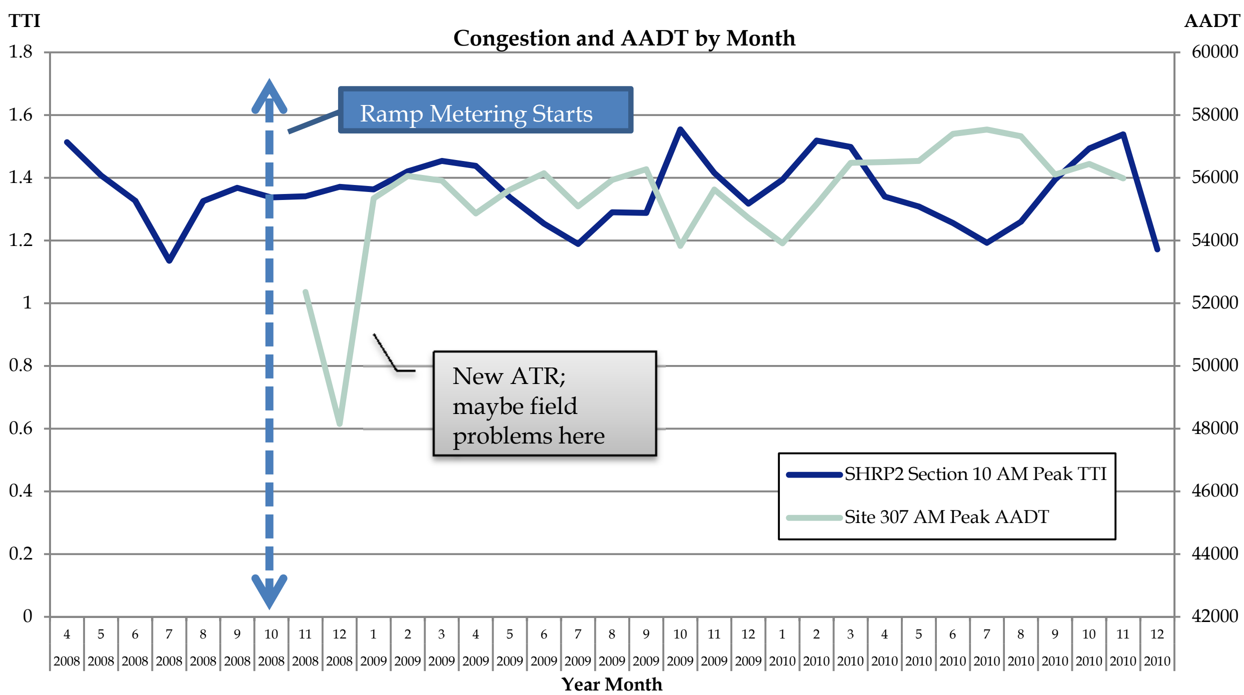

Figure 21. Graph. SHRP Section 10, AM peak.
(Source: Cambridge Systematics, Inc.)

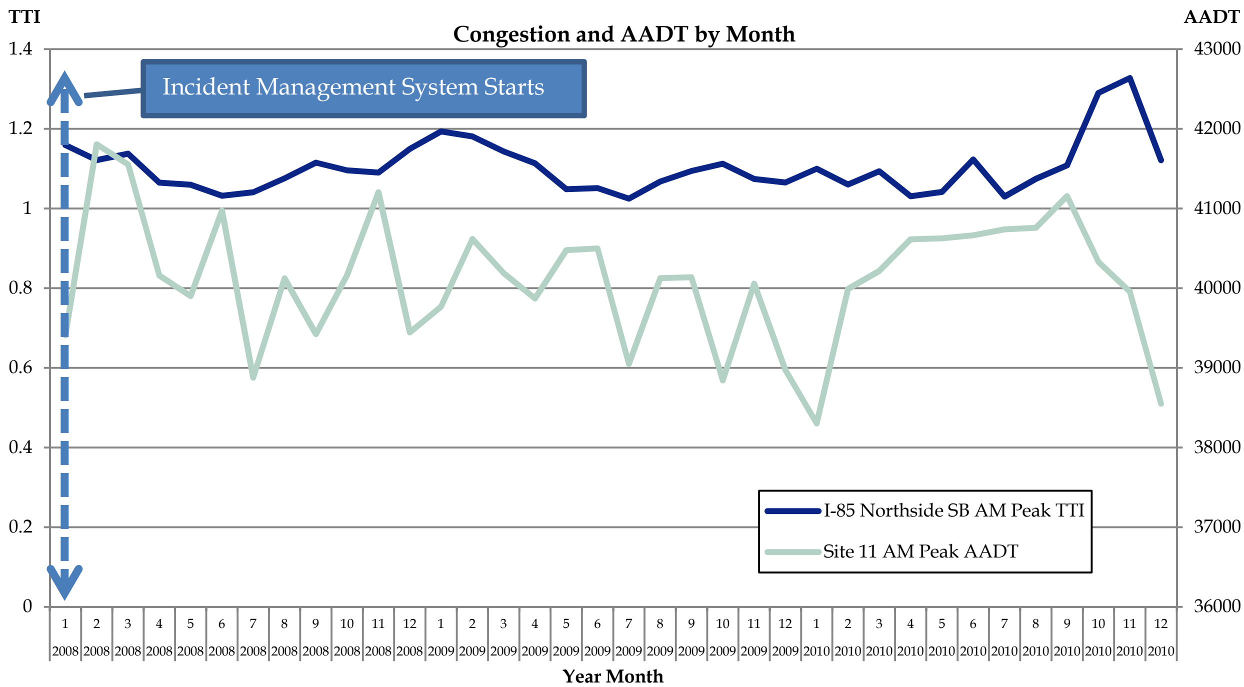

Figure 22. Graph. I-85 Northside SB, AM peak.
(Source: Cambridge Systematics, Inc.)

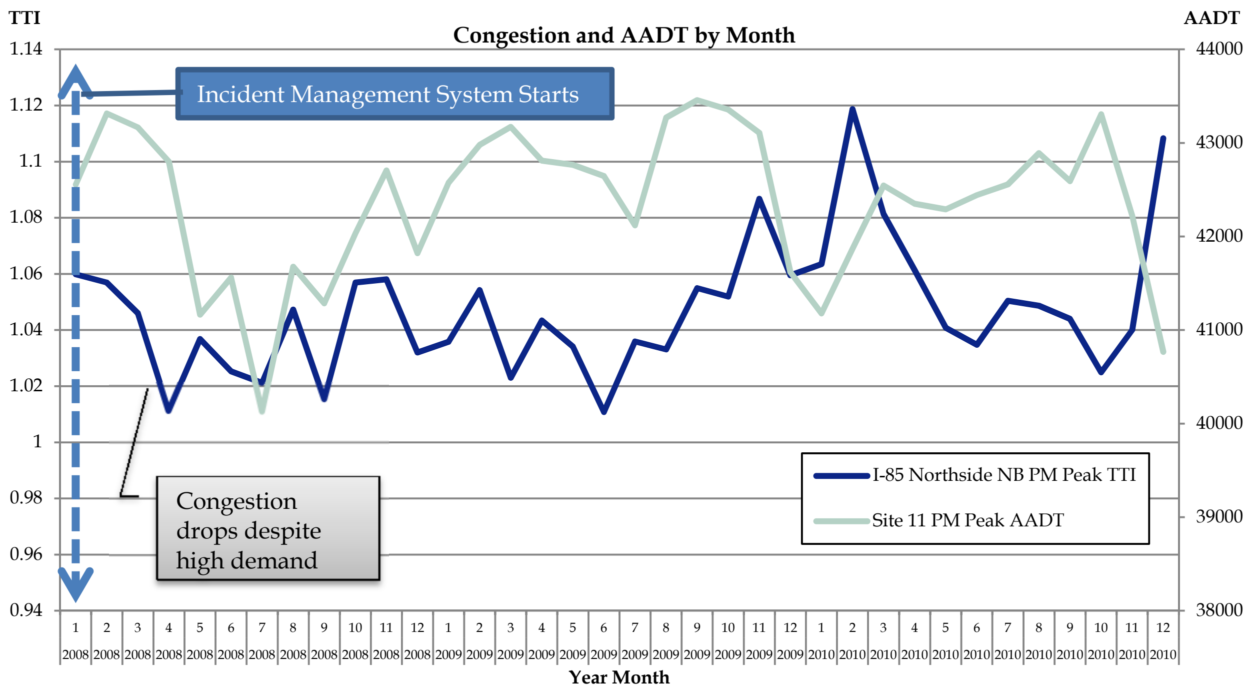

Figure 23. Graph. I-85 Northside NB, PM peak.
(Source: Cambridge Systematics, Inc.)

Discussion

This case study used the data from the Atlanta region to determine if the deployment of operations strategies led to an induced demand effect during the 2000 to 2010 period. The anlysis is complicated by several factors. The first is the sharp drop in demand and associated congestion levels in 2008 due to the economic recession – the drop makes it difficult to establish any long-term montonic trends. The second issue is that the majority of operations strategies (ramp meters, towing incentives, and traveler information) were deployed toward the end of the period (2007-2008) limiting any conclusions about the very long term (land use/location decisions) induced demand effect; such components of induced demand require a five-year "incubation" period. Third, data consistency was an issue in the analysis. Ideally, just the NaviGAtor detector data would supply all of the required data but previous experience indicated that volumes estimates from this source can be unreliable. HPMS data was examined to provide regional VMT trends but it was found to be unreliable for the years before 2007. The ATR data proved to be more trustworthy, but prior to 2007 the number of ATRs in the Atlanta region was sparse. Also, the coverage of ATRs is limited, requiring in most cases to use ATRs that are nearby the treatment sections but not located on them (except for Sites 7 and 8). Not having demand and congestion estimates exactly paired – as could be achieved if the NaviGAtor volume data were more reliable – introduces uncertainty into the section-level analysis.

Between 2002 and 2007, PM congestion grew by 12 percent, total daily demand (AADT) grew by 11 percent and PM demand grew by 9 percent. During this period there was little change in the physical capacity on the study sections, and GDOT's operations included incident management and traveler information (DMSs and Internet-based travel time postings). Without considering the congestion data, one might conclude that the operational improvements contributed to the increased demand. However, it is clear that over the 2000-2007 period, the limited operational improvements (routine incident management and DMSs) did not lead to a net decrease in travel times over multiple years, which would be required if the induced demand effect was present. Rather, the operational improvements most likely limited the growth in congestion that otherwise might have occurred. While the study did not assess the effectiveness of these strategies (in terms of what would have happened without them, a task that would require modeling), a 10 percent increase demand, when imposed on an already congested peak network, would lead to much more than a 12 percent increase in congestion; congestion expands exponentially with demand under already congested conditions.

For the period of more intensive operational deployments (2008-2010), the section-level analysis indicates that the AM and PM peak periods behave differently. Sites that peak in the morning generally saw both a decrease in demand and congestion. Sites that peak in the afternoon generally saw both demand and congestion increase. Other studies of the Atlanta ramp metering and towing recovery programs, which considered a much smaller timeframe showed positive impacts.[45] However, in terms of longer-range impacts, congestion growth seems inevitable in cases where background demand is strong, even with the presence of operational strategies.

It is clear that the growth in both demand and congestion proceeded even with these operational deployments made. Further, demand increased even in the face of increased congestion – no signficant suppression effect was observed. This indicates that factors driving regional growth are dominant over traveler behavioral effects related to travel time. Therefore, at least for the 2000-2007 period in Atlanta, the effect of operations was to manage the growth of congestion, not eliminate it.

The results found here are short term in nature. In some locations, there was no noticeable improvement in travel times due to an operations strategy, so we cannot expect there to be short-term demand shifts. In locations where travel time was improved, no appreciable increase in short-term demand was observed.

While it is not possible to say conclusively that long-term demand effects would be comparable, we note that longer-term matched-pair studies in the literature also found no measurable demand effects at the facility level. In his 2001 review of induced demand, Cervero wrote:[46]

A fairly rigorous matched-pair analysis in Melbourne, Australia recorded no induced travel over a 10-year period as a consequence of linking a major freeway to a major arterial (Luk and Chung, 1997).[47] A recent matched-pair comparison of 18 California State highway segments over the 1976 to 1996 period also found little evidence of induced demand (Mokhtarian et al., 2000).[48] The study found statistically and practically indistinguishable differences in ADT growth rates between improved and unimproved segments.

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45 *Evaluation of the Towing and Recovery Incentive Program (TRIP)*, PBS&J and Serco, February 4, 2011. http://www.timetaskforce.com/documents/TRIP/TRIP%20STUDY%20v%201%200%202011-02-04.pdf.

46 Cervero, Robert, *Induced Demand: An Urban and Metropolitan Perspective*, paper prepared for: Policy Forum: Working Together to Address Induced Demand, March 2001.

47 Luk, J. and Chung, E. 1997. Induced Demand and Road An Initial Appraisal. Research Report, ARR 299. Vermont South, Victoria, Australia: ARRB Transport Research Ltd.

48 Mokhtarian, P., Samaniego, F., Shumway, R., Willits, N., and Azari, R. 2000. Analyzing Induced Traffic from Capacity Enhancements Using Matched Pairs: A California Study. Davis: University of California, Institute of Transportation Studies, draft paper.

CHAPTER 4. RELIABILITY-LAND USE

INTRODUCTION

The objective for this component of the research project is to develop a methodology to evaluate the long-term effects of operations strategies. We interpret long-term effects to be those that are beyond the time-scale of within-day travel decisions, and in the time-scale of land use impacts such as real estate prices and rents, location choices of households, workers and firms, and real estate development outcomes.

Agencies considering the implementation of alternative operations strategies to improve reliability and reduce congestion are unlikely to take into account that there might be impacts on land use. This has two implications. First, there may be long-term benefits in terms of property value appreciation, economic development, and resulting tax revenues that have been overlooked in decision-making about system improvements that target improvements in reliability. If so, this would imply an underestimation of the benefits of such projects. Second, these land use impacts may impact travel patterns in ways that induce more travel and undermine at least part of the gains in reliability or congestion. The broader literature on induced demand suggests that transportation system interventions that improve travel time not only result in short-term responses by travelers to shift modes, times of travel and routes (Downs, 2004), but also include longer-term influence on land use outcomes that further affect travel demand (Waddell, Ulfarsson, Franklin, and Lobb, 2007; Noland, 2001). This literature has not explored, however, whether improvements in travel-time reliability might generate long-term impacts on real estate markets.

Even the casual observer would likely agree that unreliable travel time to work is problematic, and a growing body of research has begun to measure the degree to which travelers value travel-time reliability by analyzing their route or mode choices (Bates, Polak, Jones, and Cook, 2001; Lam and Small, 2001; Ettema, Tamminga, Timmermans, and Arentze, 2005; Nam, Park, and Khamkongkhun, 2005; Brownstone and Small, 2005; Small, Winston, and Yan, 2005; van Lint, van Zuylen, and Tu, 2008; Li, Hensher and Rose, 2010; Fosgerau and Karlström, 2010). To our knowledge, however, no one has yet addressed the question of whether travel-time reliability has longer-term effects beyond daily travel decisions, by influencing real estate market outcomes. Is travel-time reliability valued enough by individuals, households, and firms to be capitalized into higher real estate prices and rents in locations with more reliable accessibility? Does reliability have enough value to influence long-term choices of households or firms regarding where they rent or purchase real estate? These are the questions explored in this research.

The theoretical grounding for this research draws on urban economics and on the geography of transportation. The role of accessibility in shaping urban form and location choices has been central to the development of this literature, from the early conceptualization and measurement of accessibility (Hansen, 1959) and the emergence of urban land use models that explained the capitalization of accessibility into land values via bid-rent theory (Alonso, 1960; Muth, 1961). Recent research on the impact of accessibility has been mixed, with some scholars questioning the relative importance of accessibility in modern polycentric cities with complex household choices regarding work and residence locations (Giuliano, 2004; Gordon and Richardson, 1997), while others have explored the empirical role of accessibility at localized and regional scales on land use outcomes such as residential location choices, finding that both remain significant when carefully measured (Waddell and Nourzad, 2002; Lee, Waddell, Wang and Pendyala, 2010).

Core theoretical building blocks for this research include bid-rent theory, put forward in the early development of urban economics as a field (Alonso, 1960; Muth, 1961), and hedonic regression, a methodology to estimate the implicit prices of amenities in bundled goods, such as housing (Rosen, 1974). Combining these two building blocks, extensive research has been done to analyze how locational amenities such as accessibility are capitalized into residential property values (Nelson, 1977; Edmonds, 1983; Waddell, Berry and Hoch, 1993; Waddell and Nourzad, 2002; Lee et al., 2010), as well as apartment rents (Hoch and Waddell, 1993), and office rents (Rosen, 1984; Mills, 1992).

The logic behind this theoretical approach is quite straightforward: agents that value-specific amenities such as travel time savings will bid more in terms of rent or purchase price at those locations that have higher values of such amenities, and in so doing, they are more likely to outbid other agents for the real estate at those sites. A further consequence of this logic is that higher competition for advantageous sites results in higher land values and subsequently translates to a higher development intensity on such sites, as a result of substitution from increasingly expensive land costs to relatively less expensive capital costs in the form of taller buildings through capital-land substitution.

A final theoretical building block for this work is that of discrete choice modeling of location choice, pioneered by Daniel McFadden in the context of residential location choices (McFadden, 1978), and extended to become a foundation of most empirical research on travel demand and a critical component of operational travel demand models (Ben-Akiva and Lerman, 1987; Train, 2009). Discrete choice methods have permitted examination of the tradeoffs that households make between the structural and contextual amenities of a house, its price, and its accessibility. It therefore provides a direct approach to measuring the value of reliability and its influence on location demand. Extensive prior work on modeling residential location choices (Waddell, 1997; Waddell, 2000; Waddell, 2007; Waddell, Wang, Charlton, and Olsen, 2010), in addition to related research on modeling the location choices of firms (business location) (Shukla and Waddell, 1991; Waddell and Shukla, 1993; Waddell and Shukld, 1993; Waddell and Ulfarsson, 2003), and the workplace choices of workers (Wang, Waddell, and Outwater, 2011), provide a strong foundation for the empirical component of this research.

METHODOLOGY

In this section we describe our research approach for developing a quantitative basis for assessing the long-term effects of operations strategies. We set aside the details of the operations strategies, and focus on the outcomes of operations that could impact land use: mean travel time and its reliability. Further, we particularly focus on how travel-time reliability impacts land use, since this has not been explored previously.

We develop an application platform for simulating the effects of alternative interventions that change patterns of travel-time reliability. For this application component, we have adapted UrbanSim, an operational land use model system that has been connected to a variety of four-step and activity-based travel models in addition to dynamic assignment models (Waddell, 2011; Waddell, 2002; Waddell et al., 2007; Waddell et al., 2010; Pendyala, Konduri, Chiu, Hickman, Noh, Waddell, Wang, You and Gardner, 2012). Our approach to this task was to add travel-time reliability into UrbanSim models of residential location choice, business location choice, workplace choice, and real estate rents and prices in order to simulate their impacts across the full study area. The objective is to provide a generic capability to address long-term land use impacts of operations improvements by allowing them to be tested in a land use modeling platform that has been extended to address reliability-enhanced accessibility measures.

Study Area and Data

Our study area is the San Francisco Bay area, consisting of nine counties for which the Metropolitan Transportation Commission and the Association of Bay Area Governments develop the regional transportation plan and sustainable communities strategies. For this region, we compiled extensive land use and travel time data for the development of both the empirical research component and for the large-scale application and testing of the approach.

Figure 24. Map. San Francisco Bay Area.
(Source: http://extras.sfgate.com/img/pages/travel/maps/pdfs/sfbay01.pdf.)

We developed an extensive database for the San Francisco Bay Area containing the following data elements to reflect the real estate, business, and demographic environment, as well as transportation networks and observed travel time distributions:

- **Parcels,** including attributes such as lot size, land use, and property value.
- **Buildings,** including building type, square footage, stories, residential units.
- **Sales Transactions,** including sales of condominiums and single-family homes.

- **Rents,** including apartments, offices from CoStar, Craig's List, and other sources.
- **Businesses** from the National Establishment Time Series (NETS).
- **Household Travel Survey** from Bay Area Transportation Survey (BATS).
- **Synthetic Population** from the Metropolitan Transportation Commission, including households and persons.
- **Streets** from OpenStreetMap.
- **Travel Model Network** from the Metropolitan Transportation Commission.
- **PeMS Travel Times** from the Caltrans Performance Measurement System (PeMS) real-time traffic data on highways in California.

Travel-time reliability is intuitively linked to the width of the travel-time distribution. The reliability is quantified in various ways, including statistical range measures, buffer measures, and tardy trip indicators such as the misery index (Lomax, Schrank, Turner, and Margiotta, 2003). Comparing the 80th and 50th percentile travel times (Small et al., 2005) presents a nonparametric reliability metric with units of travel time.

Our travel time data for this project is drawn from the Caltrans Performance Measurement System (PeMS) real-time traffic data on highways in California. The average travel time and volume on each link in the network was computed at 30-minute intervals. Further processing was done to generate a set of quantile metrics: the volumes and speeds associated with the minimum, 20th, 50th (median), and 80th percentile on each link for the morning peak period on a daily basis. Only weekdays were used in this analysis.

Research Hypotheses

The empirical research objectives of this project are the following, based on hypothesized influences that reliability of travel time could influence different long-term land use outcomes. Our first hypothesis is that, after controlling for accessibility and other factors, rents, and transactions prices for real estate will be higher in locations that have relatively higher travel-time reliability, consistent with the capitalization of the amenity value of reliability into property values and rents. In short, if reliability is valued by households or firms, they will be willing to pay more in rent or purchase price for real estate in locations that are more reliably accessible, all else being equal. And as a result of competition for real estate, drawing on bid-rent theory, we should see higher market rents and transactions prices in locations with more reliable access. This hypothesis can be tested using hedonic regression models of rents and transactions prices to estimate the implicit price of reliability (Rosen, 1974).

The approach to estimating implicit prices using hedonic regression is widely used in the literature, and provides a reduced-form approach that enables assessment of overall market impacts of reliability. A complementary strategy allows us to extend this research to a more structural approach to test two further hypotheses. If we find that either residential rents and prices, or nonresidential rents, are higher in areas with higher reliability, then we can further explore the structural origins of this market effect. It could alternatively arise from influences on the supply side or the demand side of the real estate market. It is in our view more likely that travel-time reliability would influence real estate demand, since prior research has demonstrated that travelers value travel-time reliability enough to influence their mode and route choices

(Bates et al., 2001; Lam and Small, 2001; Ettema et al., 2005; Nam et al., 2005; Small et al., 2005; van Lint et al., 2008; Li et al., 2010). We know of no research that has suggested that travel-time reliability could influence the cost or feasibility of real estate development, and it seems unlikely that there should be such an effect. Consequently, our second and third hypotheses focus on the structural origins of any price effects we find by examining whether household and firm location choices are influenced by travel-time reliability.

- **Hypothesis 1:** Locations with more reliable accessibility have higher real estate prices and rents, capitalizing the amenity value of travel-time reliability.

- **Hypothesis 2:** Household residential location choices reveal a preference for residential locations that have more reliable accessibility.

- **Hypothesis 3:** Business location choices reveal a preference for establishment locations that have more reliable accessibility.

To evaluate the influence of travel time on long-term outcomes, we used the distribution of travel times as the basis for quantifying travel-time reliability. Prior work has examined simple measures such as standard deviations or other measures of variance, some research has pointed out limitations of this approach (van Lint et al., 2008). We focus in particular on the testing of accessibility using a median travel time value, and of reliability using the difference between the accessibility using the median travel time and the value using the 80th percentile of the travel time distribution.

Real Estate Prices and Rents

Real estate prices and rents provide indicators of the balance between demand and supply of land at different locations and with different land use types, and of the relative market valuations for attributes of housing, nonresidential space, and location. This role is important to the rationing of land and buildings to consumers based on preferences and ability to pay, as a reflection of the operation of actual real estate markets. Since prices enter the location choice utility functions for jobs and households, an adjustment in prices will alter location preferences. All else being equal, this will in turn cause higher price alternatives to become more likely to be chosen by occupants who have lower price elasticity of demand. Similarly, any adjustment in land prices alters the preferences of developers to build new construction by type of space, and the density of the construction.

Real estate prices are modeled using a hedonic regression of the log-transformed property value per square foot on attributes of the parcel and its environment, including land use mix, density of development, proximity of highways and other infrastructure, land use plan or zoning constraints, and neighborhood effects. The hedonic regression equation encapsulates interactions between market demand and supply, revealing an envelope of implicit valuations for location and structural characteristics (DiPasquale and Wheaton, 1996). The model was estimated from sales transactions and observed rents from MLS and CoStar data sources, using Ordinary Least Squares (OLS), using a standard semi-log specification in which the dependent variable is log-transformed:

$$log(Pi) = a_i + \beta(X_i) + E_i$$

Figure 25. Equation. Log(Pi).
(Source: DiPasquale and Wheaton, 1996.)

where i indexes locations defined as nodes on the local street network and the parcels associated with them, and *E* is the error term. Prices and rents by street node are computed as the average by building type among the parcels assigned to their nearest street node.

The independent variables influencing land prices can be organized into site characteristics, regional accessibility, and urban-design scale effects, as shown in Table 18.

Table 18. Variables in the hedonic regressions.

	Variable	**Description**
Site Characteristics	Number of stories (nonresidential)	Number of stories in building Square feet of rentable building
	Rentable building area	Log of square footage of building for nonresidential property
	Square footage of the unit	Log of square footage of the unit for residential units
	Lot size	Log of square footage of the lot
	Historic	Indicator for construction before 1940
	New	Indicator for construction after 1980
Regional Accessibility	Median accessibility	Log of number of jobs accessible within 30 minutes using median travel time
	Unreliability of accessibility	Log of (Accessibility using median travel time minus accessibility at 80^{th} percentile travel time)
Neighborhood Characteristics	Average household income	Average income at the intersection

HOUSEHOLD AND FIRM LOCATION CHOICES

In order to empirically test our second and third hypotheses, we develop multinomial logit models of household residential location choice and establishment location choice. Our approach draws on the path breaking approach to modeling individual actions using discrete choice models pioneered by Daniel McFadden on Random Utility Maximization theory (McFadden, 1974; McFadden, 1981). This approach derives a model of the probability of choosing among a set of available alternatives based on the characteristics of the chooser and the attributes of the alternative, and proportional to the relative utility that the alternatives generate for the chooser. Maximum likelihood and simulated maximum likelihood methods have been developed to estimate the parameters of these choice models from data on revealed or stated-preferences, using a wide range of structural specifications (see Train, 2003). Early application of these models were principally in the transportation field such as mode choice, but also included work on residential location choices (Quigley, 1976; Lerman, 1977; McFadden, 1978), and on residential mobility (Clark and Lierop, 1986).

Consider a model of households choosing among alternative locations in the housing market, which we index by *i*. For each agent, we assume that each alternative *i* has associated with it a utility U_i that can be separated into a systematic part, V_i, and a random part, E_i:

$$U_i = V_i + E_i$$

Figure 26. Equation. U subscript i.
(Source: Waddell, 2000.)

where $V_i = \beta \cdot\cdot x_i$ is a linear-in-parameters function, β is a vector of *k* estimable coefficients, x_i is a vector of observed, exogenous, independent alternative-specific variables that may be interacted with the characteristics of the agent making the choice, and E_i is an unobserved random term. Assuming the unobserved term in 2) to be distributed with a Gumbel distribution leads to the widely used multinomial logit model (McFadden, 1974; McFadden, 1981):

$$P_i = \frac{e^{V_i}}{\sum_j e^{V_j}}$$

Figure 27. Equation. P subscript i.
(Source: McFadden, 1974; McFadden, 1981.)

where *j* is an index over all possible alternatives. The estimable coefficients of (3), β, are estimated with the method of maximum likelihood (see for example Greene, 2002). The components of x_i are listed in Tables 19 and 20.

Table 19. Variables in the residential location choice models.

	Variable	**Description**
Renter Model	Monthly rent	Monthly rent per unit
	Number of units	Number of residential units at the intersection
	Node renters	Number of renters at the intersection
	Area renters	Number of renters in the area
Sales Model	Sales price	Sales price per unit at the intersection
	Average income	Average income at the intersection
	Number of units	Number of residential units at the intersection
Renter and Sales Models	Median accessibility	Log of number of jobs accessible within 30 minutes using median travel time
	Unreliability of accessibility	Log of (Accessibility at median travel time minus Accessibility at 80th percentile travel time)

Table 20. Variables in the nonresidential location choice models.

	Variable	Description
Area Attributes	Area	Square footage at intersection
	Percent retail	Percent of local establishments in retail
	Percent industrial	Percent of local establishments in industrial
Property Attributes	Rent	Square footage-weighted yearly rent
Regional Accessibility	Median accessibility	Log of number of jobs accessible within 30 minutes using median travel time
	Unreliability of Accessibility	Log of (Accessibility at median travel time minus Accessibility at 80th percentile travel time)

ESTIMATION RESULTS

Our empirical study of the effects of accessibility and its reliability proceeds in two parts. The first part examines the degree to which we can identify the implicit prices of reliability, which we measure as the access to jobs within 30 minutes travel time at the median of the travel time distribution, minus the same measure of accessibility computed using the 80th percentile travel time. The more unreliable the travel time is, the greater is the deviation from the median travel time, and the larger is the gap between accessibility on a typical day (the median) and on what could be considered the average worst day of the week (the 80th percentile). Areas that have unreliable freeways around them will have much lower accessibility to jobs on those 80th percentile days than they do on the median days.

Hedonic Regression of Real Estate Prices and Rents

We measure the degree to which this unreliability in accessibility is capitalized into rents and property values, using hedonic regression, for each property type. Rents and prices are aggregated by parcel to the nearest street node, and these nodes are the unit of analysis for the hedonic regression. Prices and rents are log-transformed.

Our estimation results strongly support our first hypothesis that locations with more reliable accessibility have higher real estate prices and rents, capitalizing the amenity value of travel-time reliability. The coefficients on accessibility and reliability are highly significant for both residential sales and rents. Since the coefficients are on log-transformed variables with a log-transformed-dependent variable, they can be directly interpreted as elasticities. The elasticity of accessibility is 0.24 and for reliability is 0.06. For renters the elasticity of accessibility is 0.14 and for reliability is 0.02.

For nonresidential rents, we analyzed four property types: flex space, industrial, office, and retail. For all four, accessibility is significant at the 0.1 percent level for office and retail building types, and at the 1 percent level for flex and industrial space. Unreliability was negative as expected for all four, and significant at the 0.1 percent level for industrial and retail building types, and at the 5 percent level for office. It was not significant for flex space, for which we also had few observations. The elasticities for accessibility ranged from 0.04 for flex and industrial, to 0.09 for Office and 0.22 for retail. Elasticities for reliability were 0.1 for office, 0.04 for industrial, and 0.08 for retail.

While these are relatively small elasticities, the aggregate magnitude of the effects can be substantial when accumulated across all affected properties, as we explore in a sensitivity test.

Table 21. Residential hedonic models.

Variables	**B**	**σ**	**T-score**	**Significance**
Area	0.03	0.00	33.01	***
Lot size	0.02	0.00	36.83	***
Median accessibility	0.18	0.00	108.49	***
Travel time unreliability	-0.04	0.00	−49.28	***
Average Household Income	1.42	0.00	389.60	***
Historic	0.39	0.00	117.90	***
New	0.29	0.01	51.77	***
Constant	-5.42	0.04	−131.05	***
R^2 0.49				
Adj-R^2 0.49				
Rent				
Square footage of the unit	0.69	0.01	61.47	***
Median accessibility	0.14	0.01	26.09	***
Unreliability of Accessibility	-0.02	0.00	−6.57	***
Average Household Income	0.13	0.01	11.65	***
Constant	-0.21	0.14	−1.50	
R^2 0.54, Adj-R^2 0.54				

Table 22. Nonresidential hedonic models.

Variables	**β**	**σ**	**T-score**	**Significance**
Flex				
Number of stories	0.18	0.02	9.33	***
Rentable building area	-0.11	0.01	−8.28	***
Median accessibility	0.04	0.01	3.09	**
Unreliability of Accessibility	-0.00	0.01	−0.32	
Constant	2.88	0.18	15.92	***
R^2 0.08, Adj.-R^2 0.08				
Industrial				
Number of stories	0.19	0.02	8.37	***
Rentable building area	-0.17	0.01	−20.60	***
Median accessibility	0.04	0.01	2.94	**
Unreliability of Accessibility	-0.04	0.01	−5.27	***
Constant	3.56	0.15	23.28	***
R^2 0.21, Adj.- R^2 0.21				
Office				
Number of stories	0.01	0.00	6.92	***
Rentable building area	0.02	0.01	3.20	***
Median accessibility	0.09	0.01	7.04	***
Unreliability of Accessibility	-0.01	0.01	−2.01	*
Constant	1.92	0.12	16.08	***
R^2 0.07, Adj.- R^2 0.07				

Table 22. Nonresidential hedonic models (continued).

Variables	β	σ	T-score	Significance
Retail				
Number of stories	0.09	0.02	5.18	***
Rentable building area	-0.09	0.02	−5.34	***
Median accessibility	0.22	0.02	10.34	***
Unreliability of Accessibility	-0.08	0.01	−6.82	***
Constant	1.81	0.23	7.79	***
R^2 0.13, Adj- R^2 0.12				

Table 23. Residential location choice models.

Variables	β	σ	T-score	Significance
Sales				
Sales price	-0.96	0.11	−8.67	***
Sales price times income	0.85	0.10	8.97	***
Median accessibility	-0.01	0.02	−0.38	
Unreliability of Accessibility	-0.02	0.01	−2.98	**
Average income	0.33	0.11	3.04	**
Average income squared	0.33	0.09	3.53	***
Number of units	0.53	0.01	38.40	***
Null log-likelihood -41308.38				
Converged log-likelihood -39073.17				
Log-likelihood ratio 0.05				
Rent				
Monthly rent	-0.16	0.01	−17.05	***
Median accessibility	0.04	0.01	3.00	**
Unreliability of Accessibility	-0.07	0.01	−6.12	***
Number of units	0.54	0.03	17.10	***
Number of renters in the area	0.46	0.01	31.17	***
Number of renters at the intersection	0.11	0.02	4.58	***
Null log-likelihood -19438.42				
Converged log-likelihood -16237.92				
Log-likelihood ratio 0.16				

Discrete Choice Modeling of Location Choices of Households and Firms

The second empirical component of this research is an analysis of the degree to which households and firms reveal preferences for locations with higher reliability when making location choices. We develop a series of measures of the real estate characteristics on parcels associated with their nearest street node, and use these street nodes as the geography for location choice analysis. There are approximately 200,000 street nodes, so we use random sampling of alternatives, sampling 100 alternative locations, including the chosen alternative.

For household data, the most current available travel survey we had access to at the time of this research was the Bay Area Transportation Survey (BATS) from 2000. We were able to use 8970 homeowners and 4221 renters and estimated separate Multinomial Logit models by tenure. There was no information on length of time since a household had moved into their unit, so we used the entire set of survey respondents for which there was sufficiently complete information. For firms we had access to the 2011 National Establishment Time Series (NETS) database, and sampled firms that had moved into their current location within the past five years.

Estimation results are provided in Table 23. The homeowner location choice model reveals an insignificant coefficient for accessibility at the median travel time, but a significant negative coefficient for unreliability of accessibility. This is an important finding, since it suggests that for homeowners, the reliability of travel time is a significant factor in their location choices, even while the accessibility using median travel times is not. The reasons for the latter being insignificant are potentially many, including the absence of individual-specific accessibility measures that we did not have the capacity to include in this research, but have found in other research to be important predictors of residential location (Lee et al., 2010). For renter households, we found both accessibility to be positive and significant, and unreliability of accessibility to be negative and strongly significant. In both cases, unreliability of accessibility proved to be a stronger predictor than accessibility at median travel time.

Table 24 includes the results of estimation for each industry sector, sorted in order of the number of observations available for estimation. Almost all sectors had the expected positive and significant coefficients on accessibility, and most had negative and significant coefficients on unreliability of accessibility. Unreliability was negative and significant at the 0.1 percent level for Wholesale Trade, Retail Trade (NAICS Code 44), Professional, Scientific and Technical Services, Health Care and Social Assistance. It was negative and significant at the one percent level for Manufacturing and for Other Services. It was significant only at the 5 percent level for Mining, Retail Trade (NAICS code 45). In one sector Transportation, unreliability of accessibility was positive and significant. This could correspond to the location of the Port of Oakland and the Oakland Airport near the corridors that have higher unreliability, or it might even be a case of correlation in which the more plausible direction of causation is in the opposite direction: trucking and other transportation firms whose operations might adversely influence the reliability of travel times in corridors they use heavily. This anomaly in the results may not be a fluke that needs to be explained away, but potentially an important indicator that should be explored more closely.

Table 24. Nonresidential location choice models by industry.

Variables	β	σ	T-score	Significance
Agriculture: NAICS code 11				
Area	0.25	0.09	2.83	**
Rent	-0.52	0.30	−1.71	*
Percent retail	0.10	0.44	0.23	
Percent industrial	0.10	0.44	0.23	
Median accessibility	0.14	0.04	3.96	***
Unreliability of Accessibility	-0.24	0.05	-4.37	***
Null log-likelihood -465.12				
Converged log-likelihood -444.32				
Log-likelihood ratio 0.04				
Mining: NAICS code 21				
Area	0.44	0.27	1.64	*
Rent	-0.52	1.01	-0.52	
Percent retail	-2.39	2.23	-1.07	

Table 24. Nonresidential location choice models by industry (continued).

Variables	β	σ	T-score	Significance
Mining: NAICS code 21 (continued)				
Percent industrial	-1.24	0.92	-1.34	
Median accessibility	0.74	0.15	4.99	***
Unreliability of Accessibility	-0.43	0.24	-1.79	*
Null log-likelihood -50.66				
Converged log-likelihood -39.12				
Log-likelihood ratio 0.23				
Utilities: NAICS code 22				
Area	0.64	0.12	5.23	***
Rent	-0.93	0.45	-2.10	*
Percent retail	-2.38	1.09	-2.18	*
Percent industrial	-2.51	0.81	-3.09	**
Median accessibility	0.43	0.16	2.68	**
Unreliability of Accessibility	-0.07	0.23	-0.31	
Null log-likelihood -138.16				
Converged log-likelihood -91.94				
Log-likelihood ratio 0.33				
Construction: NAICS code 23				
Area	0.32	0.02	15.35	***
Rent	-0.74	0.07	-10.09	***
Percent retail	-0.04	0.12	-0.35	
Percent industrial	0.37	0.11	3.41	***
Median accessibility	0.09	0.01	6.72	***
Unreliability of Accessibility	0.02	0.02	0.93	
Null log-likelihood -7004.46				
Converged log-likelihood -6464.33				
Log-likelihood ratio 0.08				
Manufacturing: NAICS code 31				
Area	0.38	0.05	7.62	***
Rent	-0.62	0.18	-3.52	***
Percent retail	0.21	0.27	0.77	
Percent industrial	0.17	0.29	0.61	
Median accessibility	0.14	0.03	4.28	***
Unreliability of Accessibility	-0.13	0.04	-2.96	**
Null log-likelihood -902.61				
Converged log-likelihood -768.08				
Log-likelihood ratio 0.15				
Manufacturing: NAICS code 32				
Area	0.52	0.04	11.57	***
Rent	-1.22	0.16	-7.60	***
Percent retail	-0.30	0.24	-1.26	
Percent industrial	-0.14	0.23	-0.62	
Median accessibility	0.35	0.03	11.56	***
Unreliability of Accessibility	-0.02	0.04	-0.56	
Null log-likelihood -1588.78				
Converged log-likelihood -1289.06				
Log-likelihood ratio 0.19				

Table 24. Nonresidential location choice models by industry (continued).

Variables	β	σ	T-score	Significance
Manufacturing: NAICS code 33				
Area	0.51	0.03	19.97	***
Rent	-1.21	0.09	-12.95	***
Percent retail	-0.16	0.16	-0.97	
Percent industrial	0.24	0.14	1.77	*
Median accessibility	0.80	0.02	38.42	***
Unreliability of Accessibility	-0.24	0.03	-7.82	***
Null log-likelihood -4250.57				
Converged log-likelihood -3130.23				
Log-likelihood ratio 0.26				
Wholesale Trade: NAICS code 42				
Area	0.50	0.02	23.36	***
Rent	-1.16	0.08	-15.20	***
Percent retail	-0.29	0.13	-2.29	*
Percent industrial	-0.08	0.11	-.069	
Median accessibility	0.48	0.02	30.48	***
Unreliability of Accessibility	-0.11	0.02	-4.79	***
Null log-likelihood -6046.59				
Converged log-likelihood -4950.51				
Log-likelihood ratio 0.18				
Retail Trade: NAICS code 44				
Area	0.39	0.02	16.07	***
Rent	-0.89	0.09	-10.47	***
Percent retail	0.41	0.12	3.44	****
Percent industrial	-0.25	0.13	-1.91	*
Median accessibility	0.34	0.02	21.57	***
Unreliability of Accessibility	-0.10	0.02	-4.50	***
Null log-likelihood -4996.61				
Converged log-likelihood –4532.61				
Log-likelihood ratio 0.09				
Retail Trade: NAICS code 45				
Area	0.28	0.03	8.72	***
Rent	-0.50	0.11	-4.51	***
Percent retail	0.32	0.17	1.92	*
Percent industrial	-0.22	0.18	-1.19	
Median accessibility	0.39	0.02	16.47	***
Unreliability of Accessibility	-0.07	0.03	-2.11	*
Null log-likelihood -2390.08				
Converged log-likelihood –2210.70				
Log-likelihood ratio 0.08				
Transportation: NAICS code 48				
Area	0.44	0.04	11.75	***
Rent	-1.13	0.14	-8.31	***
Percent retail	0.00	0.27	0.01	
Percent industrial	0.48	0.22	2.14	*
Median accessibility	-0.01	0.03	-0.17	
Unreliability of Accessibility	0.15	0.05	3.22	***

Table 24. Nonresidential location choice models by industry (continued).

Variables	β	σ	T-score	Significance
Manufacturing: NAICS code 33 (continued)				
Null log-likelihood -1436.81				
Converged log-likelihood –1218.86				
Log-likelihood ratio 0.15				
Warehousing: NAICS code 49				
Area	0.42	0.10	4.01	***
Rent	-1.12	0.34	-3.30	***
Percent retail	0.90	0.50	1.79	*
Percent industrial	0.51	0.68	0.75	
Median accessibility	0.18	0.08	2.27	*
Unreliability of Accessibility	0.04	0.11		
Null log-likelihood -262.49				
Converged log-likelihood –222.51				
Log-likelihood ratio 0.15				
Information: NAICS code 51				
Area	0.44	0.03	14.26	***
Rent	-0.87	0.11	-7.91	***
Percent retail	-0.94	0.17	-5.47	***
Percent industrial	-1.16	0.17	-6.90	***
Median accessibility	0.77	0.03	30.08	***
Unreliability of Accessibility	-0.05	0.04	-1.47	
Null log-likelihood -3463.09				
Converged log-likelihood –2956.41				
Log-likelihood ratio 0.15				
Finance and Insurance: NAICS code 52				
Area	0.47	0.02	20.89	***
Rent	-0.81	0.08	-10.33	***
Percent retail	-0.51	0.11	-4.61	***
Percent industrial	-2.45	0.17	-14.47	***
Median accessibility	0.43	0.02	20.98	***
Unreliability of Accessibility	-0.04	0.03	-1.26	
Null log-likelihood -4844.64				
Converged log-likelihood –4103.26				
Log-likelihood ratio 0.15				
Real Estate, Rental and Leasing: NAICS code 53				
Area	0.37	0.04	10.27	***
Rent	-0.74	0.12	-5.98	***
Percent retail	-0.15	0.14	-1.03	
Percent industrial	-1.24	0.20	-6.29	***
Median accessibility	0.32	0.02	14.92	***
Unreliability of Accessibility	-0.02	0.03	-0.72	
Null log-likelihood -3237.43				
Converged log-likelihood –3002.47				
Log-likelihood ratio 0.07				

Table 24. Nonresidential location choice models by industry (continued).

Variables	β	σ	T-score	Significance
Professional, Scientific and Technical Services: NAICS code 54				
Area	0.39	0.01	37.56	***
Rent	-0.67	0.04	-19.06	***
Percent retail	-0.63	0.06	-10.01	***
Percent industrial	-1.04	0.07	-15.71	***
Median accessibility	0.60	0.01	65.80	***
Unreliability of Accessibility	-0.11	0.01	-8.60	***
Null log-likelihood -19885.12				
Converged log-likelihood –17456.67				
Log-likelihood ratio 0.12				
Management of Companies and Enterprises: NAICS code 55				
Area	0.29	0.18	1.63	
Rent	-0.25	0.62	-0.40	
Percent retail	-0.99	0.83	-1.20	
Percent industrial	-0.54	0.98	-0.55	
Median accessibility	0.41	0.16	2.58	**
Unreliability of Accessibility	-0.19	0.23	-0.80	
Null log-likelihood -128.94				
Converged log-likelihood –114.32				
Log-likelihood ratio 0.11				
Administrative, Support, Waste Management and Remediation Services: NAICS code 56				
Area	0.24	0.02	14.43	***
Rent	-0.49	0.06	-8.75	***
Percent retail	-0.23	0.08	-3.00	**
Percent industrial	-0.50	0.09	-5.55	***
Median accessibility	0.25	0.01	24.69	***
Unreliability of Accessibility	-0.01	0.01	-0.51	
Null log-likelihood -14561.55				
Converged log-likelihood –14109.11				
Log-likelihood ratio 0.03				
Educational Services: NAICS code 61				
Area	0.42	0.05	8.76	***
Rent	-0.78	0.17	-4.60	***
Percent retail	-0.39	0.23	-1.74	*
Percent industrial	-1.34	0.26	-5.19	***
Median accessibility	0.48	0.03	14.17	***
Unreliability of Accessibility	-0.06	0.05	-1.23	
Null log-likelihood -1510.50				
Converged log-likelihood –1342.37				
Log-likelihood ratio 0.11				
Health Care and Social Assistance: NAICS code 62				
Area	0.36	0.02	16.39	***
Rent	-0.54	0.08	-7.08	***
Percent retail	-0.25	0.10	-2.55	**
Percent industrial	-1.84	0.15	-12.60	***
Median accessibility	0.43	0.02	28.55	***
Unreliability of Accessibility	-0.10	0.02	-4.48	***

Table 24. Nonresidential location choice models by industry (continued).

Variables	β	σ	T-score	Significance
Health Care and Social Assistance: NAICS code 62 (continued)				
Null log-likelihood -6387.37				
Converged log-likelihood –5690.56				
Log-likelihood ratio 0.11				
Arts, Entertainment and Recreation: NAICS code 71				
Area	0.36	0.04	8.50	***
Rent	-0.62	0.15	-4.21	***
Percent retail	-0.11	0.20	-0.55	
Percent industrial	-0.62	0.22	-2.82	**
Median accessibility	0.35	0.03	11.10	***
Unreliability of Accessibility	-0.07	0.05	-1.42	
Null log-likelihood -1662.47				
Converged log-likelihood –1495.09				
Log-likelihood ratio 0.10				
Accommodation and Food Services: NAICS code 72				
Area	0.25	0.04	5.95	***
Rent	-0.45	0.14	-3.15	***
Percent retail	0.40	0.19	2.12	*
Percent industrial	-0.24	0.23	-1.08	
Median accessibility	0.22	0.03	7.68	***
Unreliability of Accessibility	0.01	0.04	0.21	
Null log-likelihood -1699.31				
Converged log-likelihood –1602.65				
Log-likelihood ratio 0.06				
Other services: NAICS code 81				
Area	0.35	0.02	16.55	***
Rent	-0.60	0.07	-8.40	***
Percent retail	-0.03	0.10	-0.33	
Percent industrial	-0.90	0.13	-7.00	***
Median accessibility	0.34	0.02	22.34	***
Unreliability of Accessibility	-0.05	0.02	-2.41	**
Null log-likelihood -6327.50				
Converged log-likelihood –5757.50				
Log-likelihood ratio 0.09				
Public Administration: NAICS code 92				
Area	0.70	0.15	4.76	***
Rent	-1.37	0.53	-2.59	**
Percent retail	-1.48	0.75	-1.98	*
Percent industrial	-3.00	1.07	-2.80	**
Median accessibility	-0.14	0.15	-0.91	
Unreliability of Accessibility	0.33	0.20	1.64	
Null log-likelihood -207.23				
Converged log-likelihood –150.74				
Log-likelihood ratio 0.27				

Table 24. Nonresidential location choice models by industry (continued).

Variables	β	σ	T-score	Significance
Other: NAICS code 99				
Area	0.62	0.28	2.19	*
Rent	-1.74	1.23	-1.41	
Percent retail	0.84	1.51	0.56	
Percent industrial	-0.42	1.14	-0.37	
Median accessibility	0.39	0.26	1.45	
Unreliability of Accessibility	0.03	0.35	0.09	
Null log-likelihood -46.05				
Converged log-likelihood –34.32				
Log-likelihood ratio 0.25				

SENSITIVITY ANALYSIS WITH URBANSIM

The preceding models have been implemented in UrbanSim for applications testing. We have explored the sensitivity of travel-time reliability influences on business and household location and on real estate prices using a baseline alternative and two scenarios constructed to reflect different levels of operational improvements that improve reliability, focusing on the areas in the East Bay that have relatively low reliability.

Construction of Reliability Scenarios

In order to evaluate the cumulative effects of potential operational improvements that influence travel-time reliability, while controlling for the effects of such improvements on the median travel time, we devised two scenarios for sensitivity testing. The sensitivity test scenarios focus on the East Bay freeways showing high unreliability in current travel times, according to our observed data from PeMS.

Travel-time distributions were calculated for two freeways in the East Bay area (I-580 and I-880) from 2010 PeMS data for the weekday morning peak period (7:00 a.m. to 9:00 a.m.). From these, measures of the median and the 80th percentile travel time were obtained. In order to estimate what effect improving typical travel time and reliability will have by deploying operations, the following method was developed and applied by Cambridge Systematics and provided for use in sensitivity testing for this research. It is based on modeling the effect of operations improvements in order to develop factors that can be applied to the actual (empirical) measurements of travel time and reliability, as follows:

1. Define two levels of deployment (Table 25).
2. Determine peak volume and capacity values by matching each PeMS section to Highway Performance Monitoring System (HPMS) sections.
3. Estimate recurring delay for the base and deployed cases using a volume-delay function:

$$t = \frac{1+(0.1225(\frac{v}{c})8)}{FreeFlowSpeed}$$

Figure 28. Equation. Travel rate.
(Source: *Speed Adjustments Using Volume-Delay Functions*, TMIP Technical Synthesis, January 2009, http://tmiponline.org/Clearinghouse/Items/Technical_Synthesis_-_Speed_Adjustments_Using_Volume-Delay_Functions.aspx.)

where: t = travel rate (hours per mile)
v = hourly volume
c = capacity

4. Estimate incident delay for base and deployed cases using the relationships from the ITS Deployment Analysis System (IDAS); combine with recurring delay to get total delay and the overall travel time index (TTI) for each PeMS section.

Table 25. Operations deployment scenarios.

Strategy	Typical Option	Aggressive Option
Ramp Metering	+3% capacity	+5% capacity
Incident Management	-25% incident duration	-35% incident duration
Traveler Information: DMS	-0.5% total delay	Included in ATDM
Active Traffic and Demand Management (VSL, lane control, queue warning, junction control)	N/A	-10% total delay

5. Fit a logistic function to the data to predict the mean TTI after deployment as a function of the mean TTI before deployment:

$$MeanTTI' = \frac{1.9829}{1+4.3493e^{(-1.4864MeanTTI)}}$$

Figure 29. Equation. MeanTTI prime.
(Source: Cambridge Systematics, Inc.)

6. Develop predictive equations for the 50th and 80th percentile TTIs as a function of the mean TTI by fitting sigmoidal functions to the PeMS data for I-580 and I-880 separately. For example:

$$MeanTTI^{80} = \frac{4.913192}{1+e^{(-2.172337-0.9537MeanTTI)^{(1/0.026841)}}}$$

Figure 30. Equation. MeanTTI superscript 80.
(Source: Cambridge Systematics, Inc.)

7. Factor the empirical TTI percentiles (from the PeMS data) by the ratio of the deployed TTI to the base TTI.

The links of I-880 and I-580 selected for the sensitivity testing are depicted in Figure 31, along with the distance from these links that are used to tabulate the simulation results below.

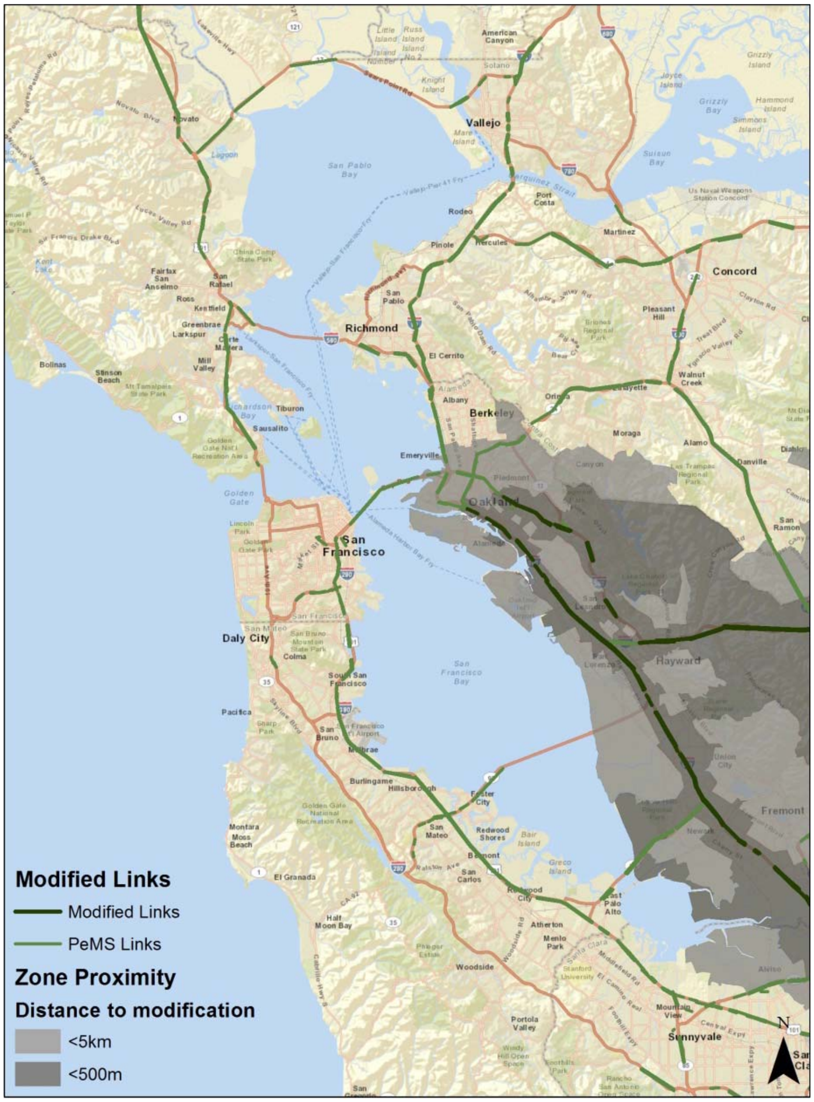

Figure 31. Map. Links modified for scenarios.
(Source: Cambridge Systematics, Inc.)

Sensitivity Analysis Results

Having constructed two scenarios, we then test these scenarios on the entire nine-county San Francisco Bay Area, using an adapted version of UrbanSim for this purpose (Waddell, 2002; Waddell, 2011). The design for the sensitivity tests was intended to help isolate the impacts of two levels of modifications to the 80th percentile travel times on selected links on I-880 and I-580 in order to bring those times closer to the median values, a change that would reflect a reliability improvement with no change in median travel time. Note that this would underestimate the expected effects of operational improvements, since it avoids reflecting the impact on median travel times. But for our research objectives, this design was preferred in order to more directly assess the reliability impacts in the aggregate.

We structured the simulation to run over six iterations, though we constrained the control totals to be static, and the real estate supply to be static, in order to focus on real estate prices and demand effects. We assumed constant and low relocation rates for firms and households, with differential rates for renters and owners. Given our sensitivity testing design, we focus on the real estate effects on prices and rents, as the location choice changes are extremely small. In further extensions of this work, we may explore real estate supply and location choice impacts in more depth.

Sensitivity tests were run on three alternatives, one of which is the reference or base case. In the reference case we leave the travel times as observed in the PeMS data for all links in the network. In Scenarios 1 and 2, we modify the selected I-880 and I-580 links as shown in Table 26. In Table 26, we provide a summary of the simulation results of the two operations deployment scenarios compared to the baseline scenario in which no changes are made to travel times.

Table 26. Operations deployment scenario results compared to baseline.

Home Prices Scenario 1	$630.9	$594.9	$-41.7	$1,184.1
Home Prices Scenario 2	$1,392.7	$1,469.9	$-498.5	$2,364.1
Home Prices Scenario 1	1.0%	0.6%	0.0%	0.2%
Home Prices Scenario 2	2.2%	1.5%	-0.1%	0.3%
Residential Rent Scenario 1	$1.6	$1.2	$-0.3	$2.6
Residential Rent Scenario 2	$3.5	$3.3	$-1.7	$5.1
Residential Rent Scenario 1	0.5%	0.2%	0.0%	0.1%
Residential Rent Scenario 2	1.0%	0.6%	0.0%	0.1%
Nonresidential Rent Scenario 1	$14.0	$9.7	$99.2	$122.9
Nonresidential Rent Scenario 2	$31.4	$25.2	$245.1	$301.8
Nonresidential Rent Scenario 1	0.4%	0.2%	0.1%	0.1%
Nonresidential Rent Scenario 2	0.9%	0.6%	0.2%	0.2%

Prices and rents are in millions.
Rents are annual.

The magnitudes of the impacts of the operations deployment scenarios are relatively modest in percentage terms, as would be expected for such an intervention. The largest percentage impacts occur on residential property values for owner-occupied units, with a 1.0 percent impact in the nearest homes in Scenario 1, and a 2.2 percent impact in Scenario 2. These effects decay significantly between 0.5 KM and 5 KM from the impacted highway segments, and are 0.1 percent or less beyond 5 KM. Interestingly, the effects remain positive when cumulated across the entire region, amounting to 0.2 percent of total owner-occupied property values in Scenario 1, and 0.3 percent in Scenario 2. When considered in absolute terms, the size of these impacts is impressive: the cumulative regional impact on owner-occupied property values is $1.184 Billion in Scenario 1, and $2.364 billion in Scenario 2. It would appear that reliability improvements are rather highly valued by homeowners, and there are many properties that would be affected by such changes, leading to very substantial regional impacts.

Results for residential rental properties also are impacted substantially by the operations deployment scenarios, though the percentage and absolute values of these impacts are smaller. The percentage impacts on annual rents were 0.5 percent in the closest properties in Scenario 1, and 1.0 percent in those properties in Scenario 2. Cumulative regional effects were 0.1 percent for both scenarios. The annual impact of the scenarios across the region was estimated to be $2.6 in Scenario 1, and $5.1 in Scenario 2. Note that these are annual rents, and have not been converted to price-equivalents for comparison to owner-occupied housing.

To give another frame of reference for these impacts, the owner-occupied homes within 0.5 KM of the affected highways are estimated to gain $2,600 on average in Scenario 1, and $5,800 in Scenario 2. Annual rents would increase by $212 in Scenario 1 and $454 in Scenario 2 on renter-occupied units, suggesting that there could be distributional impacts to consider from such improvements, with property owners reaping the windfall, and renters potentially bearing heavier rent burdens.

Nonresidential rents also were found to rise significantly as a consequence of these operations deployment scenarios. Space within 0.5 KM of the affected highway segments would be estimated to rise by $14.0 million (0.4 percent) in Scenario 1, and $31.5 million (0.9 percent) in Scenario 2. Across the region, these impacts accumulate to $122.9 million (0.1 percent) in Scenario 1, and $301.8 million (0.2 percent) in Scenario 2. These also are annual impacts, so the long-term impacts would accumulate across multiple years, with some discount rate.

Conclusions

This research has explored a question that has not received prior research attention. In light of the results of both our empirical research results, and the sensitivity tests of plausible operations deployment scenarios, we find that the reliability of accessibility does impact real estate markets significantly. It clearly impacts residential prices and rents, as well as nonresidential rents. The magnitude of these effects is highest close to the interventions, but extends well beyond the immediate area, and our results suggest that there may be substantial regional benefits to improving travel-time reliability that have been previously overlooked, resulting in an underestimate of the benefits from such projects.

There are of course caveats on our research findings. First, the sensitivity tests were constructed somewhat manually and in a way that lent itself to helping to answer our questions on the impact of reliability improvements while holding median travel times constant. In reality, operations improvements would generally improve both the median and the 80th percentile travel times. Second, we only studied one metropolitan area, during one period of time. The San Francisco Bay Area may have idiosyncrasies that might make our results less general. We think the research should be replicated in other metropolitan areas that vary in size and other dimensions. Finally, we focused on roadway operations and travel-time reliability, and transit reliability was not part of the scope of this research. Given the magnitude of the impacts we found, we think it would be promising to conduct similar research on transit reliability.

One sobering aspect of this research is that it begins to suggest that the state of the practice, and to a large extent, even the state of the art in travel modeling, is designed to squeeze out information on travel time variability, rendering the models useless for examining the impacts of operations changes on reliability. Our initial hope was to be able to combine land use modeling and transport modeling in a way that consistently dealt with travel time distributions, but this was not possible with available travel models. It seems that much more research needs to be oriented in the direction of developing travel models that generate well-calibrated distributions of travel times, rather than a single, fixed-point result of an assumed equilibration process. It turns out that reliability is more important than had been previously assumed, and both travel and land use models should reconsider how best to incorporate travel time variability into their design.

REFERENCES

Note: Due to the large number of references for this chapter, we have organized them as endnotes rather than footnotes.

Alonso, W. (1960). A theory of the urban land market, Papers in Regional Science 16(1): 149-157.

Bates, J., Polak, J., Jones, P. and Cook, A. (2001). The valuation of reliability for personal travel, Transportation Research Part E: Logistics and Transportation Review 37(23): pp. 191-229. URL: http://www.sciencedirect.com/science/article/pii/S1366554500000119.

Ben-Akiva, M. and Lerman, S. R. (1987). Discrete Choice Analysis: Theory and Application to Travel Demand, The MIT Press, Cambridge, Massachusetts.

Brownstone, D. and Small, K. A. (2005). Valuing time and reliability: assessing the evidence from road pricing demonstrations, Transportation Research Part A: Policy and Practice 39(4): 279-293.

Clark, W. A. V. and Lierop, W. F. J. V. (1986). Residential mobility and household location modeling, Handbook of Regional and Urban Economics, Volume 1, Elsevier Science Publishers BV, pp. 97-132.

DiPasquale, D. and Wheaton, W. (1996). Urban Economics and Real Estate Markets, Prentice Hall: Englewood Cliffs, New Jersey.

Downs, A. (2004). Still Stuck in Traffic: Coping with Peak-Hour Congestion, The Brookings Institution, Washington, D.C.

Edmonds, Radcliffe G., J. (1983). Travel time valuation through hedonic regression, Southern Economic Journal 50(1): pp. 83-98. URL: http://www.jstor.org/stable/1058042.

Ettema, D., Tamminga, G., Timmermans, H. and Arentze, T. (2005). A microsimulation model system of departure time using a perception updating model under travel time uncertainty, Transportation Research Part A 39: 325-344.

Fosgerau, M. and Karlström, A. (2010). The value of reliability, Transportation Research Part B: Methodological 44(1): 38-49.

Giuliano, G. (2004). The Geography of Urban Transportation, 3rd edn, Guilford Publications, Incorporated, chapter Land Use Impacts of Transportation Investments – Highway and Transit, pp. 237-273.

Gordon, P. and Richardson, H. (1997). Are compact cities a desirable goal?, Journal of the American Planning Association 63(1): 95-106. Greene, W. H. (2002). Econometric Analysis, 5th edn, Pearson Education. Hansen, W. (1959). How accessibility shapes land use, Journal of the American Institute of Planners 25(2): 73-76.

Hoch, I. and Waddell, P. (1993). Apartment rents: Another challenge to the monocentric model, Geographical Analysis 25(1): 20-34. URL: http://dx.doi.org/10.1111/j.1538-4632.1993.tb00277.x.

Lam, T. C. and Small, K. A. (2001). The value of time and reliability: measurement from a value pricing experiment, Transportation Research Part E: Logistics and Transportation Review 37(23): 231- 251. URL: http://www.sciencedirect.com/science/article/pii/S1366554500000168

Lee, B., Waddell, P., Wang, L. and Pendyala, R. (2010). Reexamining the influence of work and nonwork accessibility on residential location choices with a microanalytic framework, Environment and planning. A 42(4): 913.

Lerman, S. (1977). Location, housing, automobile ownership, and the mode to work: A joint choice model, Transportation Research Board Record 610: 6-11.

Li, Z., Hensher, D. A. and Rose, J. M. (2010). Willingness to pay for travel-time reliability in passenger transport: A review and some new empirical evidence, Transportation Research Part E: Logistics and Transportation Review 46(3): 384-403. URL: http://www.sciencedirect.com/science/article/pii/S1366554509001550

Lomax, T., Schrank, D., Turner, S. and Margiotta, R. (2003). Selecting travel reliability measures, Technical report, Texas Transportation Institute.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior, in P. Zarembka (ed.), Frontiers in Econometrics, Academic Press, New York, pp. 105-142.

McFadden, D. (1978). Modeling the choice of residential location, in A. Karlqvist, L. Lundqvist, F. Snickars and J. Wiebull (eds), Spatial Interaction Theory and Planning Models, North Holland, Amsterdam, pp. 75-96.

McFadden, D. (1981). Econometric models of probabilistic choice, in C. Manski and D. McFadden (eds), Structural Analysis of Discrete Data with Econometric Applications, MIT Press, Cambridge, MA, pp. 198-272.

Mills, E. (1992). Office rent determinants in the Chicago area, Real Estate Economics 20(2): 273-287.

Muth, R. F. (1961). The spatial structure of the housing market, Papers in Regional Science 7(1): 207-220. URL: http://dx.doi.org/10.1111/j.1435-5597.1961.tb01780.x

Nam, D., Park, D. and Khamkongkhun, A. (2005). Estimation of value of travel-time reliability, Journal of Advanced Transportation 39(1): 39-61. URL: http://dx.doi.org/10.1002/atr.5670390105

Nelson, J. P. (1977). Accessibility and the value of time in commuting, Southern Economic Journal 43(3): pp. 1321-1329. URL: http://www.jstor.org/stable/1057789.

Noland, R. B. (2001). Relationships between highway capacity and induced vehicle travel, Transportation Research Part A: Policy and Practice 35(1): 47-72.
URL: http://www.sciencedirect.com/science/article/pii/S0965856499000476

Pendyala, R., Konduri, K., Chiu, Y., Hickman, M., Noh, H., Waddell, P., Wang, L., You, D. and Gardner, B. (2012). An integrated land use-transport model system with dynamic time-dependent activity-travel microsimulation, 91st Annual Meeting of the Transportation Research Board, Washington, D.C.

Quigley, J. (1976). Housing demand in the short-run: An analysis of polytomous choice, Explorations in Economic Research 3: 76-102.

Rosen, K. (1984). Toward a model of the office building sector, Real Estate Economics 12(3): 261-269.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition, Journal of Political Economy 82(1): 34-null.

Shukla, V. and Waddell, P. (1991). Firm location and land use in discrete urban space: A study of the spatial structure of Dallas-Fort Worth, Regional Science and Urban Economics 21(2): 225-253.
URL: http://www.sciencedirect.com/science/article/pii/016604629190035L

Small, K. A., Winston, C. and Yan, J. (2005). Uncovering the distribution of motorists' preferences for travel time and reliability, Econometrica 73(4): 1367-1382.
URL: http://dx.doi.org/10.1111/j.1468-0262.2005.00619.x

Train, K. E. (2003). Discrete Choice Methods with Simulation, Cambridge University Press.

Train, K. E. (2009). Discrete Choice Methods with Simulation, Cambridge University Press.

van Lint, J., van Zuylen, H. J. and Tu, H. (2008). Travel time unreliability on freeways: Why measures based on variance tell only half the story, Transportation Research Part A 42: 258-277.

Waddell, P. (1997). Household Choice and Urban Structure: A Re-Assessment of the Behavioral Foundations of Urban Models of Housing, Labor and Transportation Markets, Ashgate, University of Texas at Dallas.

Waddell, P. (2000). A behavioral simulation model for metropolitan policy analysis and planning: Residential location and housing market components of UrbanSim, Environment and Planning B: Planning and Design 2000 27(2): 247-263.

Waddell, P. (2002). UrbanSim: Modeling urban development for land use, transportation, and environmental planning, Journal of the American Planning Association 68(3): 297-314.

Waddell, P. (2007). Accessibility and residential location: the interaction of workplace, housing tenure, residential mobility and location choice, in J. Preston, F. Pagliara and D. Simmonds (eds), Modeling Residential Location Choice, Ashgate. in press.

Waddell, P. (2011). Integrated land use and transportation planning and modeling: Addressing challenges in research and practice, Transport Reviews 31(2): 209-229.

Waddell, P., Berry, B. J. and Hoch, I. (1993). Residential property values in a multimodal urban area: New evidence on the implicit price of location, Journal of Real Estate Finance and Economics 7: 117-141.

Waddell, P. and Nourzad, F. (2002). Incorporating non-motorized mode and neighborhood accessibility in an integrated land use and transportation model system, Transportation Research Record (1805): 119-127.

Waddell, P. and Shukla, V. (1993). Employment dynamics, spatial restructuring, and the business cycle, Geographical Analysis 25(1): 35-52. URL: http://dx.doi.org/10.1111/j.1538-4632.1993.tb00278.x

Waddell, P. and Shukld, V. (1993). Manufacturing location in a polycentric urban area: a study in the composition and attractiveness of employment subcenters, Urban Geography 14(3): 277-296.

Waddell, P. and Ulfarsson, G. F. (2003). Accessibility and agglomeration: Discrete-choice models of employment location by industry sector, 2003 Annual Meeting of the Transportation Research Board, Washington, D.C.

Waddell, P., Ulfarsson, G., Franklin, J. and Lobb, J. (2007). Incorporating land use in metropolitan transportation planning, Transportation Research Part A: Policy and Practice 41: 382-410.

Waddell, P., Wang, L., Charlton, B. and Olsen, A. (2010). Microsimulating parcel-level land use and activity-based travel: Development of a prototype application in San Francisco, Journal of Transportation and Land Use 3(2): 65-84.

Wang, L., Waddell, P. and Outwater, M. (2011). Incremental integration of land use and activity-based travel modeling: Work-at-home and out-of-home workplace choices. Transportation Research Board 89th Annual Meeting Compendium of Papers DVD.

CHAPTER 5. SHORT-TERM EMISSIONS IMPACTS OF OPERATIONS STRATEGIES

OVERVIEW

One of the motivations for conducting this project was to determine the effect that operations strategies have on emissions. That is, how will changes in traffic flow effected by operations result in changes in emissions. Traditionally, the impact of transportation improvements on emissions have been linked via changes in average speed. However, because the effect of operations strategies may more to smooth traffic flow in breakdown and near-breakdown conditions than to change overall speed greatly, this approach has been criticized.

The need to model emissions at a more detailed level has led to the development of emissions models based on vehicle activity (i.e., modal emissions models); see Chapter 2.0 for a discussion of these models. These models are capable of using second-by-second speed and acceleration activity from individual vehicles, also known as vehicle trajectories, as input. Vehicle trajectories can be measured in the field using specialized equipment, but for forecasting, microscopic traffic simulation models can provide them.

Integration of traffic and emissions models is still in the formative stages. As far back as the early 1990s, such integration had been accomplished for the first generation of microscopic traffic simulation models, FRESIM and NETSIM, developed and supported by FHWA. In these models, a series of lookup tables were used to estimate emissions (carbon monoxide, nitrous oxides, and hydrocarbons) and fuel consumption. The tables were defined by instantaneous speeds and accelerations and were accessed every second for every vehicle; the data were based on testing a very limited sample of vehicles conducted in the mid-1980s. Thus, total emissions and fuel consumption were built up from the lowest level possible. However, subsequent research has shown that vehicle emission production is a more complex process involving factors beyond speed and acceleration, including engine load, engine characteristics, and other factors, so the simple lookup table approach has been abandoned.

One of the first efforts to link modal emissions and microscopic traffic simulation models was the Comprehensive Modal Emissions Model (CMEM) developed under NCHRP Project 25-11.[(49)] Figure 32 shows the CMEM's link-level fuel consumption modeling methodology. Subsequently, other modal emissions models, including MOVES, have been used in conjunction with simulation models. A few examples include:

- CMEM has developed a plug-in to the Paramics microsimulation model, which calculates emission data for every vehicle in a Paramics simulation at every second.[(50)]

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[49] Barth, Matthew *et al.*, *Development of a Comprehensive Modal Emissions Model*, Web-Only Document 122, Transportation Research Board, April 2000, http://onlinepubs.trb.org/onlinepubs/nchrp /nchrp_w122.pdf.

[50] http://www.cert.ucr.edu/cmem/model.html.

- SHRP 2 Project C10B developed a direct connection between the DynusT mesoscopic simulation model and MOVES.[(51)]
- FHWA's, *Advances in Project-Level Emissions Analyses*, linked the Transmodeler microscopic simulation model with MOVES.[(52)]

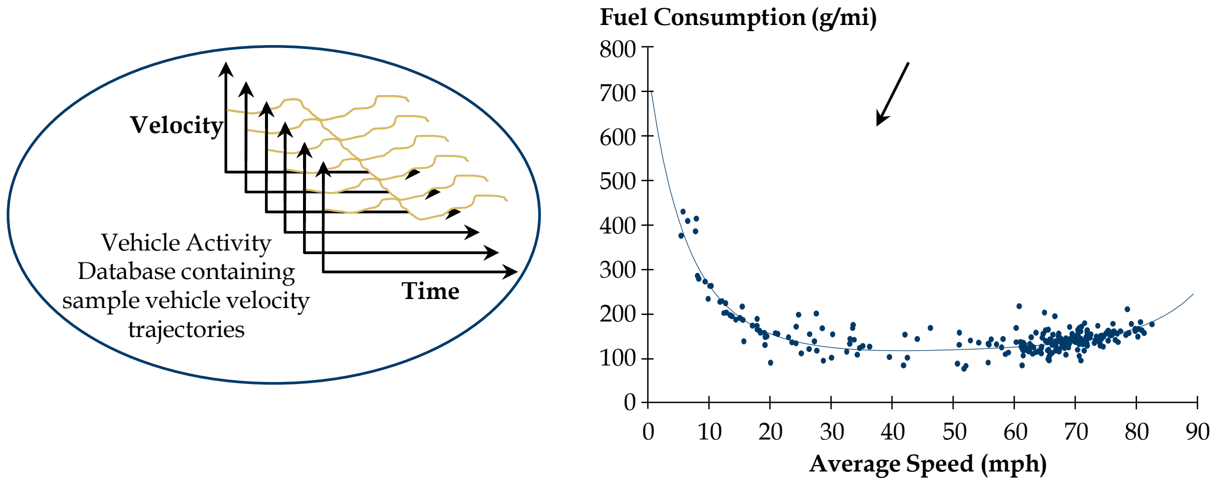

Figure 32. Graph. CMEM's link-level fuel consumption modeling methodology.
(Source: Scoara, George and Barth, Matt, *CMEM User's Guide, Version 3.01,* University of California, Riverside Center for Environmental Research and Technology, June 2006.)

For this project, it was decided to use a microscopic simulation that already been calibrated and used to analyze operational strategies in conjunction with the MOVES model. Details are provided below.

STUDY DESIGN

Area Studied

The simulation model that was previously used to assess the benefits of Integrated Corridor Management (ICM) in the Interstate-15 (I-15) corridor in San Diego, California was selected (microscopic formulation of the TransModeler software).[(53)] The I-15 corridor site in San Diego, California extends from the interchange with State Road (SR) 163 in the south to the interchange with SR 78 in the north, a freeway stretch of approximately 20 miles. Also included in the study area are the following roadways:

- Centre City Parkway.

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[51] http://www.shrp2c10.org/SHRPC10Portal/Home.aspx.

[52] E.H. Pechan and Associates et al., "Advances in Project Level Analyses,"" prepared for FHWA, Contract No. DTFH61-10-C-0006, November 4, 2010.

[53] Cambridge Systematics, "Integrated Corridor Management: Analysis, Modeling, and Simulation for the I-15 Corridor in San Diego, California,"" prepared for FHWA, December 2011.

- Pomerado Road.
- Rancho Bernardo Road.
- Camino Del Norte Road.
- Ted Williams Parkway.
- Black Mountain Road.
- Scripps Parkway.

Figure 33 illustrates the Pioneer Corridor and the roadways included in the study area. I-15 is an 8- to 10-lane freeway section in San Diego providing an important connection between San Diego and cities like Poway, Mira Mesa, and Escondido, and destinations to the northeast. Figure 34 indicates the geographic location of the corridor along with the extents of the mainline study area.

The current operations on I-15 include two center-median lanes that run along eight miles of I-15 between SR 163 in south and Ted William Pkwy (SR 56) in the north. These center-median lanes are reversible high-occupancy vehicle (HOV) lanes that operate in the southbound direction in the AM peak period and in the northbound direction during the PM peak period. The current operations also allow single occupancy vehicles (SOV) to utilize the roadway for a price, thereby operating as high-occupancy toll (HOT) lanes.

The I-15 corridor is one of three primary north-south transportation corridors in San Diego County, and is the primary north-south highway in inland San Diego County, serving local, regional, and interregional travel. The corridor is a heavily utilized regional commuter route, connecting communities in northern San Diego County with major regional employment centers. The corridor is situated within a major interregional goods movement corridor, connecting Mexico with Riverside and San Bernardino counties, as well as Las Vegas, Nevada.

Modeling Approach

The microscopic component of TransModeler was utilized for the analysis of the corridor. This model also was used to evaluate the response of drivers in incident situations when they are faced with high levels of congestion. When a driver's path choice is reevaluated, the path costs (e.g., segment travel times) are reconsidered. For driver groups defined in the model parameters as having access to real-time travel information (i.e., informed drivers), an updated travel timetable was used to evaluate path costs. Drivers belonging to a driver group that do not have access to real-time information will reconsider their paths using the same (i.e., historical) travel time information used to evaluate their pretrip paths.

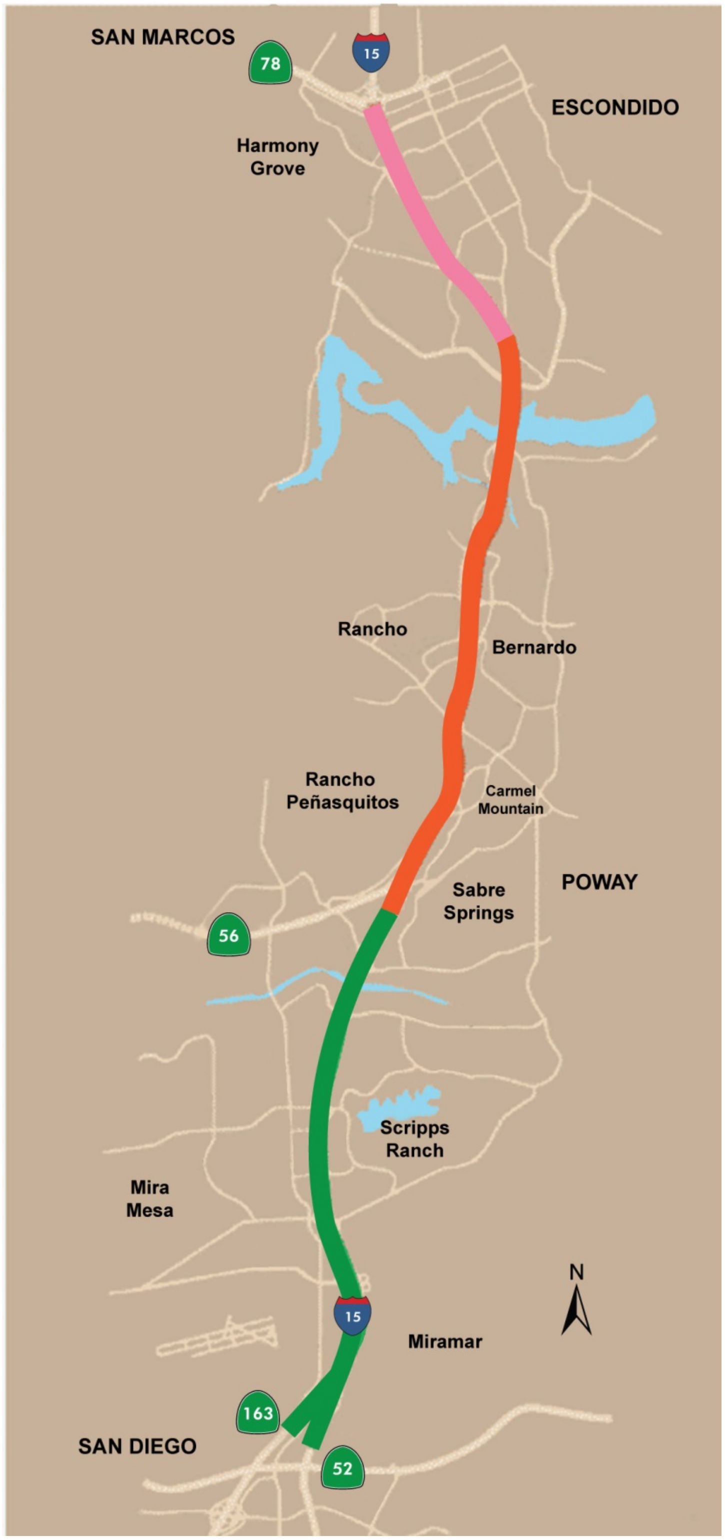

Figure 33. Map. Study area I-15 corridor in San Diego, California.
(Source: Cambridge Systematics, Inc.)

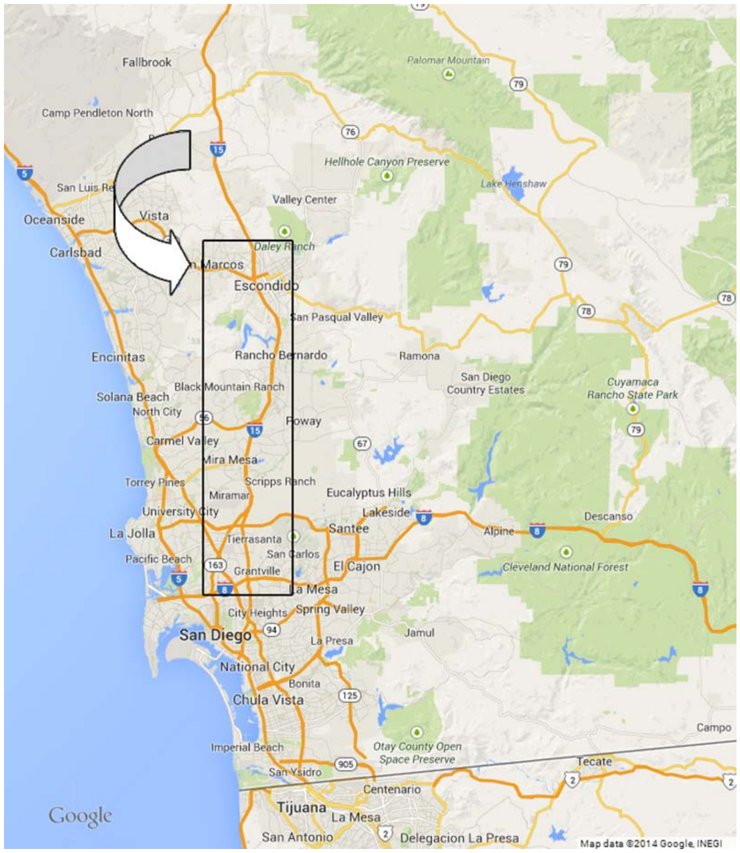

Figure 34. Map. Location and geographic boundaries of corridor.
(Source: Cambridge Systematics, Inc., ©2014 Google, INEGI.)

The traffic assignment models within TransModeler allow the use of static and dynamic assignment procedures based on requirements of different study types. Traffic assignment models are used to estimate the flow of traffic on a network. These models take as input a matrix of flows that indicate the volume of traffic between origin and destination (O-D) pairs. The flows for each O-D pair are loaded onto the network based on the travel time or impedance of the alternative paths that could carry this traffic. For traffic simulation models, the flow on a network is modeled by representing individual vehicle movements, and subsequently the link-based performance measures are evaluated based on movements of these individual vehicles as they rest in queues, travel in free flow, or maneuver through congestion. Whether all vehicles traveling a given path reach all links on the path within a given analysis period is dependent on time-variant travel conditions in the network.(54) Stochastic User Equilibrium (SUE) was used in the simulation model. This algorithm is premised on the assumption that travelers have imperfect information about network paths and/or vary in their perceptions of network attributes. At stochastic user equilibrium, no travelers believe that they can increase their expected utility by choosing a different path.

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[54] TransModeler User Manual.

The San Diego Association of Governments' (SANDAG) Travel Demand Model (TDM) for the region was used to develop the trip tables and networks for the I-15 Corridor. The simulation model was run for three hours, 6:00 a.m. to 9:00 a.m. period. The demand levels were taken directly from the ICM study for 2012. Because the AM period was analyzed, I-15 Southbound was selected for the freeway-based treatments because its traffic peaks in the AM.

Vehicle trajectories were specified as output from the simulation model. The records represent the speed and acceleration of every vehicle during every second of simulation, resulting in several hundreds of millions individual records. A computer script was written to convert these records into operating mode distributions and link summary inputs to the MOVES model, which was then used to derive emission estimates.

Analysis Scenarios

Table 27 shows the scenarios that were run with the model. We refer to them as "primary" to distinguish from a set of different tests focused on variable speed limits (VSL), discussed below.

Table 27. Primary analysis scenarios for the I-15 simulations.

Scenario	Ramp Metering		Incident Present?	Active Signal Control	Incident Management	Traveler Info
	SDRMS	ALINEA				
A	X					
B		X				
C[55]	X		Major	X		X
C2	X		Major	X		
D	X		Minor			X
D2	X		Minor			
E	X		Minor		X	X
E2	X		Minor		X	
F (base case)						
G	X			X		
H	X			X		X

[a]Scenarios C and C2 were not used as a basis for comparing results, just as a test case to see how the model behaved under extreme conditions.

The strategy definitions are as follows:

[55] Scenarios C and C2 were not used as a basis for comparing results, just as a test case to see how the model behaved under extreme conditions.

- Ramp Metering. Two ramp metering strategies were implemented. ALINEA (a local feedback ramp metering control system) was applied to Scenario B while SDRMS (San Diego Ramp Metering System) was applied to the remaining scenarios except the base case.

- Incidents. An incident was set up in Scenarios C through E, blocking certain lanes between Scripps Poway interchange and Mira Mesa interchange on the southbound I-15 mainline from 7:00 a.m. for a certain period (as shown in Figure 35). The incident in Scenarios C and C2 blocks four of six lanes from 7:00 to 7:30 and blocks three of six lanes from 7:30 to 8:00. The incident in Scenarios D, D2, E, and E2 blocks one of six lanes. It lasts from 7:00 to 7:30 for Scenarios D and D2 and from 7:00 to 7:20 for Scenario E and E2 respectively. The shortened duration for E and E2 is to replicate the effect of incident management.

- Traveler Information. There are two group of drivers set up in this model, informed drivers (30 percent) and uninformed drivers (70 percent). In the with traveler information scenarios, updated travel times can be set up such that it is accessible to all the informed drivers if a rerouting maneuver is desired. For every 15 minutes in the simulation timeframe, updated travel times are distributed to all the informed drivers and free-flow travel times are distributed to all the uninformed drivers. For every 15 minutes, if an alternative route has 50 percent (defined by reroute threshold) reduction in generalized cost (i.e., travel time and toll) compared to the current path, the informed driver will switch to the alternative route.

- Active Signal Control. Responsive signals also are implemented in some scenarios. Signals are adjusted to optimized timing plans based on different traffic volumes on the parallel arterials which serve as alternative routes after the incident happens.

In addition, a special analysis of variable speed limits was undertaken with the model, which included the following scenarios:

- VSL with base demand.
- VSL with 10 percent increase demand on I-15 southbound.
- No VSL with 10 percent increase in demand on I-15 southbound.

RESULTS

Primary Scenarios

Tables 28 through 31 show the emissions and system performance results for the different scenarios in the corridor.

Reader's Note: We have chosen to list the results in this and subsequent sections by individual roadway sections. The reader should focus first on the total network results, the last rows in the tables, highlighted in bold, and then use the individual results for details.

Considering all highways in the study network – as well as I-15 southbound (the focus of most strategies), the operations strategies produce reductions in all emissions, including CO_2. Note that the basis of comparison is different for the types of scenarios. In Table 28, the base is Scenario F. In Table 29, the base condition is Scenario D for Scenario E, and Scenario D2 for Scenario E2. System performance results are provided to help explain some of the results, but can only go so far. The emissions estimates are based on second-by-second vehicle trajectories, not average system speeds. Therefore, the modal profiles for two runs with the same average speeds can be quite different.

In the ramp meter only scenarios (A and B), the parallel arterial's (Pomerado Road) emissions increase, likely due to increased stop time on the ramps as shown in the decreased speeds on Pomerado Road, the arterial parallel to I-15. This small increase is more than compensated for elsewhere in the network. Part of the beneficial emission effect can be seen in the slight decrease in VMT for Scenarios A and B compared to the Base, presumably as travelers shorten their trips to take advantage of improved I-15 southbound conditions. This is an extremely important point: emissions are a function of not only improved travel conditions (e.g., higher speeds, fewer stops) but also of trip length. Ramp metering on the target section (I-15 southbound) shows slight improvement in this section's speed, with the advanced ALINEA algorithm outperforming the standard algorithm.

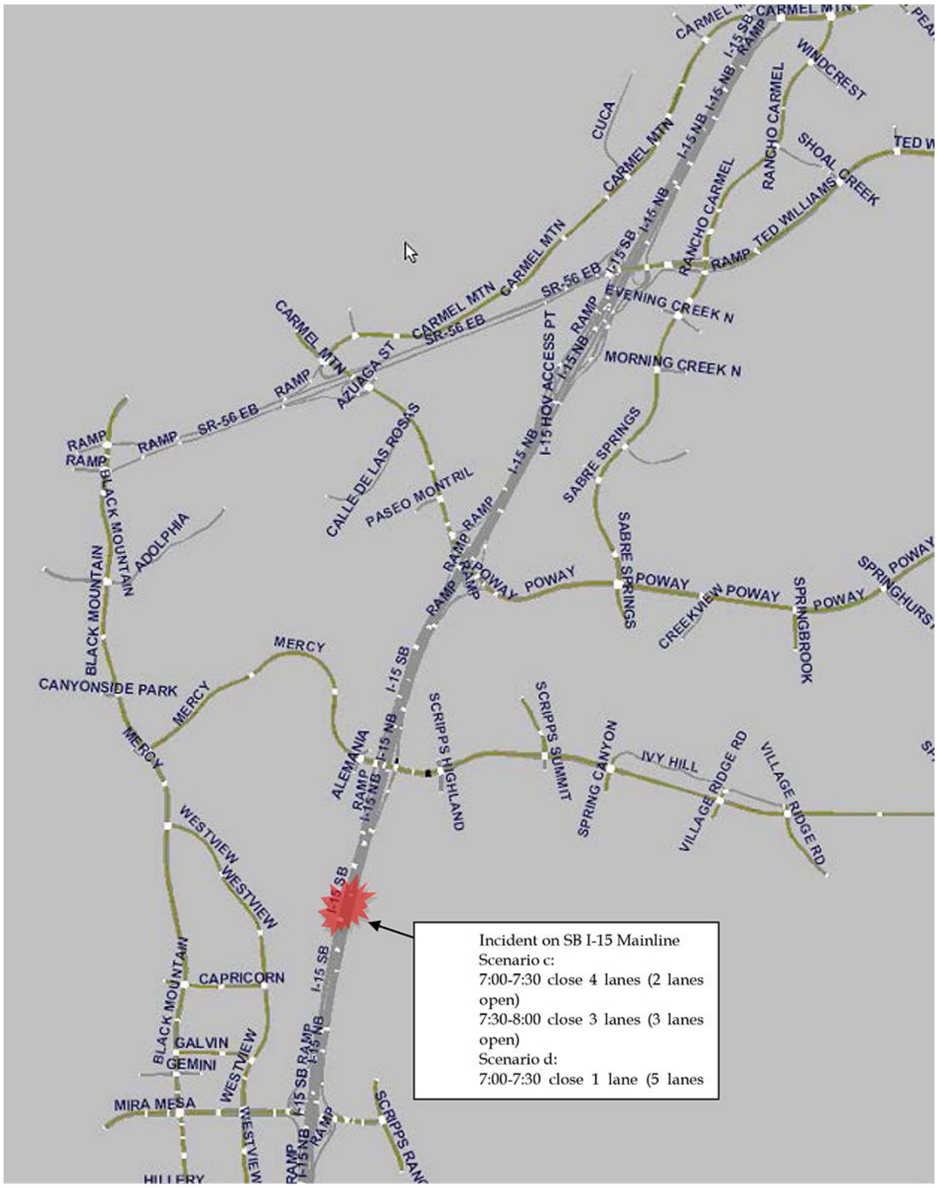

Figure 35. Map. Incident setup.
(Source: Cambridge Systematics, Inc.)

Adding active signal control to ramp metering in Scenarios G and H further extends both the emission and system performance benefits. Note that Scenario G outperforms Scenario H in terms of system emissions, even though Scenario H has traveler information added. This is most probably due to the reduced VMT in Scenario G. With traveler information deployed, overall system speeds are improved, but they appear to come at the expense of increased trip length as travelers choose less congested – but more circuitous – routes.

In the incident scenarios (Tables 30 and 31), some routes experience an increase in emissions, due to increased VMT from diversions responding caused by the severe congestion. In fact, VMT is not constant across all scenarios. This is because of the diversion feature in the model.

At any time, the route choice model can be reevaluated in order to update the path choices of drivers en route to their destinations. This model also was used to evaluate the response of drivers in incident situations when they are faced with high levels of congestion. When a driver's path choice is reevaluated, the path costs (e.g., segment travel times) are reconsidered. For driver groups defined in the model parameters as having access to real-time travel information (i.e., informed drivers), an updated travel timetable was used to evaluate path costs. Drivers belonging to a driver group that do not have access to real-time information will reconsider their paths using the same (i.e., historical) travel time information used to evaluate their pretrip paths.

On the I-15 Southbound target section, VMT is substantially higher for Scenario E (incident management plus traveler information) than for either the base or incident management only scenarios. However, the same effect of traveler information is observed here as for the nonincident scenarios, i.e., VMT is higher with traveler information deployed.

The ability of the simulation model to represent the effect traveler information is most likely problematic. Therefore, the Scenario D/Scenario E comparisons cannot be fully trusted. Focusing on just the comparison between Scenario D2 and E2, VHT was reduced by six percent with the addition of incident management on I-15 Southbound. Systemwide CO_2 and other emissions also were reduced as a result of incident management emissions, with CO_2 emissions dropping by over seven percent.

Table 28. Emission results for primary scenarios, 2010 (nonincident scenarios).

6:00 a.m. to 9:00 a.m.			**Emissions (grams)**				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NOx**
Black Mountain Expwy	scenario_A	9,594	7,044,845	4.13%	93,865	2,994	15,448
Black Mountain Expwy	scenario_B	9,197	7,008,406	3.59%	96,632	2,915	15,881
Black Mountain Expwy	Base	10,352	6,765,509		95,438	2,806	15,305
Black Mountain Expwy	scenario_G	10,812	6,638,842	-1.87%	95,103	2,745	15,306
Black Mountain Expwy	scenario_H	10,452	6,626,596	-2.05%	94,349	2,776	15,424
Carmel Mountain Expwy	scenario_A	4,309	2,907,180	0.73%	51,873	1,238	6,924
Carmel Mountain Expwy	scenario_B	4,361	2,894,335	0.28%	51,591	1,235	6,925
Carmel Mountain Expwy	Base	4,816	2,886,183		51,597	1,228	6,925
Carmel Mountain Expwy	scenario_G	4,803	2,723,066	-5.65%	43,797	1,213	5,929
Carmel Mountain Expwy	scenario_H	4,882	2,937,542	1.78%	52,440	1,250	7,069
I-15 NB	scenario_A	289,513	104,558,162	-4.33%	1,058,182	31,576	239,653
I-15 NB	scenario_B	289,598	105,364,626	-3.60%	1,075,848	32,087	240,067
I-15 NB	Base	297,336	109,295,860		1,121,967	33,210	250,478
I-15 NB	scenario_G	282,783	104,808,784	-4.11%	1,066,312	31,960	239,578
I-15 NB	scenario_H	292,487	108,973,584	-0.29%	1,127,518	33,546	247,793
I-15 SB	scenario_A	yes435,030	213,456,303	-1.73%	1,867,652	80,948	413,619
I-15 SB	scenario_B	433,340	208,735,871	-3.91%	1,890,718	76,079	421,936
I-15 SB	Base	420,698	217,218,389		1,954,660	81,830	427,100
I-15 SB	scenario_G	421,320	188,302,302	-13.31%	1,823,462	65,871	398,333
I-15 SB	scenario_H	418,841	203,885,665	-6.14%	1,910,878	74,227	417,795

Table 28. Emission results for primary scenarios, 2010 (non-incident scenarios, continued).

6:00 a.m. to 9:00 a.m.			Emissions (grams)				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NOx**
Other Fwys/Expys and Major Arterials	scenario_A	81,497	58,168,884	-0.25%	747,604	25,171	122,648
Other Fwys/Expys and Major Arterials	scenario_B	81,160	59,070,832	1.29%	760,056	25,542	125,076
Other Fwys/Expys and Major Arterials	Base	90,458	58,316,447		753,250	25,153	123,247
Other Fwys/Expys and Major Arterials	scenario_G	93,510	56,799,069	-2.60%	756,325	24,310	121,797
Other Fwys/Expys and Major Arterials	scenario_H	94,426	56,399,555	-3.29%	751,274	24,110	121,424
Pomerado Rd	scenario_A	28,106	21,551,594	2.00%	244,971	9,468	42,992
Pomerado Rd	scenario_B	27,850	21,910,938	3.70%	246,868	9,631	43,703
Pomerado Rd	Base	31,581	21,129,853		245,072	9,163	43,000
Pomerado Rd	scenario_G	32,921	17,457,167	-17.38%	231,456	7,224	37,600
Pomerado Rd	scenario_H	35,003	16,982,701	-19.63%	231,020	6,969	37,345
Total, All Highways	**scenario_A**	**848,049**	**407,686,968**	**-1.91%**	**4,064,147**	**151,395**	**841,284**
Total, All Highways	**scenario_B**	**845,506**	**404,985,008**	**-2.56%**	**4,121,713**	**147,489**	**853,588**
Total, All Highways	**Base**	**855,241**	**415,612,241**		**4,221,984**	**153,390**	**866,055**
Total, All Highways	**scenario_G**	**846,149**	**376,729,230**	**-9.36%**	**4,016,455**	**133,323**	**818,543**
Total, All Highways	**scenario_H**	**856,091**	**395,805,643**	**-4.77%**	**4,167,478**	**142,879**	**846,849**

Scenario A: ramp metering
Scenario B: ALINEA ramp metering
Scenario G: ramp metering, active signal control
Scenario H: ramp metering, active signal control, traveler information

Table 29. System Performance Measures, 6:00 a.m. to 9:00 a.m., 2010 (nonincident scenarios).

Route	Scenario	VMT	VMT Relative to base	VHT	VHT Relative to Base	System Speed
Black Mountain Expressway	scenario_A	9,594	-7.32%	578	13.78%	16.6
Black Mountain Expressway	scenario_B	9,197	-11.16%	547	7.68%	16.8
Black Mountain Expressway	Base	10,352		508		20.4
Black Mountain Expressway	scenario_G	10,812	4.44%	487	-4.13%	22.2
Black Mountain Expressway	scenario_H	10,452	0.97%	513	0.98%	20.4
Carmel Mountain Expressway	scenario_A	4,309	-10.53%	153	1.32%	28.2
Carmel Mountain Expressway	scenario_B	4,361	-9.45%	154	1.99%	28.3
Carmel Mountain Expressway	Base	4,816		151		31.9
Carmel Mountain Expressway	scenario_G	4,803	-0.27%	211	39.74%	22.8
Carmel Mountain Expressway	scenario_H	4,882	1.37%	154	1.99%	31.7
I-15 NB	scenario_A	289,513	-2.63%	4,557	-4.16%	63.5
I-15 NB	scenario_B	289,598	-2.60%	4,652	-2.17%	62.3
I-15 NB	Base	297,336		4,755		62.5
I-15 NB	scenario_G	282,783	-4.89%	4,697	-1.22%	60.2
I-15 NB	scenario_H	292,487	-1.63%	4,910	3.26%	59.6
I-15 SB	scenario_A	435,030	3.41%	18,898	-2.21%	23.0
I-15 SB	scenario_B	433,340	3.01%	16,732	-13.42%	25.9
I-15 SB	Base	420,698		19,325		21.8
I-15 SB	scenario_G	421,320	0.15%	13,260	-31.38%	31.8
I-15 SB	scenario_H	418,841	-0.44%	13,260	-31.38%	31.6

Table 29. System Performance Measures, 6:00 a.m. to 9:00 a.m., 2010 (nonincident scenarios) (continued).

Route	Scenario	VMT	VMT Relative to base	VHT	VHT Relative to Base	System Speed
Other Fwys/Expys and Major Arterials	scenario_A	81,497	-9.91%	3,506	12.82%	23.2
Other Fwys/Expys and Major Arterials	scenario_B	81,160	-10.28%	3,774	21.43%	21.5
Other Fwys/Expys and Major Arterials	Base	90,458		3,108		29.1
Other Fwys/Expys and Major Arterials	scenario_G	93,510	3.37%	3,903	25.60%	24.0
Other Fwys/Expys and Major Arterials	scenario_H	94,426	4.39%	1,611	-48.15%	58.6
Pomerado Road	scenario_A	28,106	-11.00%	2,479	9.06%	11.3
Pomerado Road	scenario_B	27,850	-11.81%	2,547	12.05%	10.9
Pomerado Road	Base	31,581		2,273		13.9
Pomerado Road	scenario_G	32,921	4.24%	1,409	-38.01%	23.4
Pomerado Road	scenario_H	35,003	10.84%	1,250	-45.01%	28.0
Total, All Highways	scenario_A	848,049	-0.84%	30,171	0.17%	28.1
Total, All Highways	scenario_B	845,506	-1.14%	28,406	-5.69%	29.8
Total, All Highways	Base	855,241		30,120		28.4
Total, All Highways	scenario_G	846,149	-1.06%	23,967	-20.43%	35.3
Total, All Highways	scenario_H	856,091	0.10%	21,698	-27.96%	39.5

Table 30. Emission results for primary scenarios, 2010 (incident scenarios).

6:00 a.m. to 9:00 a.m.			Emissions				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NOx**
Black Mountain Expwy	scenario_D	10,510	6,612,747		93,907	2,776	15,239
Black Mountain Expwy	scenario_D2	10,352	6,630,833		94,364	2,731	15,132
Black Mountain Expwy	scenario_E	11,173	7,012,707	6.05%	99,367	2,966	15,830
Black Mountain Expwy	scenario_E2	11,159	7,253,787	9.39%	100,984	3,053	16,385
Carmel Mountain Expwy	scenario_D	4,917	2,954,354		52,713	1,256	7,036
Carmel Mountain Expwy	scenario_D2	4,784	2,859,546		51,033	1,217	6,846
Carmel Mountain Expwy	scenario_E	4,916	2,962,320	0.27%	52,780	1,261	7,094
Carmel Mountain Expwy	scenario_E2	4,970	3,054,455	6.82%	54,347	1,304	7,304
I-15 NB	scenario_D	293,290	108,978,872		1,120,279	33,379	249,102
I-15 NB	scenario_D2	297,320	109,779,783		1,129,933	33,453	252,169
I-15 NB	scenario_E	286,463	105,920,289	-2.81%	1,084,187	32,254	242,596
I-15 NB	scenario_E2	286,324	106,184,196	-3.28%	1,085,910	32,348	243,117
I-15 SB	scenario_D	416,604	208,120,832		1,918,518	76,583	419,330
I-15 SB	scenario_D2	414,197	211,701,360		1,929,704	80,855	410,968
I-15 SB	scenario_E	430,183	182,615,160	-12.26%	1,831,966	62,389	397,495
I-15 SB	scenario_E2	410,096	186,308,356	-11.99%	1,862,559	64,489	403,501
Other Fwys/Expys and Major Arterials	scenario_D	94,486	54,899,300		744,233	23,297	119,262
Other Fwys/Expys and Major Arterials	scenario_D2	89,531	57,420,501		744,110	24,812	121,060
Other Fwys/Expys and Major Arterials	scenario_E	98,903	55,771,900	1.59%	765,045	23,507	122,122
Other Fwys/Expys and Major Arterials	scenario_E2	99,511	58,187,213	1.34%	787,434	24,579	126,858

Table 30. Emission results for primary scenarios, 2010 (incident scenarios, continued).

6:00 a.m. to 9:00 a.m.			Emissions				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NOx**
Pomerado Rd	scenario_D	34,917	17,214,891		231,881	7,049	37,527
Pomerado Rd	scenario_D2	31,381	21,087,603		243,132	9,221	42,131
Pomerado Rd	scenario_E	38,660	18,930,927	9.97%	251,358	7,707	41,510
Pomerado Rd	scenario_E2	38,750	18,952,848	-10.12%	251,671	7,727	41,691
Total, All Highways	**scenario_D**	**854,724**	**398,780,996**		**4,161,531**	**144,340**	**847,496**
Total, All Highways	**scenario_D2**	**847,565**	**409,479,626**		**4,192,276**	**152,289**	**848,306**
Total, All Highways	**scenario_E**	**870,298**	**373,213,303**	**-6.41%**	**4,084,703**	**130,084**	**826,647**
Total, All Highways	**scenario_E2**	**850,810**	**379,940,855**	**-7.21%**	**4,142,905**	**133,500**	**838,856**

Scenario D: ramp metering, traveler information
Scenario D2: ramp metering
Scenario E: ramp metering, incident management, traveler information
Scenario E2: ramp metering, incident management

Table 31. System performance measures, 6:00 a.m. to 9:00 a.m., 2010 (incident scenarios).

Route	Scenario	VMT	VMT Relative to Base	VHT	VHT Relative to Base	System Speed (mph)
Black Mountain Expressway	scenario_D	10,510		474		22.2
Black Mountain Expressway	scenario_D2	10,352		462		22.4
Black Mountain Expressway	scenario_E	11,173	6.31%	481	1.48%	23.2
Black Mountain Expressway	scenario_E2	11,159	7.80%	464	0.43%	24.0
Carmel Mountain Expressway	scenario_D	4,917		156		31.5
Carmel Mountain Expressway	scenario_D2	4,784		215		22.3
Carmel Mountain Expressway	scenario_E	4,916		160		30.7
Carmel Mountain Expressway	scenario_E2	4,970		158		31.5
I-15 NB	scenario_D	293,290		4,789		61.2
I-15 NB	scenario_D2	297,320		5,113		58.1
I-15 NB	scenario_E	286,463	-2.33%	4,877	1.84%	58.7
I-15 NB	scenario_E2	286,324	-3.70%	5,024	-1.74%	57.0
I-15 SB	scenario_D	416,604		17,879		23.3
I-15 SB	scenario_D2	414,197		25,322		16.4
I-15 SB	scenario_E	430,183	3.26%	16,637	-6.95%	25.9
I-15 SB	scenario_E2	410,096	-0.99%	23,781	-6.09%	17.2
Other Fwys/Expys and Major Arterials	scenario_D	94,486		3,155		30.0
Other Fwys/Expys and Major Arterials	scenario_D2	89,531		3,799		23.6
Other Fwys/Expys and Major Arterials	scenario_E	98,903	4.67%	3,284	4.10%	30.1
Other Fwys/Expys and Major Arterials	scenario_E2	99,511	11.15%	3,994	5.13%	24.9

Table 31. System performance measures, 6:00 a.m. 9:00 a.m., 2010 (incident scenarios) (continued).

Route	Scenario	VMT	VMT Relative to Base	VHT	VHT Relative to Base	System Speed (mph)
Pomerado Road	scenario_D	34,917		1,161		30.1
Pomerado Road	scenario_D2	31,381		1,324		23.7
Pomerado Road	scenario_E	38,660	10.72%	1,201	3.45%	32.2
Pomerado Road	scenario_E2	38,750	23.48%	1,404	6.04%	27.6
Total, All Highways	scenario_D	854,724		27,614		31.0
Total, All Highways	scenario_D2	847,565		36,235		23.4
Total, All Highways	scenario_E	870,298	1.82%	26,640	-3.53%	32.7
Total, All Highways	scenario_E2	850,810	0.38%	34,825	-3.89%	24.4

Figures 36 and 37 were developed from the link-level MOVES output for all scenarios to see if the results were reasonable. The freeway curve in Figure 36 mimics that shown in Barth and Boriboonsomsin, which was developed with independent data.(56) For a given speed value (for speeds above about 15 mph), there is a spread in the data indicating that different operating modes are being used. Note that the freeway curve stops at 65 mph – the data in Barth and Boriboonsomsin show that the curve turns positive at speeds above 70 mph.

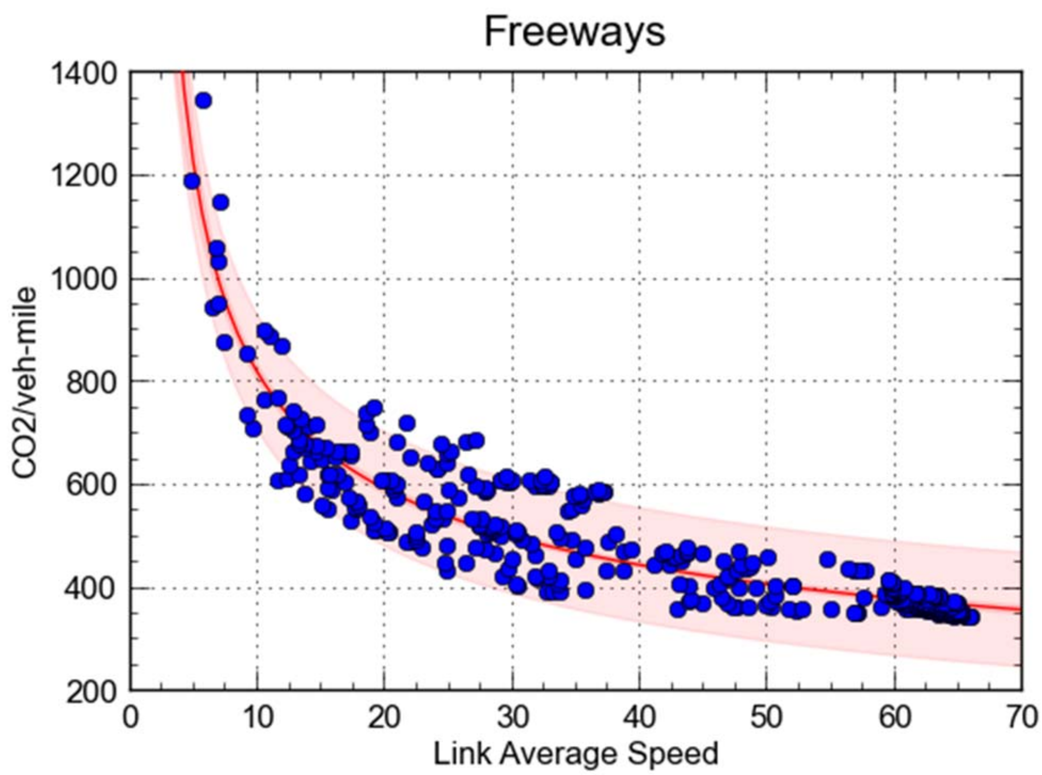

Figure 36. Scatter graph. CO_2 emission rates from MOVES outputs, freeways.
(Source: Cambridge Systematics, Inc.)

[56] Barth, Matthew and Boriboonsomsin, Kanok, "Real World CO_2 Impacts of Traffic Congestion," submitted to Transportation Research Board Annual Meeting, 2008.

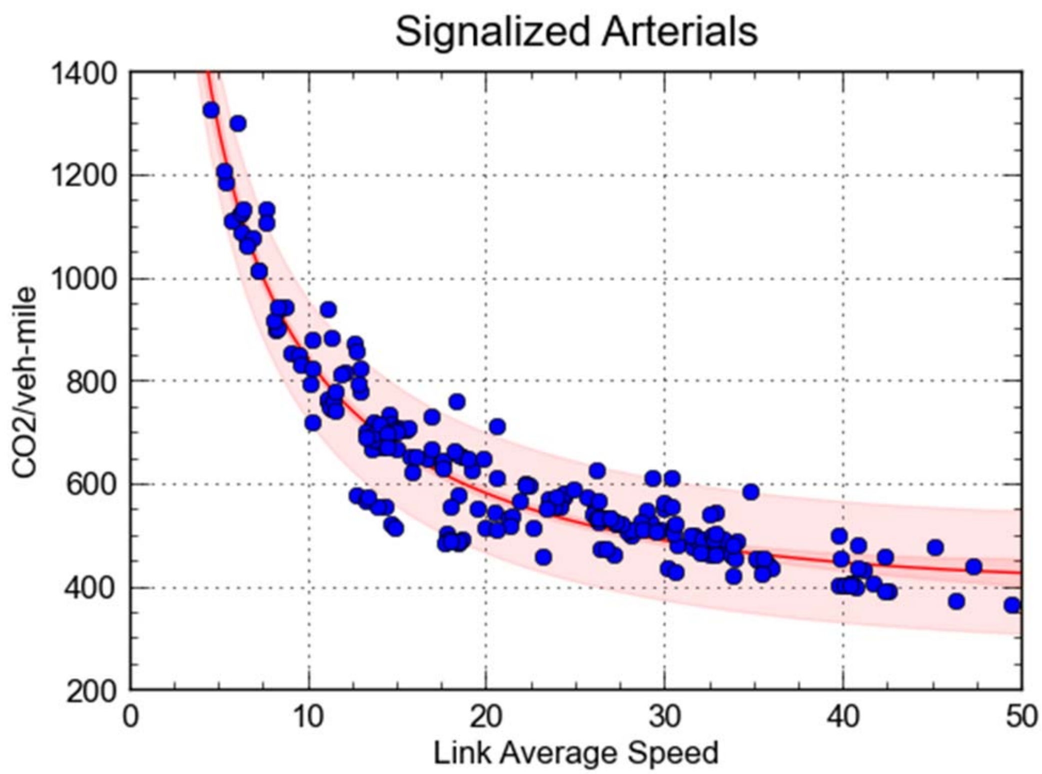

Figure 37. Scatter graph. CO_2 emission rates from MOVES outputs, arterials.
(Source: Cambridge Systematics, Inc.)

Variable Speed Limit Scenarios

Because VSL is relatively new and some of its potential benefits have been called into question, it was first decided to test the traffic flow effects of VSL before proceeding to emissions analysis. As shown below, we could not find any appreciable traffic flow effect in this corridor for VSL treatment, Therefore, we did not conduct any emissions analysis.

Two profiles are used in the analysis of the VSL strategies, they are shown below compared to the capacity at the bottleneck (Figure 38).

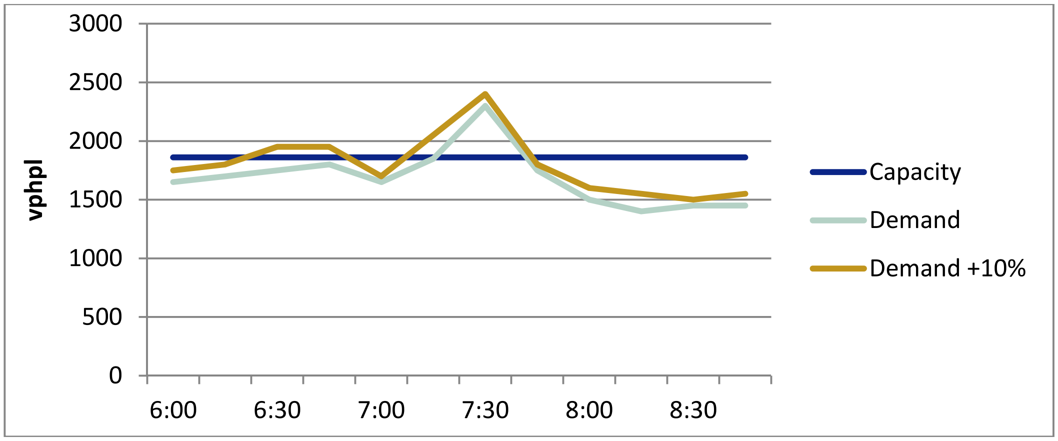

Figure 38. Line graph. Demand profile at the analysis bottleneck.
(Source: Cambridge Systematics, Inc.)

The congestion along the corridor under the two demand profiles is represented by the speed plots below (Figures 39 and 40).

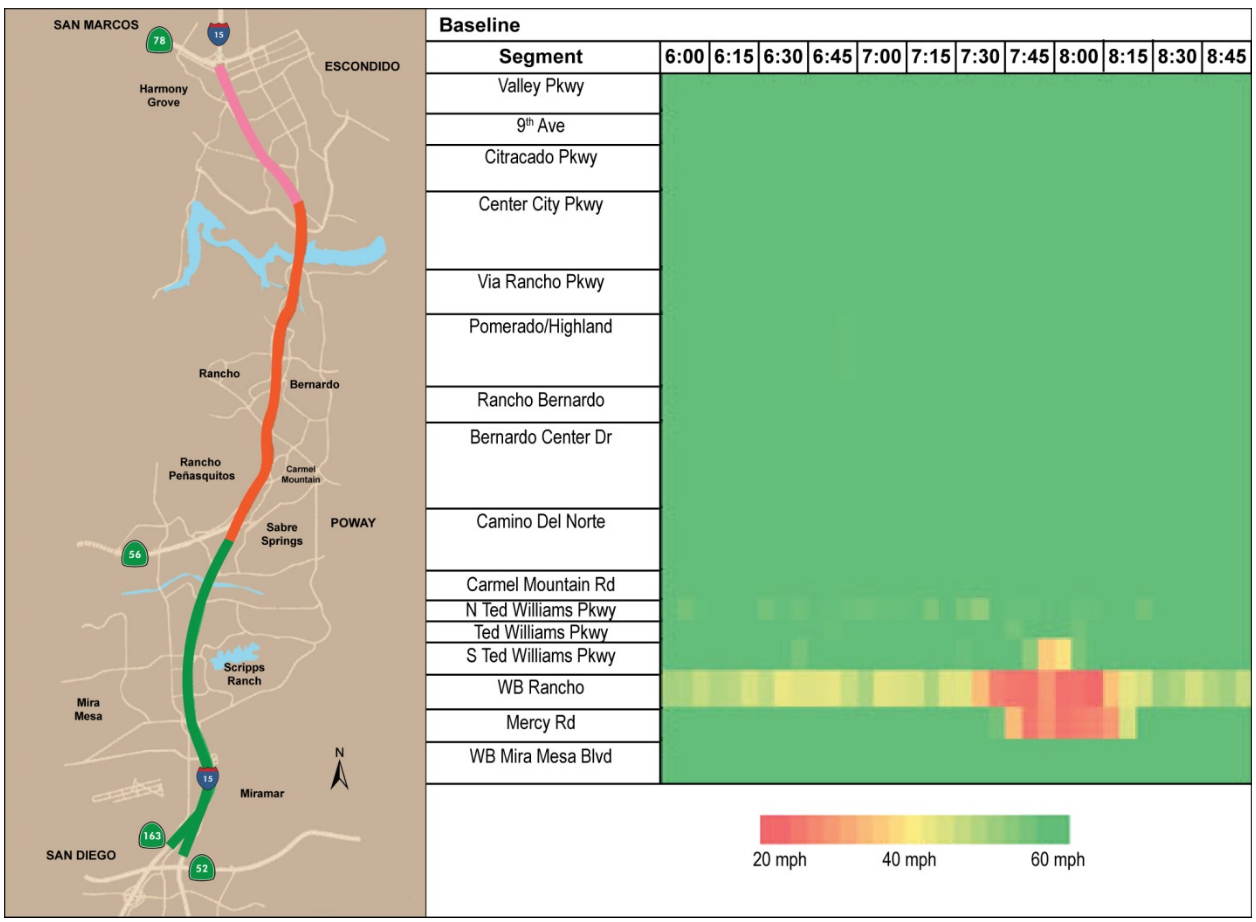

Figure 39. Map and graph. Speed profile under normal demand, no VSL.
(Source: Cambridge Systematics, Inc.)

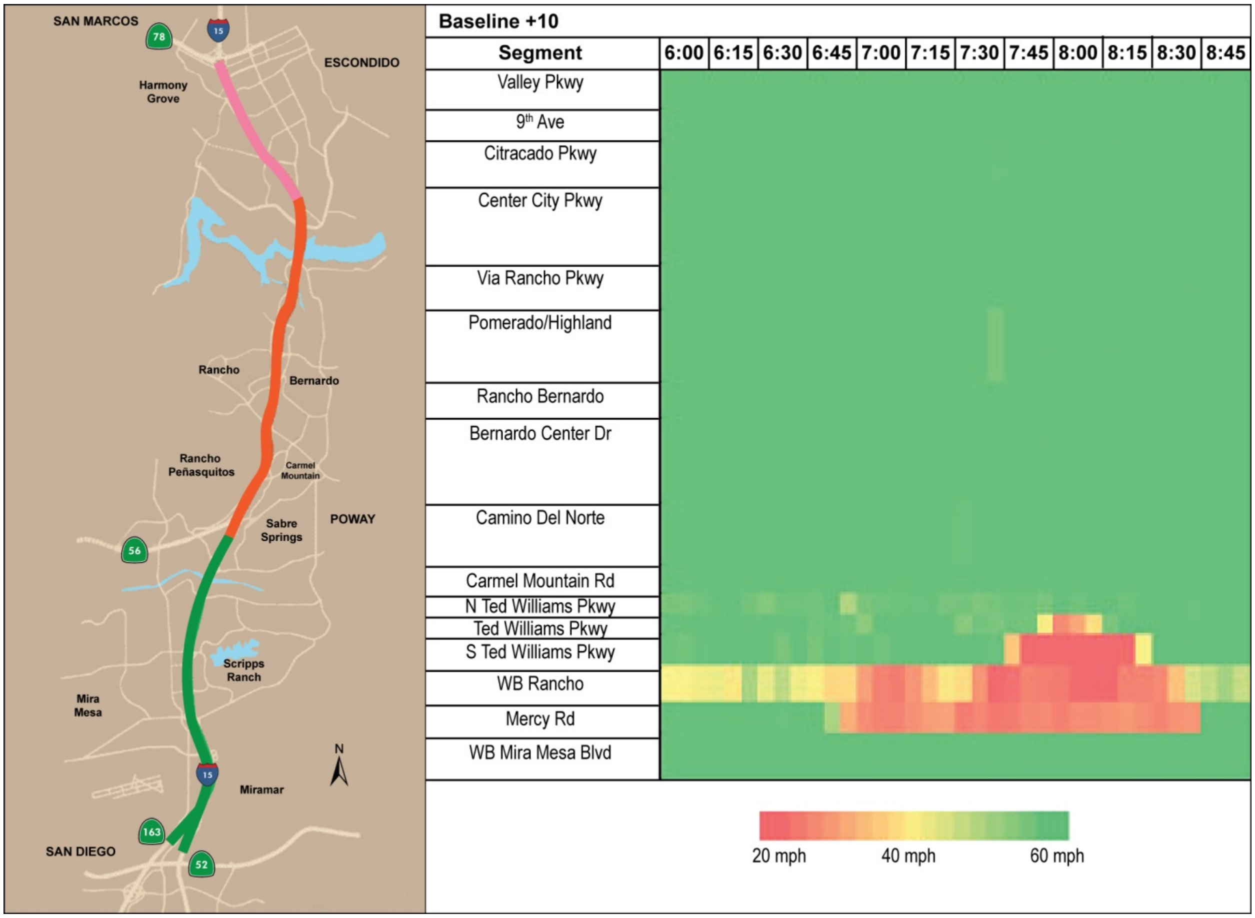

Figure 40. Map and graph. Speed profile under high demand, no VSL.
(Source: Cambridge Systematics, Inc.)

The first VSL strategy applied to the corridor is a standard VSL strategy aimed at improving safety at the upstream end of the queue where heavy and unanticipated breaking occur. VSL signs are positioned upstream of the bottleneck every 1,000 feet. When speeds drop below 45 mph a message warning of congestion is displayed. And, when a speed drop below 30 mph is detected downstream the VSL sign changes to 30 mph and the upstream VSL sign changes to 45 mph. This strategy therefore follows the back of the queue first warning with a 45 mph speed restriction and then a 30 mph speed restriction.

The congestion when applying this strategy is shown below using speed plots (Figures 41 and 42).

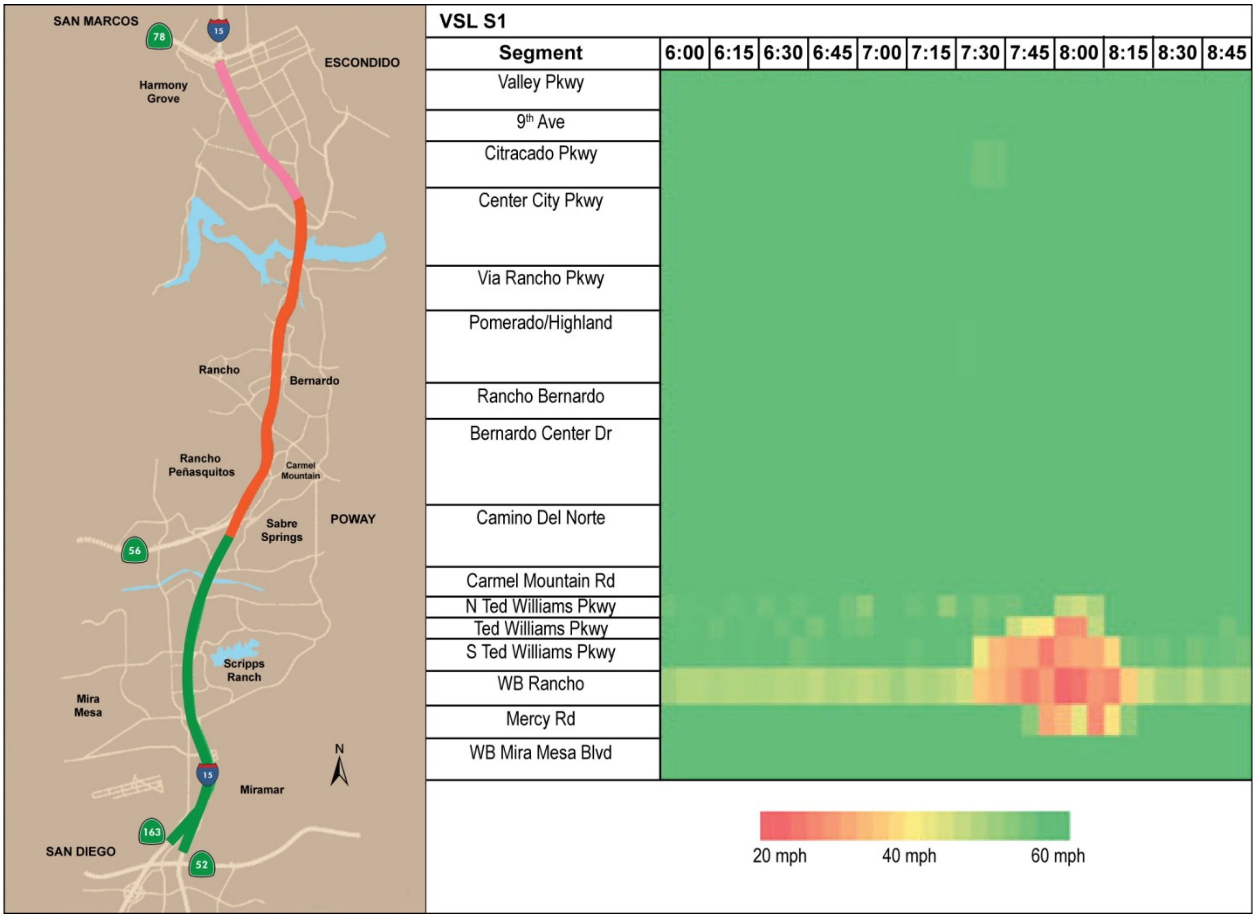

Figure 41. Map and graph. Speed profile under normal demand with traditional VSL.
(Source: Cambridge Systematics, Inc.)

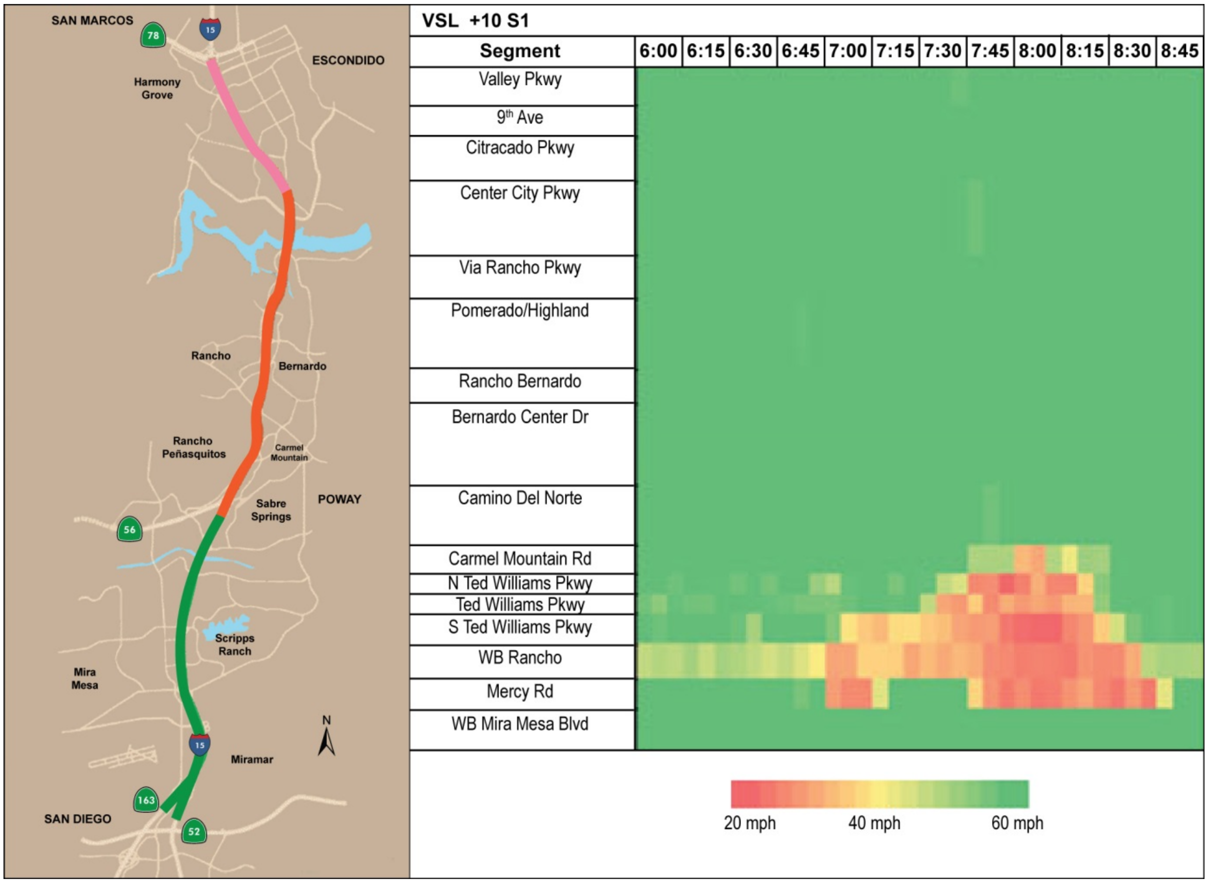

Figure 42. Map and graph. Speed profile under high demand with traditional VSL.
(Source: Cambridge Systematics, Inc.)

The traditional VSL strategy elongated the congestion physically and temporally, while reducing the intensity of the speed decreases within the congested area. The next measure analyzed is delay. A comparison of delay along the corridor (Table 32) will indicate whether the freeway performance is improved by the VSL strategy.

Table 32. Freeway delay (vehicle hours).

	Normal Demand	**High Demand**
No VSL	540	990
Traditional VSL	600	1,120

The second VSL strategy is a nontraditional strategy, one that attempts to reduce congestion at a bottleneck by “metering” mainline volume miles upstream of the bottleneck. For this study the nontraditional strategy was applied approximately 4.5 miles upstream of the bottleneck, 1 mile upstream of the maximum extent of the queue under normal conditions.

The nontraditional VSL strategy was applied over approximately 5.5 miles of mainline freeway and was responsive to traffic conditions at the bottleneck location. When speeds at the bottleneck dropped below 30 mph the VSL strategy was applied, when they increased to between 30 mph and 45 mph the VSL signs changed from 30 mph to 45 mph and when the speeds increased above 45 mph the VSL strategy stopped. Warning upstream of the upcoming VSL signs was given throughout the application of the strategy.

The speed profiles for the application of the nontraditional VSL strategy are shown for both the normal and high-demand scenario (Figures 43 and 44).

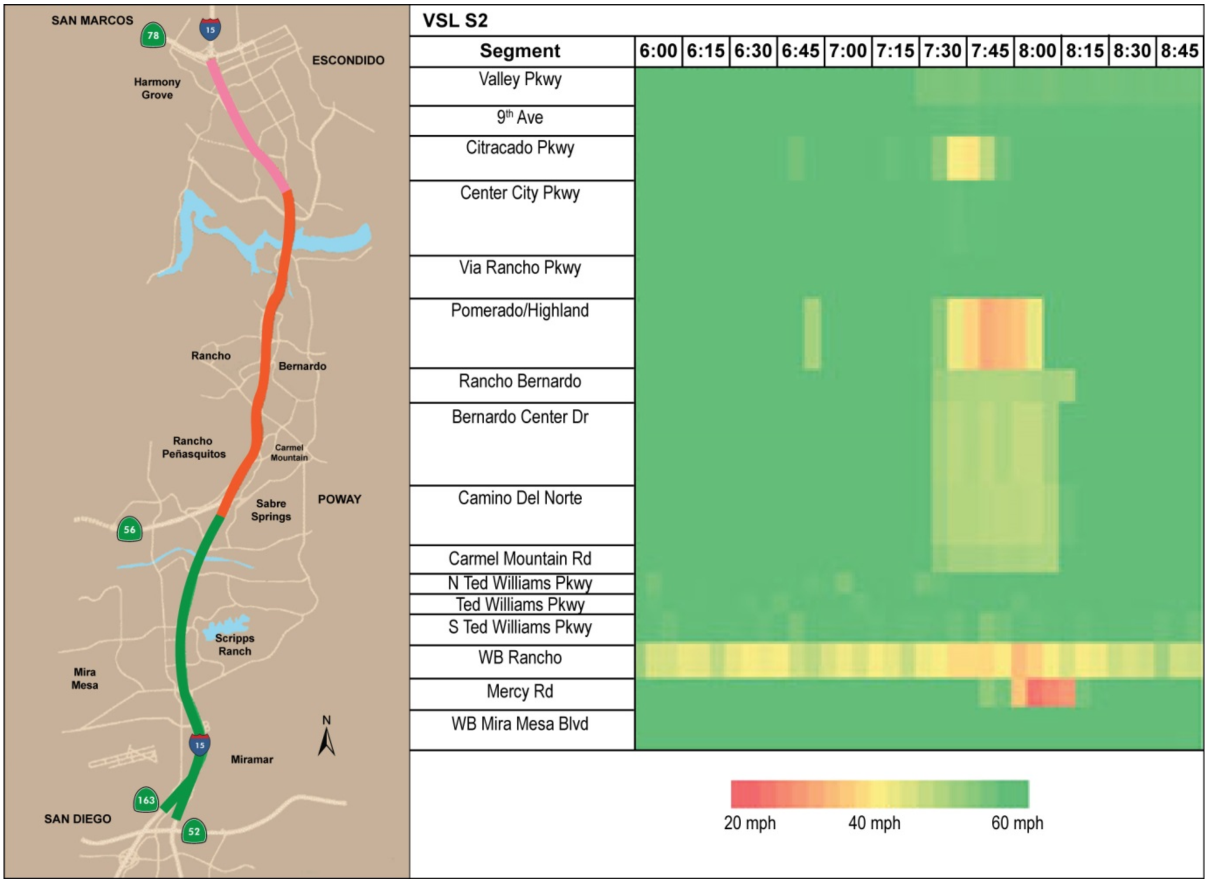

Figure 43. Map and graph. Speed profile under normal demand with nontraditional VSL. (Source: Cambridge Systematics, Inc.)

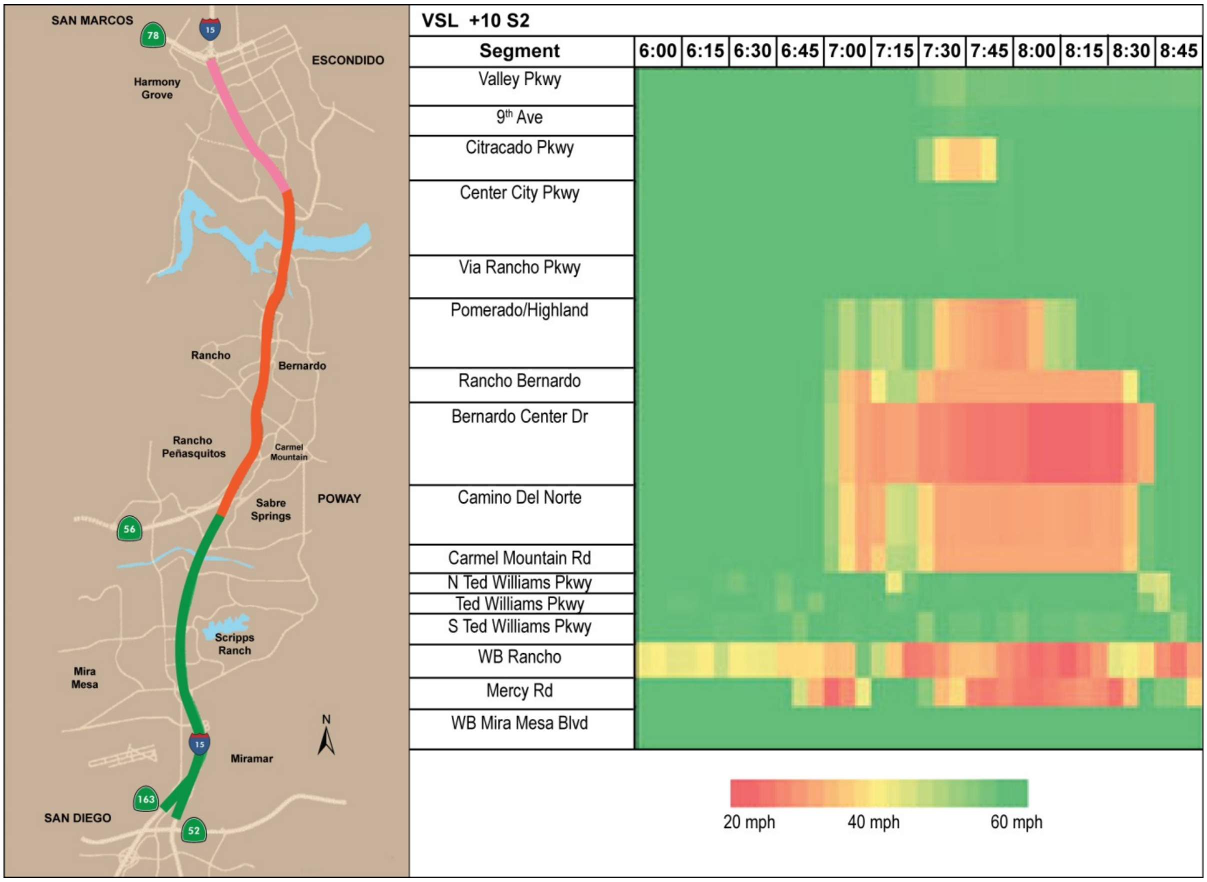

Figure 44. Map and graph. Speed profile under high demand with nontraditional VSL.
(Source: Cambridge Systematics, Inc.)

In both the normal and high-demand scenarios the nontraditional VSL strategy successfully reduced the size duration of congestion at the bottleneck location. But, as the delay results show (Table 33), the total freeway delay is greater than both the existing condition and traditional VSL strategy. This is likely due to the great extent over which the nontraditional VSL strategy was applied as well as the unforeseen bottleneck that appears at Bernardo Center Dr. when the strategy is applied in the high-demand scenario.

Table 33. Freeway delay (vehicle hours).

	Normal Demand	High Demand
No VSL	540	990
Traditional VSL	600	1120
Nontraditional VSL	690	2000

These results indicate that VSL, as applied in this corridor, has no appreciable effect on overall delay.

Modeling Challenges and Limitations

Vehicular emissions are a result of two interacting factors: amount of travel (VHT) and the driving profiles of the vehicles involved. Microsimulation models do an excellent job at capturing system performance measures because they model individual vehicle movements. They also can provide modal activity of vehicles, but they have not been calibrated to provide second-by-second vehicle trajectories but rather have been calibrated to system performance. This is a limitation of the models used in this analysis. Therefore, the degree that simulation models replicate vehicle trajectories is not known – this a limitation of the analysis.

VMT fluctuates from run-to-run, even when there is only a slight difference between runs (e.g., the two types of ramp metering in Scenarios A and B). As previously discussed, the TransModeler application used in this study assigns a trip table (demand between origins and destinations) using the stochastic user equilibrium approach, so some differences in VMT will result from the assignment process. This is to be expected, as it more realistically represents how travelers behave, but it makes isolation of the improvements' effects difficult. Transmodeler also has a feature that allows simulation of traveler information. In our tests, we observed erratic behavior in this algorithm for the incident scenarios, in terms of widely different network VMT. We are uncertain how realistically this algorithm behaves, and identify the incident scenarios with traveler information as an improvement as problematic.

CHAPTER 6. LONG-TERM REGIONAL IMPACTS OF OPERATIONS STRATEGIES

INTRODUCTION

The I-15 simulation analysis established the short-term emissions benefits of operations strategies. However, the main impetus for conducting the study was to determine if improvements due to operations strategies changed ***long-term traveler behavior***, and the degree to which behavioral changes impact the effectiveness of operations strategies. Specifically, is VMT over the long term increased due to less congested travel caused by operational improvements.

As discussed in Chapter 1, a decision to direct the project toward an advanced modeling framework to study long-term travel behavior changes was made. Initially it was thought that the SHRP 2 C10B, *Partnership to Develop an Integrated, Advanced Travel Demand Model and a Fine-grained, Time-Sensitive Network*, would be used. SHRP 2 C10B was underway at the same time as this project, but its original schedule showed that its scenario testing would coincide with this project. Unfortunately, SHRP 2 C10B experienced a long scheduling delay which put it out reach of this project. Also, because it was an experimental framework, it also experienced convergence problems during its operation.

For these reasons, an alternative modeling framework was chosen. The travel demand model framework developed by the Metropolitan Transportation Commission (MTC), the MPO for the San Francisco Bay Area for several reasons:

- It is an activity-based model, which reflects trip-making in a realistic way.
- The UrbanSim land use model, one of the most sophisticated models of its kind, provides land use “simulation” where one of the inputs is the performance of the transportation system.
- Team member Urban Analytics could easily adapt its original reliability research (Chapter 4) to the UrbanSim model, providing a way to incorporate reliability into long-term travel decisions.

The MTC model’s main shortcoming is that it uses traditional traffic assignment methods to estimate system performance. However, the primary output desired from the model is the change in demand. Also, postprocessors were developed to refine the speed estimates, calculate emissions, and produce reliability statistics (see below).

METHODOLOGY

The methodology for this approach is summarized in Figure 45. In this chapter, we provide the details on the method.

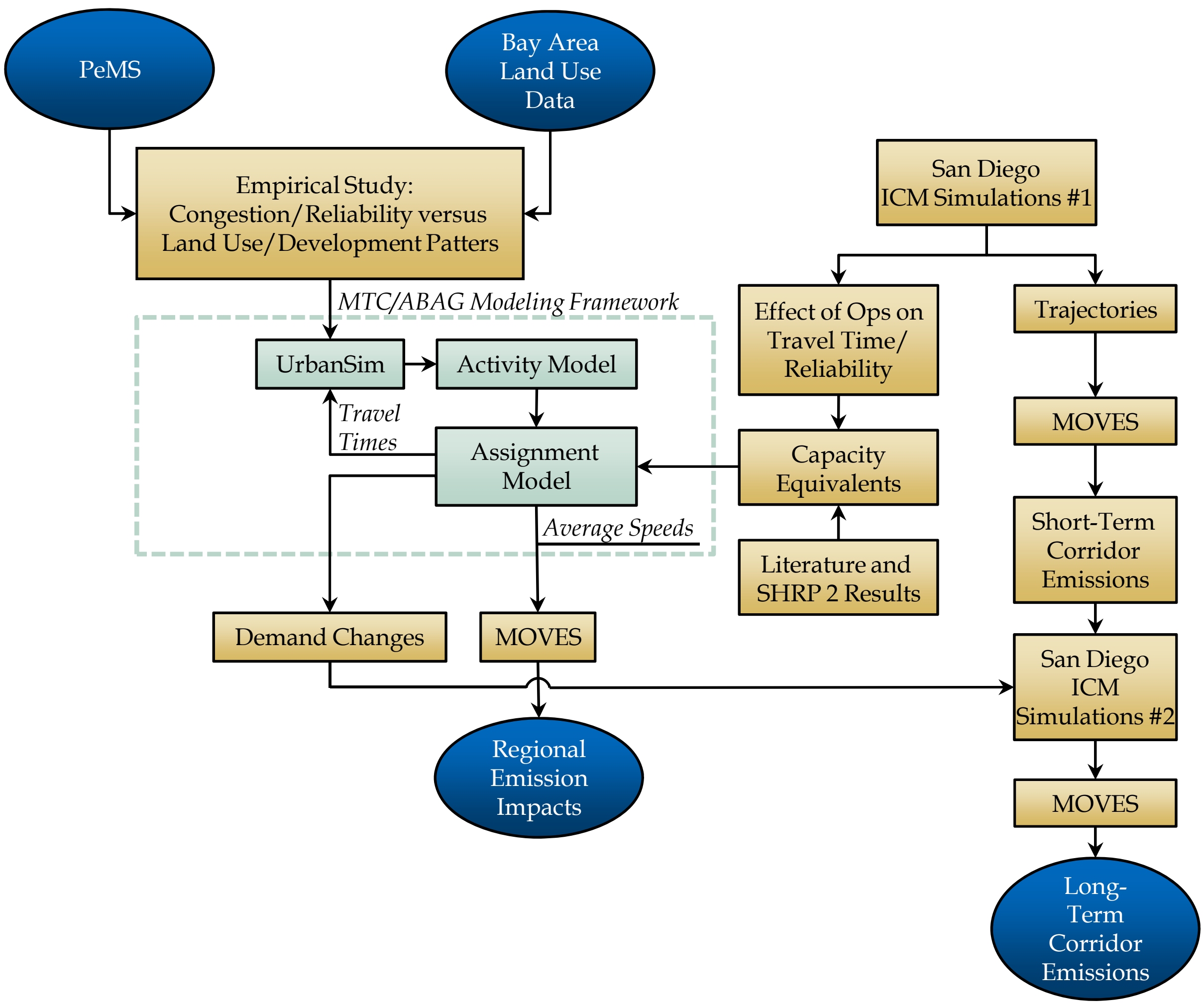

Figure 45. Flowchart. Final study approach, advanced modeling phase.
(Source: Cambridge Systematics, Inc.)

Operations Strategies Considered

The following five deployment scenarios were studied with the MTC model:

- Scenario 1: Active Signal Control (major arterials).
- Scenario 2: Ramp Meters (freeways).
- Scenario 3: Incident Management (freeways).
- Scenario 4: Active Traffic and Demand Management (ATDM; freeways).
- Scenario 5: ATDM + Signal Control.

The reliability research presented in Chapter 4 indicated that the East Bay area had many highways that would be considered to be unreliable. Therefore, the deployment of these strategies was confined to Alameda and Contra Costa counties but included all the applicable highways in those counties.

Analytical Basis for Studying Operations Strategies

Economic theory holds that, among many other factors, long-term changes in travel behavior – in terms of additional and/or longer trips – are a function of developers and travelers responding to system conditions. If conditions are improved, travel increases because developers and travelers change their behavior to take advantage of lower travel costs. Likewise, if conditions degrade, travel is suppressed, according to theory. Traditionally, the measure of network performance used to estimate shifts in travel behavior is average (or typical) travel time. Recently however, it has been noted that travel-time reliability – how travel time varies due to variability in the underlying causal factors of congestion – also is an important consideration that affects developers' and travelers' behavior. The research presented in Chapter 4 documents the changes on land use patterns caused by this effect.

Reliability is affected not only by the disruptions caused by events like incidents, inclement weather, and work zones but also by demand and its interaction with physical capacity. In fact, reliability is a function of the interaction of all these factors.[(57,58)] The implication of this is that any strategy that affects disruptions, demand, or capacity will have an effect on reliability, albeit to different degrees. Further, research has shown that the average travel time is correlated with common measures of reliability (e.g., 95th percentile travel time).

The mechanisms for affecting travel time within travel demand models – or macroscopic and mesoscopic simulations models for that matter – is to change link capacity or volume. For capital expansion projects (e.g., more through lanes, interchange reconstruction) capacity is directly affected. In travel demand models, the change in capacity results in a change in travel time that then affects traveler behavior. A large number of past studies have documented the decrease in travel times and delay due to implementing operations strategies. A few studies also have shown that operations strategies also improve reliability, in addition to reducing overall delay. Therefore, to model the reduction in travel times caused by operations strategies (at least the ones studied here), we have chosen to translate their effects through capacity increases. Our rationale for taking this approach is given below.

It would have been desirable to have both travel time and reliability in a model affecting travel behavior, and methods to estimate this change exist and were applied for the land use portion of the framework. However, the ABM portion is not currently capable of using this information. In Chapter 2 we reviewed some of the recent work on the valuation of reliability and its inclusion in models, primarily undertaken in the SHRP 2 program. The concept put forth is that reliability should be considered as an extra factor in the utility function used to derive travel demand – essentially this increases the total cost associated with a travel choice. Chapter 2 also proposed a simple way to accommodate this factor by constructing a *travel time equivalent*, the sum of the

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[57] Kittelson Associates et al., "SHRP 2 – L08: Incorporation of Travel-time reliability into the HCM. Final Report," Transportation Research Board, April 2013.

[58] Cambridge Systematics et al., SHRP 2 – L03: Analytic Procedures for Determining the Impacts of Reliability Mitigation Strategies, Transportation Research Board, 2013.

average/typical travel time and a reliability component that is scaled using a reliability ratio (value of reliability to travelers divided by the value of average time).

However, when we approached the two MPOs involved in this study (Sacramento Council of Governments, which was involved in SHRP 2 C10B, and MTC), they were highly reluctant to use travel time equivalents as part of the feedback loop because their models had been calibrated to average travel times only. Until travel demand models, especially activity-based ones, include reliability implicitly when they are initially developed, adding reliability to travel decisions at their source will have to wait. As discussed in the next subchapter, an approximation for this effect has been included and tested in several MPO models, including MTC's. This approximation basically shifts the volume-delay function used in traffic assignment to the left, which has the same effect as the travel time equivalent approach: it increases travel time, i.e., the cost associated with travel.

The mechanism we have chosen to study the effects of operations strategies is capacity. In some cases, operations strategies directly affect capacity (e.g., ramp metering, junction control, hard shoulder running). Incident management and work zone management also affect capacity directly, although the effect is in terms of reduction of the time that capacity was lost. Studies of active signal control systems most often define the effect in terms of increased speeds or reduced delay, although the mechanism by which this achieved is more efficiently signal timing, which has the practical effect of increasing throughput (capacity) at signals. So, it is not a stretch to use capacity as the means for modeling the effects of the operations strategies studied here.

Even though the travel behavior effects of reliability are handled only crudely, the current study did conduct original research on the effect of reliability on land use, and subsequently incorporated it into the MTC modeling framework.

Determining Capacity Equivalents for Operations Strategies

Because the MTC travel model uses a traditional traffic assignment process, the ability to model traffic flow is limited. The model is only sensitive to free-flow speed and volume-to-capacity (v/c) ratios, and since volume is derived by the model, capacity is the only practical way to replicate the effect of operations within the model.

Traffic assignment procedures use speed-flow functions (sometimes called volume-delay functions) to compute the impedance on links in the network. The higher the impedance, they less likely vehicles are to be assigned to a particular link. While v/c is the only independent variable in a speed-flow function (assuming that free-flow speed is fixed), a variety of functional forms have been used to fit speed-flow functions. Most of the earlier forms were built around modeling recurring (i.e., those related strictly to volumes and physical capacity) conditions. An example is the original Bureau of Public Roads (BPR) function and several variations on it, such as the one developed by Cambridge Systematics and JHK Associates in the early 1990s (Figure 46):

$$Speed = FreeFlowSpeed/(1 + (0.1225 * [v/c]^8))$$

Figure 46. Equation. Speed.
(Source: *Speed Adjustments Using Volume-Delay Functions*, TMIP Technical Synthesis, January 2009, http://tmiponline.org/Clearinghouse/Items/Technical_Synthesis_-_Speed_Adjustments_Using_Volume-Delay_Functions.aspx.)

These earlier forms eventually came under criticism for not replicating measured conditions in the field. This led, for example, to work by the Atlanta Regional Commission (ARC) to develop a conical form of the function that matched data from ITS detectors fairly well. It should be pointed out that the field data included the effect of nonrecurring congestion sources, because it was continuously collected, so the net effect is to have a way to estimate ***overall average speeds*** from just the v/c ratio. MTC currently uses a variant of the BPR function for freeways that is almost identical in its prediction to the ARC conical model:

$$Speed = FreeFlowSpeed/(1 + (0.2 * [4v/3c]^6))$$

Figure 47. Equation. Speed.
(Source: MTC Technical Memo, March 6, 2012, http://mtcgis.mtc.ca.gov/foswiki/pub/Main/Documents/2012_03_06_RELEASE_Volume_delay_functions.pdf.)

The MTC reformulation also is based on matching predicted speeds to ITS detector data. Both the ARC and MTC functions predict much lower speeds than traditional functions at the same v/c value. This has the effect of at least loosely accounting for the effect of nonrecurring congestion in the assignment process. It also leads to gradually increasing impedance for v/cs less than 1.0 which may help with convergence.

A more direct account of nonrecurring factors was recently completed by the Puget Sound Regional Council (PSRC).[(59)] They developed an "certainty-equivalent delay penalty" that is added to their usual volume delay function; this has the effect if shifting the function slightly to the left.

The ARC, MTC, and PSRC activities all account for nonrecurring sources in general, but do not provide a way to estimate the impacts that operations strategies have. For that, the effects of operations must be translated in terms of capacity. In fact, MTC currently does this for ramp metering on freeways and signal coordination on arterials:

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[59] Puget Sound Regional Council, *Benefit-Cost Analysis: General Methods and Approach*, July 2009, Updated March 2010.

- Ramp metering capacity:

    - 2,150 pcphpl[60] (compared to 2,050 for CBD).
    - 2,200 pcphpl (compared to 2,100 for urban and 2,150 for suburban).

- Signal Coordination:

    - 1,050 pcphpl (compared to 1,000).

Translating operations effects into capacity equivalents can sometimes be direct (e.g., ramp metering) if field studies have been done. In other cases, it is necessary to derive the capacity equivalent analytically. Studies usually report delay, and sometimes reliability, savings due to operational improvements. The challenge then becomes "what equivalent physical capacity increase would have produced the delay savings"? A simple approach to doing this uses a BPR variant that is focused on recurring delay; in this case we have chosen the CS/JHK function because it mimics the steepness of many functions currently in use when v/c > 1.0. For this analysis, we assume that the delay savings accrue in congested conditions at v/c = 1.1. We first estimate the delay at v/c = 1.1, reduce the delay by percentage reduction from a previous study, find the new v/c level that corresponds to that delay, and calculate the capacity increase that would produce the new v/c value.

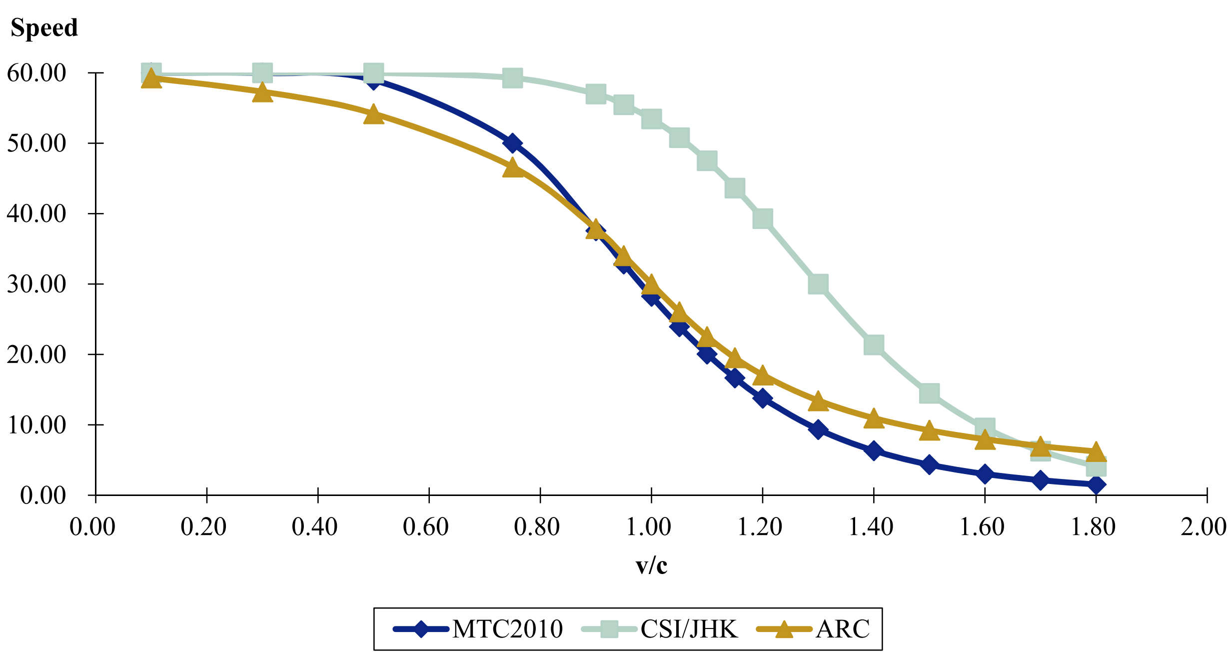

Figure 48. Graph. Comparison of selected speed-flow curves.
(Source: Cambridge Systematics, Inc.)

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[60] Passenger cars per hour per lane.

For incidents, the situation is more complex because the delay savings do not accrue to the recurring portion of delay. For this we need to estimate both recurring and incident delay. The ITS Deployment Analysis System (IDAS) has a series of tables that estimate incident delay as a function of v/c and number of lanes.(61) These were developed with a stochastic procedure using data from incident management systems on incident duration and lane blockages. Equations were fit to these data for this project:

$$D_u = -0.0111207/(1 - 1471.33*e^{-6.84985X})$$

Figure 49. Equation. Two-lane freeways.
(Source: Cambridge Systematics, *IDAS Users Manual*, 2009, http://idas.camsys.com/documentation.htm.)

$$D_u = -0.0085068/(1 - 1871.9*e^{-7.13809X})$$

Figure 50. Equation. Three-lane freeways.
(Source: Cambridge Systematics, *IDAS Users Manual*, 2009, http://idas.camsys.com/documentation.htm.)

$$D_u = -0.0067667/(1 - 1827.18*e^{-7.10896X})$$

Figure 51. Equation. Four-lane freeways.
(Source: Cambridge Systematics, *IDAS Users Manual*, 2009, http://idas.camsys.com/documentation.htm.)

Where:

D_u = incident delay rate, hours per mile
X = v/c; max = 1.0

Using both the BPR (the CS/JHK equation) and IDAS curves provides an estimate of total delay. At v/c = 1.1, the total delay rate is 0.0409 hours per mile (0.0199 for incident delay plus 0.0210 for recurring delay). The corresponding value that the BPR curve would predict this delay rate for is v/c = 1.365. The effect of incident management strategies is most often to reduce incident duration. This can be accounted for by taking advantage of the fact that incident delay is a function of the square of incident duration:(62)

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[61] http://idas.camsys.com/userManual/App_b.pdf.

[62] H. Cohen and F. Southworth (1999) On the measurement and valuation of travel time variability due to incidents on freeways. *Journal of Transportation and Statistics 2.2*: 123-132. Also, the University of Maryland, as part of the ongoing CHART evaluations, developed a predictive equation model based on running experiments with microscopic simulation where the exponent on incident duration is 1.78.

$$AdjustedIncidentDelay = D_u * (1 - R_d)^2$$

Figure 52. Equation. Adjusted incident delay.
(Source: Cambridge Systematics, *IDAS Users Manual*, 2009,
http://idas.camsys.com/documentation.htm.)

Where:

R_d = Percent reduction in incident duration

With this knowledge, a new incident delay and total delay is computed, the v/c value predicted by the BPR function is found, and percent increase in capacity that would produce this value is calculated. Continuing the example, assuming a 25 percent decrease in incident duration is effected by incident management and two lanes in one direction:

$$\begin{aligned} AdjustedIncidentDelay &= 0.0199 * (1 - 0.25)^2 \\ &= 0.0112 \\ AdjustedTotalDelay &= 0.0112 + 0.0210 \\ &= 0.0322 \end{aligned}$$

Figure 53. Equation. Adjusted incident delay; adjusted total delay.
(Source: Cambridge Systematics, Inc.)

The v/c value that would produce a delay rate of 0.0322 using the BPR function is 1.280. Therefore, there is a 7 percent capacity increase due to an incident management program that reduces incident duration by 25 percent.

A summary of the capacity equivalents for the operations strategies to be studied is shown in Table 34.

Table 34. Capacity equivalents for operations strategies.

Operations Strategy	Capacity Equivalent and Justification
Ramp metering	**Three percent**; Zhang, L. and D. Levinson. Ramp Metering and Freeway Bottleneck Capacity. *Transportation Research: A Policy and Practice* 44(4), May 2010, pp. 218-235.
Incident Management	Two unidirectional lanes: **7 percent** Three plus unidirectional lanes: **6 percent**; based on empirical delay analysis and 25 percent reduction in incident duration
Active signal control	**Seven percent**; based on empirical delay analysis assuming that active signal control reduced delay by 25 percent (MTC value is 5 percent capacity increase)
ATDM	**Twenty percent**; meant cover multiple improvement types, including ramp metering, lane control, queue warning, junction control, and traveler information[a]

[a]http://ops.fhwa.dot.gov/publications/fhwahop10031/sec3.htm.

Modeling Steps

The modeling sequence starts with the 2010 base conditions for land use and network state from the most recent application of the model by MTC (Figure 54). It was determined that only one iteration of the entire framework (2015) should be attempted because it was uncertain how the reliability-modified version of UrbanSim would behave. Therefore, to replicate the effect of increased congestion in future years, it was decided to adjust the volume-delay functions for freeways and major arterials to induce extra congestion; this was done my adding a factor that increased the v/c ratio by 30 percent.

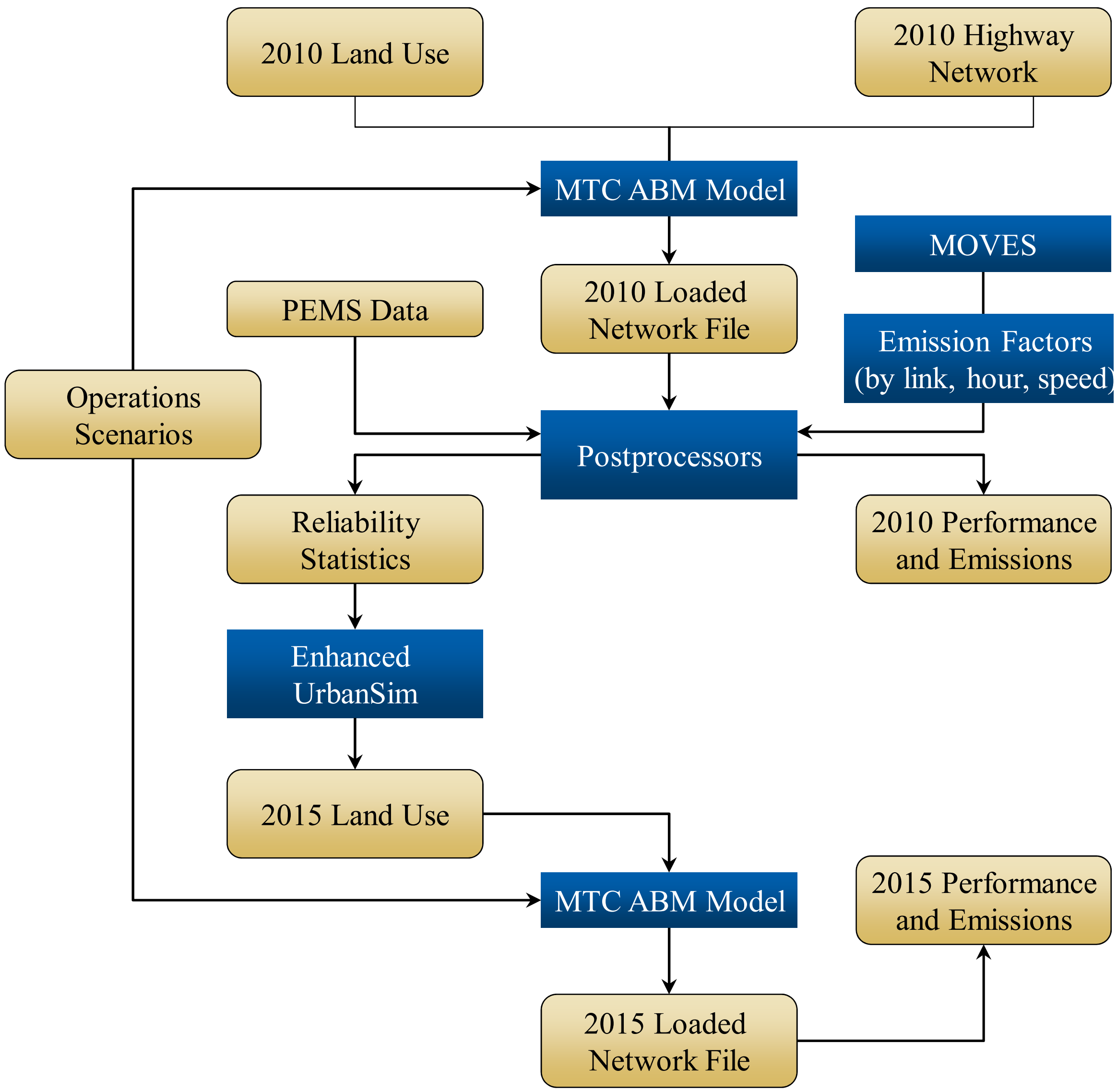

Figure 54. Flowchart. Regional emission modeling using the MTC model.
(Source: Cambridge Systematics, Inc.)

The output of the model produced a loaded network file that was postprocessed. First, because the MTC model works on periods of the day, the assigned volume was broken out to individual hours using factors developed by MTC. Then, hourly speeds were estimated with MTC's volume-delay functions. The MOVES model was run to develop hourly emission rates by speed range for the AM peak period (the period chosen for study), and emissions were calculated by link.

A separate postprocessor was used to develop reliability statistics for feedback into the UrbanSim model. For this, we used the finding that reliability statistics can be related to the mean travel time. Using PeMS data, functions to predict the median and 80th percentile travel times from the mean travel were developed individually for I-580 and I-880 in Alameda and Contra Costs counties. Other freeways used the I-880 function and signalized arterials used the relationship developed by SHRP 2 Project L03. The median and 80th percentile travel times are used in the enhanced version of UrbanSim as the measure of the reliability "space."

The modeling using the enhanced UrbanSim/MTC model provides an estimate of the regional impact of operations strategies on emissions and performance. However, because performance is based on volume-delay functions rather than more sophisticated traffic modeling, performance and emissions estimates are crude. Because travel demand models are geared to estimating demand rather than performance, we use the changes in VMT that result from deploying operations strategies to modify the demand used in the I-15 simulation tests.

REGIONAL MODELING RESULTS

Base Year (2010) Results, AM Peak Period

Table 35 shows the results of the 2010 model runs for the base case and each scenario for the AM peak period (6:00 to 10:00 a.m.). Regionally, under most scenarios, emissions generally decrease by a fractional amount (less than one percent). CO_2 emissions decrease fractionally for all scenarios except for ramp meters. VMT increases proportionately to the "aggressiveness" of the operations strategy. Likewise, VHT decreases proportionately to the aggressiveness strategy. The net effect is that although the deployment of operations leads to increased VMT, the increase is small enough – and the benefit of operations is large enough – that emissions drop marginally in the short run.

The VMT increase is likely due to changes in demand patterns predicted by the activity-based portion of the model. The MTC model is set up to perform four iterations for each model run. At the end of each iteration, the traffic assignment results are fed back to the ABM and travel behavior is updated. The improved travel conditions created by the operations strategies are leading to changes in demand patterns. The largest increases occur within the treatment area (Alameda and Contra Costa counties) but VMT also increases in adjacent counties.

What are the sources of the VMT increase? As shown back in Table 4, several possible sources exist. In addition to rerouting during the traffic assignment phase – which is actually likely to be close to zero – VMT in the ABM also can be affected by:

- Time of Day/Schedule (peak spreading).
- Destination/Stop Location (improved accessibility effect combined with negative pricing effect on trip distribution for nonwork trips.
- Joint Travel Arrangements (planned carpool/escorting).
- Tour Frequency, Sequence, and Formation of Trip Chains (lower tour frequency and higher chaining propensity).
- Daily Pattern Type (more compressed workdays and work from home).
- Usual Locations and Schedule for Nonmandatory Activities (compressed/chain patterns).

Table 35. AM peak period performance results, 2010 MTC Model runs.

VHT	VMT	HC (grams)	CO (grams)	NOx (grams)	CO2 (grams)	County	Highway Type
Base							
343,568	11,582,560	1,262,663	27,083,364	11,169,580	6,210,504,349	Remainder of Area	Freeway
152,840	2,166,450	392,671	6,271,028	2,855,753	1,606,732,330	Remainder of Area	Expressway
63,818	1,589,041	185,509	3,645,045	1,146,570	809,213,677	Remainder of Area	Collector
187,652	5,210,839	551,201	11,294,481	3,423,125	2,481,248,722	Remainder of Area	Arterial
305,635	8,348,239	1,015,974	20,080,531	8,045,557	4,687,953,422	Alameda/Contra Costa	Freeway
73,648	329,299	84,589	1,105,842	618,699	309,503,463	Alameda/Contra Costa	Expressway
53,062	1,058,754	141,071	2,595,094	820,211	587,490,181	Alameda/Contra Costa	Collector
130,908	3,350,238	367,297	7,420,142	2,183,500	1,638,131,995	Alameda/Contra Costa	Arterial
1,311,129	**33,635,421**	**4,000,976**	**79,495,527**	**30,262,996**	**18,330,778,140**		
S1: Active Signal Control							
343,304	11,576,688	1,261,320	27,070,528	11,161,438	6,204,976,096	Remainder of Area	Freeway
152,513	2,168,006	393,927	6,284,369	2,861,256	1,611,175,680	Remainder of Area	Expressway
63,757	1,587,687	185,412	3,642,553	1,145,518	808,732,230	Remainder of Area	Collector
187,782	5,213,571	552,483	11,308,731	3,428,449	2,485,652,547	Remainder of Area	Arterial
305,111	8,345,165	1,016,681	20,088,493	8,049,673	4,690,034,745	Alameda/Contra Costa	Freeway
72,670	332,532	85,370	1,116,542	623,106	312,544,663	Alameda/Contra Costa	Expressway
52,877	1,053,423	140,256	2,580,578	816,039	584,211,094	Alameda/Contra Costa	Collector
124,947	3,370,896	357,639	7,319,342	2,164,664	1,609,086,110	Alameda/Contra Costa	Arterial
1,302,960	**33,647,967**	**3,993,088**	**79,411,136**	**30,250,142**	**18,306,413,165**		
-0.623%	**0.037%**	**-0.197%**	**-0.106%**	**-0.042%**	**-0.133%**	**Compared to Base**	
S2: Ramp Meters							
346,028	11,588,102	1,267,989	27,138,783	11,191,204	6,225,734,233	Remainder of Area	Freeway
153,101	2,167,932	394,120	6,287,219	2,861,918	1,611,906,308	Remainder of Area	Expressway
63,827	1,588,017	185,416	3,643,397	1,145,680	808,765,334	Remainder of Area	Collector
188,345	5,220,900	553,344	11,327,560	3,433,396	2,489,216,990	Remainder of Area	Arterial
297,062	8,460,037	1,002,540	20,169,985	8,059,392	4,676,599,450	Alameda/Contra Costa	Freeway
72,998	328,837	84,117	1,099,443	616,529	307,991,828	Alameda/Contra Costa	Expressway
52,743	1,052,670	140,396	2,581,347	815,703	584,517,697	Alameda/Contra Costa	Collector
130,342	3,339,830	365,492	7,387,607	2,174,084	1,631,048,141	Alameda/Contra Costa	Arterial
1,304,446	**33,746,325**	**3,993,413**	**79,635,341**	**30,297,906**	**18,335,779,980**		
-0.510%	**0.330%**	**-0.189%**	**0.176%**	**0.115%**	**0.027%**	**Compared to Base**	

Table 35. AM Peak Period performance results, 2010 MTC Model runs (continued).

VHT	VMT	HC (grams)	CO (grams)	NO_x (grams)	CO_2 (grams)	County	Highway Type
S3: Incident Management							
348,499	11,593,971	1,267,048	27,139,371	11,188,287	6,225,503,367	Remainder of Area	Freeway
151,787	2,167,842	393,847	6,285,265	2,859,813	1,611,041,911	Remainder of Area	Expressway
63,698	1,587,486	185,388	3,642,163	1,145,529	808,634,827	Remainder of Area	Collector
188,183	5,221,420	552,147	11,316,489	3,429,792	2,485,388,776	Remainder of Area	Arterial
283,147	8,699,197	983,904	20,462,131	8,132,149	4,690,061,565	Alameda/Contra Costa	Freeway
65,373	326,527	82,844	1,087,757	608,524	304,213,797	Alameda/Contra Costa	Expressway
51,450	1,023,921	136,540	2,509,287	792,482	568,280,085	Alameda/Contra Costa	Collector
124,894	3,261,390	352,626	7,161,690	2,111,122	1,579,060,291	Alameda/Contra Costa	Arterial
1,277,032	**33,881,754**	**3,954,345**	**79,604,153**	**30,267,697**	**18,272,184,619**		
-2.601%	**0.732%**	**-1.165%**	**0.137%**	**0.016%**	**-0.320%**	**Compared to Base**	
S4: ATDM							
352,870	11,609,056	1,272,211	27,205,182	11,211,086	6,242,479,060	Remainder of Area	Freeway
153,064	2,171,283	395,736	6,307,951	2,867,549	1,617,681,290	Remainder of Area	Expressway
63,867	1,589,828	185,694	3,647,890	1,147,416	809,939,561	Remainder of Area	Collector
188,799	5,228,478	554,219	11,345,428	3,438,179	2,493,008,923	Remainder of Area	Arterial
273,187	8,951,921	977,672	20,909,871	8,248,298	4,737,912,890	Alameda/Contra Costa	Freeway
58,518	322,420	75,954	1,033,198	566,116	283,574,694	Alameda/Contra Costa	Expressway
50,456	1,001,101	133,653	2,454,651	774,466	555,894,433	Alameda/Contra Costa	Collector
121,446	3,199,702	344,583	7,006,472	2,068,064	1,545,170,047	Alameda/Contra Costa	Arterial
1,262,207	**34,073,788**	**3,939,722**	**79,910,643**	**30,321,173**	**18,285,660,898**		
-3.731%	**1.303%**	**-1.531%**	**0.522%**	**0.192%**	**-0.246%**	**Compared to Base**	
S5: ATDM + Signal Control							
352,669	11,610,621	1,274,067	27,220,404	11,218,758	6,247,910,589	Remainder of Area	Freeway
152,536	2,169,793	394,662	6,295,738	2,863,252	1,613,924,954	Remainder of Area	Expressway
63,795	1,589,268	185,601	3,646,582	1,146,597	809,546,694	Remainder of Area	Collector
188,374	5,226,018	553,884	11,339,755	3,436,200	2,491,593,743	Remainder of Area	Arterial
270,505	8,927,788	968,088	20,810,332	8,197,204	4,708,591,041	Alameda/Contra Costa	Freeway
57,024	323,500	76,256	1,038,153	567,250	284,740,324	Alameda/Contra Costa	Expressway
49,828	993,879	132,750	2,437,782	769,081	552,052,770	Alameda/Contra Costa	Collector
115,612	3,208,040	334,226	6,886,853	2,043,228	1,512,451,075	Alameda/Contra Costa	Arterial
1,250,344	**34,048,907**	**3,919,535**	**79,675,599**	**30,241,569**	**18,220,811,190**		
-4.636%	**1.229%**	**-2.036%**	**0.227%**	**-0.071%**	**-0.600%**	**Compared to Base**	

It is difficult to know the contribution of each of these factors to the VMT change. However, by looking at the daily statistics from the model output, it is possible that some trips are diverting into the AM peak period from the early AM period (Table 36). However, the increases in both the midday and PM peak periods indicate that there may be more and longer trips generated. A more detailed analysis of trip lengths is given for the 2015 results.

Table 36. MTC model VMT by time period and strategy.

	Regional VMT		
	Scenario		
Time Period	**Base Line (No Operations)**	**ATDM**	**Percent Change**
12:00 a.m. to 6:00 a.m.	6,607,953	6,522,810	-1.29%
6:00 a.m. to 10:00 a.m.	36,592,898	37,015,375	1.15%
10:00 a.m. to 3:00 p.m.	38,265,835	38,450,855	0.48%
3:00 p.m. to 7:00 p.m.	40,838,810	41,317,940	1.17%
7:00 p.m. to 12:00 a.m.	23,396,374	23,374,069	-0.10%

Note: VMT calculated in this table from origins and destinations, not links on the loaded network. To classify VMT by county, or origin, VMT for each OD pair is calculated as the (Total Trips between that OD) x (Shortest Distance between that OD on the final loaded network).

Forecast Year (2015) Results, AM Peak Period

The 2015 model run includes the reliability effect on land use patterns caused by the performance of the 2010 runs, as accounted for by the modified version of UrbanSim. (UrbanSim internally simulates land use year-by-year.) The network in these runs is more congested than the 2010 runs, which was congested also, due to the 30 percent increase placed on the v/c ratio (Table 37).

Table 37. Congested VMT proportions, 2015 Bay Area network.

	Percent of VMT at v/c >= 0.95			
Highway Type	**6:00-7:00 a.m.**	**7:00-8:00 a.m.**	**8:00-9:00 a.m.**	**9:00-10:00 a.m.**
Freeway	1%	90%	87%	20%
Arterial	13%	58%	54%	22%

Figure 55 shows the reallocation of households for the most aggressive operations scenario (Scenario 5: ATDM and Signal Control) compared to the base. The area in and around the treatment areas received more growth at the expense of locations north of the Bay and on the extreme western edge of the area. Employment follows a similar pattern (Figure 56).

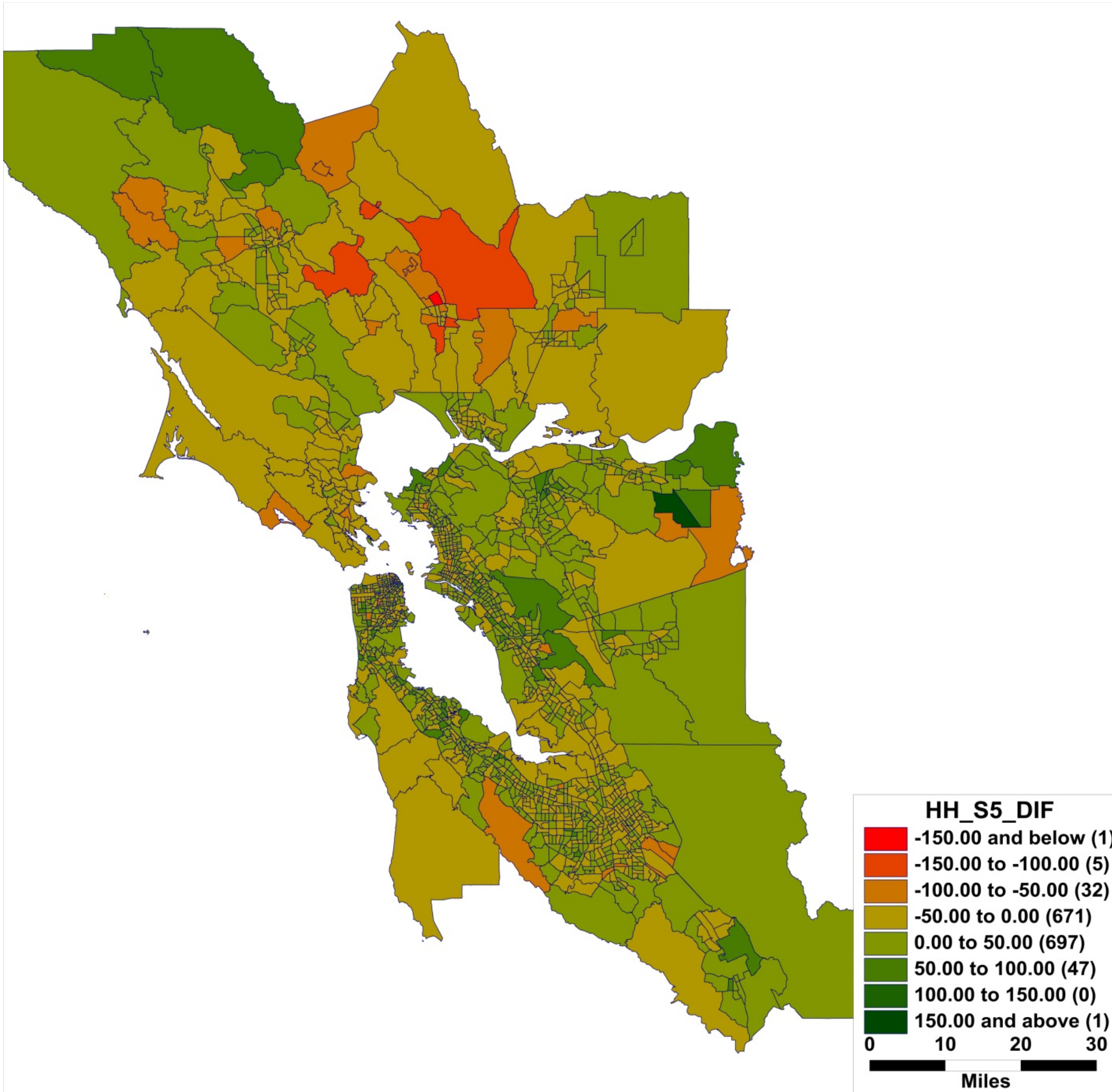

Figure 55. Map. Households.
(Source: Cambridge Systematics, Inc.)

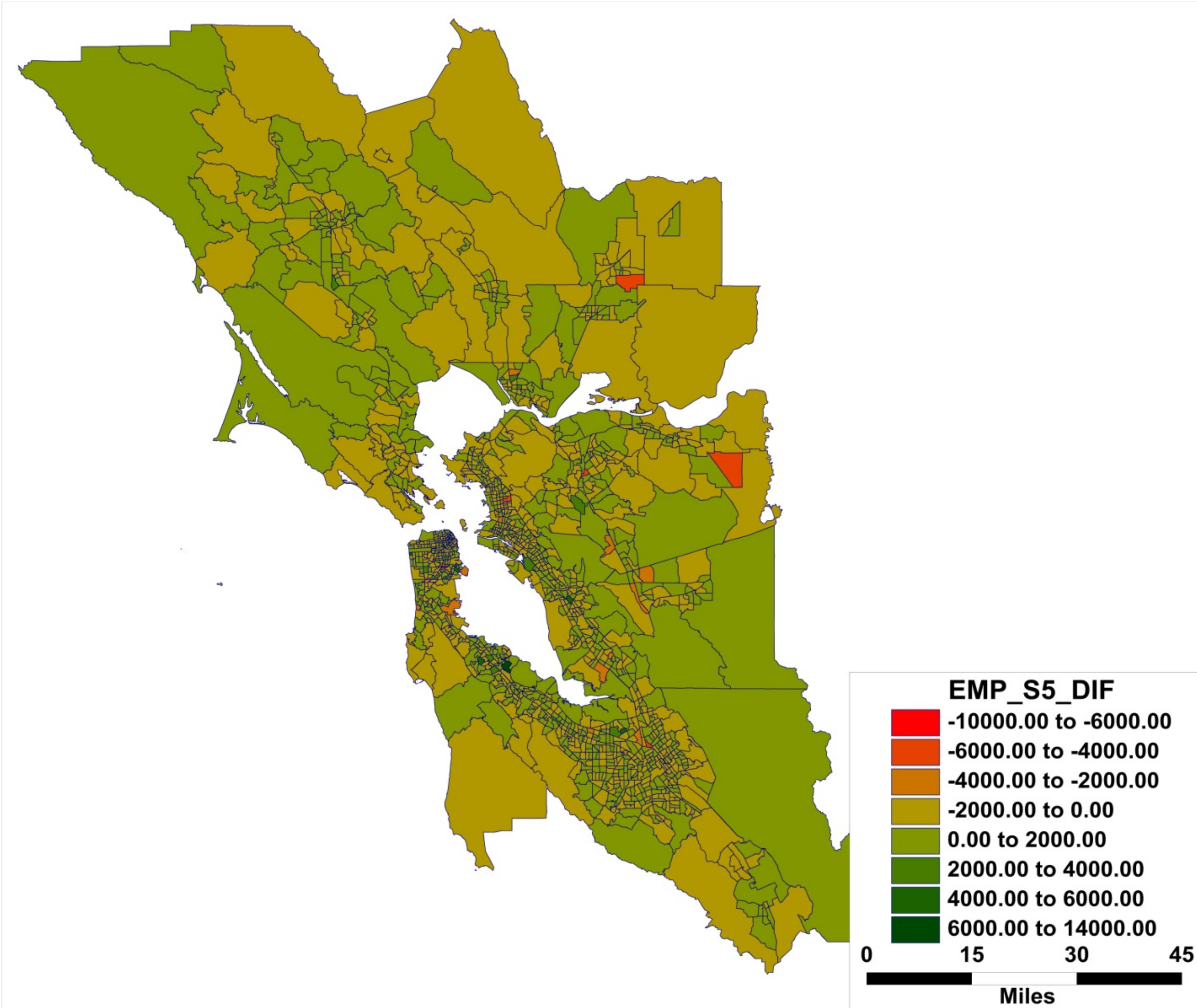

Figure 56. Map. Employment.
(Source: Cambridge Systematics, Inc.)

The performance and emissions results are shown in Table 38. Regionally, base condition VMT increased 7.2 percent and VHT increased by 11.0 percent from 2010. As with the 2010 runs, VMT increases for each strategy over the base condition. The less aggressive operations strategies – signal control, ramp meters, and incident management – lead to a slight increases in emissions; the highest increase in CO_2 is for ramp meters, which shows a one percent increase. For the aggressive ATDM strategies, the stronger effect on congestion (speeds) is enough to overcome the effect of increased VMT, resulting in reduced CO_2 and hydrocarbon emissions.

An analysis of predicted trips in the model was undertaken to determine possible sources of the VMT increase. Table 39 shows the results comparing the base to Scenario 5 (ATDM + active signal control). The number of trips increased marginally (less than 0.2 percent) with the aggressive operations deployment. Average trip length increased by slightly more than 0.5 percent. The improved travel times are allowing travelers to make longer trips, thus increasing VMT for the operations deployment scenario.

Table 38. AM Peak Period performance results, 2015 MTC Model runs.

VHT	VMT	HC (grams)	CO (grams)	NOx (grams)	CO2 (grams)	County	Highway Type
Base							
393,442	12,220,861	1,391,605	28,980,315	12,031,835	6,725,341,432	Remainder of Area	Freeway
203,091	2,232,154	452,916	6,941,974	3,058,643	1,803,303,437	Remainder of Area	Expressway
70,516	1,699,923	202,232	3,945,188	1,237,705	877,737,718	Remainder of Area	Collector
212,841	5,803,389	616,269	12,567,232	3,825,586	2,788,290,112	Remainder of Area	Arterial
344,807	9,017,018	1,146,229	21,833,457	8,916,526	5,168,631,628	Alameda/Contra Costa	Freeway
53,693	447,662	105,937	1,400,605	850,541	401,278,728	Alameda/Contra Costa	Expressway
43,328	1,000,917	122,043	2,361,566	723,370	523,529,941	Alameda/Contra Costa	Collector
133,975	3,644,769	379,789	7,806,632	2,321,493	1,736,559,231	Alameda/Contra Costa	Arterial
1,455,694	**36,066,694**	**4,417,021**	**85,836,970**	**32,965,699**	**20,024,672,227**		
							S1: Active Signal Control
401,189	12,235,788	1,407,291	29,108,165	12,111,596	6,771,984,953	Remainder of Area	Freeway
210,244	2,233,149	458,109	6,987,465	3,083,708	1,821,727,703	Remainder of Area	Expressway
70,211	1,692,140	200,330	3,914,745	1,229,353	870,927,062	Remainder of Area	Collector
217,332	5,839,349	623,574	12,681,287	3,860,783	2,816,641,776	Remainder of Area	Arterial
352,711	9,040,657	1,155,142	21,915,153	8,968,814	5,198,016,564	Alameda/Contra Costa	Freeway
64,623	450,265	121,429	1,515,780	947,536	444,682,425	Alameda/Contra Costa	Expressway
45,054	1,020,770	126,875	2,429,240	746,644	540,825,139	Alameda/Contra Costa	Collector
129,173	3,674,163	372,257	7,733,173	2,313,768	1,715,854,911	Alameda/Contra Costa	Arterial
1,490,537	**36,186,280**	**4,465,007**	**86,285,007**	**33,262,202**	**20,180,660,532**		
2.394%	**0.332%**	**1.086%**	**0.522%**	**0.899%**	**0.779%**	**Compared to Base**	
							S2: Ramp Meters
412,555	12,257,958	1,430,489	29,340,667	12,213,152	6,838,410,969	Remainder of Area	Freeway
217,915	2,241,396	472,475	7,108,349	3,169,096	1,864,040,915	Remainder of Area	Expressway
69,972	1,707,420	201,162	3,938,447	1,239,070	875,662,292	Remainder of Area	Collector
218,600	5,852,889	625,950	12,721,092	3,873,175	2,824,919,458	Remainder of Area	Arterial
334,638	9,100,367	1,114,007	21,776,535	8,813,243	5,108,859,854	Alameda/Contra Costa	Freeway
54,719	448,766	118,162	1,494,533	927,374	434,993,500	Alameda/Contra Costa	Expressway
45,209	1,022,070	127,399	2,436,657	748,002	543,320,260	Alameda/Contra Costa	Collector
133,636	3,659,023	380,477	7,829,279	2,327,038	1,740,989,328	Alameda/Contra Costa	Arterial
1,487,244	**36,289,890**	**4,470,120**	**86,645,558**	**33,310,149**	**20,231,196,576**		
2.167%	**0.619%**	**1.202%**	**0.942%**	**1.045%**	**1.031%**	**Compared to Base**	

Table 38. AM Peak Period performance results, 2015 MTC Model runs (continued).

VHT	VMT	HC (grams)	CO (grams)	NO_x (grams)	CO_2 (grams)	County	Highway Type
S3: Incident Management							
420,623	12,284,568	1,452,433	29,553,596	12,309,064	6,906,416,238	Remainder of Area	Freeway
220,438	2,234,450	472,066	7,099,075	3,163,275	1,860,908,081	Remainder of Area	Expressway
71,097	1,718,773	203,593	3,978,073	1,249,326	885,263,311	Remainder of Area	Collector
220,621	5,871,394	630,957	12,801,334	3,890,856	2,843,785,980	Remainder of Area	Arterial
311,644	9,335,684	1,075,367	21,911,966	8,802,176	5,073,471,508	Alameda/Contra Costa	Freeway
41,124	433,648	99,753	1,344,461	806,987	380,812,945	Alameda/Contra Costa	Expressway
40,595	962,200	114,665	2,244,048	684,110	495,535,864	Alameda/Contra Costa	Collector
124,718	3,520,726	358,209	7,441,855	2,215,235	1,651,602,071	Alameda/Contra Costa	Arterial
1,450,860	36,361,443	4,407,042	86,374,408	33,121,030	20,097,795,998		
-0.332%	**0.817%**	**-0.226%**	**0.626%**	**0.471%**	**0.365%**	**Compared to Base**	
							S4: ATDM
409,444	12,266,027	1,425,388	29,343,076	12,180,066	6,831,481,924	Remainder of Area	Freeway
217,300	2,236,041	471,569	7,101,660	3,161,113	1,861,368,136	Remainder of Area	Expressway
69,847	1,693,870	200,032	3,915,810	1,227,647	870,221,590	Remainder of Area	Collector
217,401	5,847,082	625,607	12,720,431	3,863,574	2,823,521,406	Remainder of Area	Arterial
295,085	9,605,683	1,054,067	22,270,882	8,907,319	5,089,339,035	Alameda/Contra Costa	Freeway
43,240	430,154	99,172	1,336,598	803,978	378,176,406	Alameda/Contra Costa	Expressway
39,468	949,106	112,658	2,208,121	672,798	487,438,437	Alameda/Contra Costa	Collector
120,181	3,435,328	345,476	7,215,036	2,148,394	1,599,164,007	Alameda/Contra Costa	Arterial
1,411,967	**36,463,293**	**4,333,969**	**86,111,614**	**32,964,889**	**19,940,710,940**		
-3.004%	**1.100%**	**-1.880%**	**0.320%**	**-0.002%**	**-0.419%**	**Compared to Base**	

Table 38. AM Peak Period performance results, 2015 MTC Model runs (continued).

VHT	VMT	HC (grams)	CO (grams)	NO_x (grams)	CO_2 (grams)	County	Highway Type
S5: ATDM + Signal Control							
410,868	12,276,848	1,426,967	29,352,749	12,193,872	6,837,747,991	Remainder of Area	Freeway
219,959	2,247,907	474,433	7,139,118	3,176,150	1,871,409,334	Remainder of Area	Expressway
70,181	1,699,644	201,245	3,934,436	1,233,409	874,906,948	Remainder of Area	Collector
218,231	5,868,687	628,089	12,768,659	3,879,236	2,834,607,628	Remainder of Area	Arterial
298,693	9,626,802	1,058,957	22,306,865	8,934,607	5,110,098,537	Alameda/Contra Costa	Freeway
47,552	434,007	113,545	1,441,772	895,480	419,204,124	Alameda/Contra Costa	Expressway
39,577	939,996	111,495	2,185,333	666,320	482,448,682	Alameda/Contra Costa	Collector
115,999	3,451,111	338,955	7,149,167	2,137,742	1,579,924,272	Alameda/Contra Costa	Arterial
1,421,061	**36,545,003**	**4,353,686**	**86,278,098**	**33,116,816**	**20,010,347,516**		
-2.379%	**1.326%**	**-1.434%**	**0.514%**	**0.458%**	**-0.072%**	**Compared to Base**	
S6: Regional ATDM + Signal Control							
354,439	12,902,696	1,339,086	29,873,455	12,215,778	6,758,789,530	Remainder of Area	Freeway
198,047	2,188,079	449,505	6,826,640	3,059,808	1,783,296,299	Remainder of Area	Expressway
69,238	1,666,312	197,860	3,864,653	1,210,458	859,553,531	Remainder of Area	Collector
200,271	5,664,682	589,402	12,115,961	3,702,167	2,681,332,522	Remainder of Area	Arterial
302,019	9,644,383	1,064,017	22,388,120	8,959,102	5,127,966,003	Alameda/Contra Costa	Freeway
47,307	436,356	113,753	1,446,595	897,455	420,327,610	Alameda/Contra Costa	Expressway
39,593	940,007	111,573	2,186,386	666,067	482,674,153	Alameda/Contra Costa	Collector
116,115	3,451,998	339,289	7,155,253	2,138,793	1,580,848,575	Alameda/Contra Costa	Arterial
1,327,028	36,894,513	4,204,484	85,857,063	32,849,627	19,694,788,222		
-8.839%	2.295%	-4.812%	0.023%	-0.352%	-1.647%	Compared to Base	

Table 39. Bay Area regional trip making, 2015.

County	No. Trips			Average Trip Length (mi)		
	Base	Scen. 5	Percent Change	Base	Scen. 5	Percent Change
San Francisco	292,162	292,917	0.26%	7.40	7.44	0.49%
San Mateo	414,952	414,959	0.00%	8.92	8.92	0.02%
Santa Clara	1,112,990	1,113,110	0.01%	8.41	8.44	0.28%
Alameda	825,565	827,738	0.26%	9.08	9.15	0.83%
Contra Costa	586,928	588,966	0.35%	9.42	9.49	0.78%
Solano	235,684	236,438	0.32%	10.82	10.91	0.82%
Napa	79,934	79,885	-0.06%	9.85	9.94	0.99%
Sonoma	291,865	292,106	0.08%	9.50	9.54	0.44%
Marin	139,109	139,567	0.33%	9.72	9.80	0.86%
External	83,397	83,396	0.00%	33.58	33.74	0.47%
TOTAL	**4,062,586**	**4,069,082**	**0.16%**	**9.48**	**9.53**	**0.54%**

Note: “Scen. 5” is Scenario 5, ATDM + active signal control.

As shown in Table 38, an additional scenario was created for the 2015 runs: Scenario 6, deployment of ATDM and active signal control on **all** freeways and arterials in the nine county region, respectively. This run is not “complete” in the sense that there was no 2010 run on which to base land use changes. (It used land use input from Scenario 5.) It was created to see what effect full operations deployment might have. If full deployment had been achieved in 2010, would population and employment be shifted around as shown above? Our guess is that most of the shifting would be from outside the region, as the travel time improvements would be ubiquitous within the region, thereby not giving any location an advantage in terms of accessibility. Still, the regional deployment scenario results in a 2.3 percent increase in VMT, an 8.8 percent decrease in VHT, and a decrease in CO_2 emissions of 1.6 percent. The VMT increase is double what it is for deployment in only Alameda and Contra Costa counties, indicating that the improved regional travel times are having an effect on regional traveler behavior. Despite the VMT increase, regional deployment of aggressive operations is seen as having a positive impact on CO_2 emissions.

The above results may be dependent on the nature of congestion in the network, which is severe. To test this, we took the model runs from above and postprocessed to get hourly speeds and emissions, but without the 30 percent increase in the v/c ratio.

I-15 TRAFFIC SIMULATION ANALYSIS WITH UPDATED DEMAND

The final step in the analysis was to use the long-term demand shifts obtained in the regional modeling analysis as input to the I-15 traffic simulation framework to get more refined emissions estimates. Ideally, this task would be done simultaneously with the land use/demand modeling step, but as previously noted, the complete modeling framework for doing so does not exist.

Several scenarios from the original I-15 runs were selected for conducting the comparisons. Table 40 shows the scenarios and the demand changes that were used. The demand changes are based on the data in Table 40. It should be noted that, as shown in the MTC model runs, there will be demand changes beyond the small subarea covered by the I-15 test network.

Table 40. Demand changes applied to I-15 scenarios.

Scenario	Features	Demand Changes
A	Ramp metering	+1.0% major arterials
E	Ramp metering Minor Incident with TIM Traveler Information	+3.5% I-15 SB -3.5% major arterials
E2	Ramp metering Minor Incident with TIM	+3.5% I-15 SB -3.5% major arterials
G	Ramp metering Active signal control	+2.0% I-15 SB +1.0% major arterials
H	Ramp metering Active signal control Traveler Information	+2.5% I-15 SB +1.5% major arterials

Modifying demands in the traffic simulation model is an indirect task. VMT is "emergent" from the model; it is not an input. Rather, VMT is a result from the loading of trip tables onto the network. Therefore, the trip tables were modified using the following steps. Vehicles moving in the southbound direction of I-15 and on Pomerado Road were identified and their paths were traced backwards and forward to identify those origins and destinations in the trip matrix that assign vehicles to the SB direction of I-15; this is known as "select link analysis. After the select link analysis was performed, the flow of those O/D pairs was increased or decreased in the trip matrix that take I-15 SB or Pomerado Road in the base-year model.

The results are shown in Tables 41 and 42. The scenarios tagged with "_Incr" represent the new simulation runs with the demand changes. The original runs also are shown for comparison. The base condition for the nonincident scenarios is Scenario F, as before (no operations treatments deployed.) For the incident scenarios, the base condition for is Scenario D for Scenario E and E_Incr and Scenario D2 for Scenario E2 and E2_Incr.

Overall, the increased demand scenarios for nonincident conditions still show a benefit (decrease in CO_2 emissions), albeit smaller than for original scenarios. This result may be an artifact of trying to get VMT increases on the network by modifying the trip table – trips will be redistributed to some degree by the model. Still, this is a representation of how the system will "handle" additional demand, much better than trying to force the target VMT onto the desired roadways. These results are similar to those obtained with the MTC travel model for the high order MTC Scenarios S4 through S6 which represent bundles of strategies similar to what is done for the I-15 tests.

As with the original demand runs, the effect of adding traveler information is likely problematic due to how the model simulates it – the "G" scenarios outperform the "H" scenarios even though the latter have traveler information added. The "H" scenarios have a higher VMT, indicating more circuitous routing. As shown back in Table 29, the overall system speed also is higher for the "H" scenarios. These conditions would lead to increased emissions for the "H" versus the

"G" scenarios, assuming the internal algorithm is acting reasonably. Unfortunately, there is no way to validate the reasonableness; research on how travelers react to information is lacking.

However, the ability to replicate the network VMT changes noted in the MTC runs by adjusting the TransModeler trip table proved to be very difficult. In all cases, adjusting the origin-destination flows by the percentages in Table 40 resulted in less VMT than observed in the MTC model. This may reflect the differences in assignment procedures between the travel demand and simulation model. It also points out the problems associated with trying to integrate two separate modeling frameworks. In any event, because the VMT gains are not as large as originally planned, despite multiple attempts to adjust the trip table, the emission reductions in Tables 41 and 42 are most probably overestimated. Because the gains are still relatively large, though, we would expect that some reductions would still remain, or that the change would be so small that the net effect would be neutral.

The incident scenarios exhibit a similar pattern, but with Scenario E_Incr showing a slight increase (half a percent) in CO_2 emissions. These results are in contrast to the MTC results for incident management which showed an increase in CO_2 emissions. However, the MTC network was for a generalized condition – the capacity was increased to reflect the cumulative annual effect of incident management (seven percent) rather than modeling a specific incident, as is done for I-15. In the I-15 case, the net capacity equivalent increase is much larger. The MTC model showed that when capacity is only increased marginally (e.g., Scenarios S1 through S3), the effect of the increased demand causes emissions to increase, whereas when it is larger, the effect of the improvement absorbs the increased demand. This may in fact be a function of the volume-delay relationship used in the MTC model.

Table 41. I-15 Traffic simulation results with increased demand, nonincident scenarios.

6:00 a.m. to 9:00 a.m.			Emissions				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NO_x**
Black Mountain Expressway	base	10,352	6,765,509		95,438	2,806	15,305
Black Mountain Expressway	scenario_A	9,594	7,044,845	4.13%	93,865	2,994	15,448
Black Mountain Expressway	scenario_A_Incr	10,742	7,887,795	16.59%	91,975	2,674	15,010
Black Mountain Expressway	scenario_G	10,812	6,638,842	-1.87%	95,103	2,745	15,306
Black Mountain Expressway	scenario_G_Incr	10,594	6,414,223	-5.19%	93,105	2,647	15,080
Black Mountain Expressway	scenario_H	10,452	6,626,596	-2.05%	94,349	2,776	15,424
Black Mountain Expressway	scenario_H_Incr	10,926	6,975,757	3.11%	100,259	2,952	15,771
Carmel Mountain Expressway	base	4,816	2,886,183		51,597	1,228	6,925
Carmel Mountain Expressway	scenario_A	4,309	2,907,180	0.73%	51,873	1,238	6,924
Carmel Mountain Expressway	scenario_A_Incr	4,758	2,862,494	-0.82%	51,480	1,220	6,885
Carmel Mountain Expressway	scenario_G	4,803	2,723,066	-5.65%	43,797	1,213	5,929
Carmel Mountain Expressway	scenario_G_Incr	4,723	3,337,988	15.65%	57,768	1,647	7,957
Carmel Mountain Expressway	scenario_H	4,882	2,937,542	1.78%	52,440	1,250	7,069
Carmel Mountain Expressway	scenario_H_Incr	4,912	3,000,084	3.95%	60,795	1,788	8,612
I-15 NB	base	297,336	109,295,860		1,121,967	33,210	250,478
I-15 NB	scenario_A	289,513	104,558,162	-4.33%	1,058,182	31,576	239,653
I-15 NB	scenario_A_Incr	278,534	101,954,652	-6.72%	1,026,712	30,888	231,951
I-15 NB	scenario_G	282,783	104,808,784	-4.11%	1,066,312	31,960	239,578
I-15 NB	scenario_G_Incr	282,195	105,752,063	-3.24%	1,019,619	30,777	231,155
I-15 NB	scenario_H	292,487	108,973,584	-0.29%	1,127,518	33,546	247,793
I-15 NB	scenario_H_Incr	295,704	110,172,293	0.80%	1,128,082	33,848	250,221

Table 41. I-15 Traffic simulation results with increased demand, nonincident scenarios (continued).

6:00 a.m. to 9:00 a.m.			Emissions				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NO_x**
I-15 SB	base	420,698	217,218,389		1,954,660	81,830	427,100
I-15 SB	scenario_A	435,030	213,456,303	-1.73%	1,867,652	80,948	413,619
I-15 SB	scenario_A_Incr	432,522	211,748,653	-2.52%	1,845,240	80,381	411,965
I-15 SB	scenario_G	421,320	188,302,302	-13.31%	1,823,462	65,871	398,333
I-15 SB	scenario_G_Incr	427,786	190,829,990	-12.15%	1,765,743	60,263	387,891
I-15 SB	scenario_H	418,841	203,885,665	-6.14%	1,910,878	74,227	417,795
I-15 SB	scenario_H_Incr	423,449	206,128,407	-5.11%	1,911,833	75,224	421,555
I-15 SB	scenario_F	420,698	217,218,389		1,954,660	81,830	427,100
Other Fwys/Expys and Major Arterials	base	90,458	58,316,447		753,250	25,153	123,247
Other Fwys/Expys and Major Arterials	scenario_A	81,497	58,168,884	-0.25%	747,604	25,171	122,648
Other Fwys/Expys and Major Arterials	scenario_A_Incr	92,853	59,216,202	1.54%	727,231	22,357	116,213
Other Fwys/Expys and Major Arterials	scenario_G	93,510	56,799,069	-2.60%	756,325	24,310	121,797
Other Fwys/Expys and Major Arterials	scenario_G_Incr	92,291	53,693,987	-7.93%	734,386	22,746	116,776
Other Fwys/Expys and Major Arterials	scenario_H	94,426	56,399,555	-3.29%	751,274	24,110	121,424
Other Fwys/Expys and Major Arterials	scenario_H_Incr	92,149	55,407,653	-4.99%	745,615	23,817	118,645
Pomerado Road	base	31,581	21,129,853		245,072	9,163	43,000
Pomerado Road	scenario_A	28,106	21,551,594	2.00%	244,971	9,468	42,992
Pomerado Road	scenario_A_Incr	33,966	26,045,133	23.26%	293,087	11,293	51,540
Pomerado Road	scenario_G	32,921	17,457,167	-17.38%	231,456	7,224	37,600
Pomerado Road	scenario_G_Incr	33,804	16,755,750	-20.70%	224,404	6,877	36,466
Pomerado Road	scenario_H	35,003	16,982,701	-19.63%	231,020	6,969	37,345
Pomerado Road	scenario_H_Incr	36,480	18,857,549	-10.75%	247,990	7,818	40,789

Table 41. I-15 Traffic simulation results with increased demand, nonincident scenarios (continued).

6:00 a.m. to 9:00 a.m.			**Emissions**				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NO_x**
Total, All Highways	**base**	**855,241**	**415,612,241**		**4,221,984**	**153,390**	**866,055**
Total, All Highways	**scenario_A**	**848,049**	**407,686,968**	**-1.91%**	**4,064,147**	**151,395**	**841,284**
Total, All Highways	**scenario_A_Incr**	**853,375**	**409,714,929**	**-1.42%**	**4,035,726**	**148,814**	**833,563**
Total, All Highways	**scenario_G**	**846,149**	**376,729,230**	**-9.36%**	**4,016,455**	**133,323**	**818,543**
Total, All Highways	**scenario_G_Incr**	**851,392**	**376,784,001**	**-9.34%**	**3,895,024**	**124,957**	**795,326**
Total, All Highways	**scenario_H**	**856,091**	**395,805,643**	**-4.77%**	**4,167,478**	**142,879**	**846,849**
Total, All Highways	**scenario_H_Incr**	**8 63,620**	**400,541,744**	**-3.63%**	**4,194,575**	**145,446**	**855,592**
Note: VMT for the increased demand scenarios were lower than the target values developed by the MTC regional model; see text for explanation							

Table 42. I-15 Traffic simulation results with increased demand, incident scenarios.

9:00 a.m. to 9:00 a.m.			**Emissions**				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NO_x**
Black Mountain Expwy	scenario_D	10,510	6,612,747		93,907	2,776	15,239
Black Mountain Expwy	scenario_D2	10,352	6,630,833		94,364	2,731	15,132
Black Mountain Expwy	scenario_E	11,173	7,012,707	6.05%	99,367	2,966	15,830
Black Mountain Expwy	scenario_E_Incr	10,782	6,951,142	5.12%	98,729	2,885	15,913
Black Mountain Expwy	scenario_E2	11,159	7,253,787	9.39%	100,984	3,053	16,385
Black Mountain Expwy	scenario_E2_Incr	10,982	6,798,387	2.53%	95,149	2,837	15,441

Table 42. I-15 Traffic simulation results with increased demand, incident scenarios (continued).

9:00 a.m. to 9:00 a.m.			Emissions				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NO_x**
Carmel Mountain Expwy	scenario_D	4,917	2,954,354		52,713	1,256	7,036
Carmel Mountain Expwy	scenario_D2	4,784	2,859,546		51,033	1,217	6,846
Carmel Mountain Expwy	scenario_E	4,916	2,962,320	0.27%	52,780	1,261	7,094
Carmel Mountain Expwy	scenario_E_Incr	4,795	3,600,557	21.87%	64,111	1,535	8,587
Carmel Mountain Expwy	scenario_E2	4,970	3,054,455	6.82%	54,347	1,304	7,304
Carmel Mountain Expwy	scenario_E2_Incr	4,859	2,915,883	1.97%	52,162	1,243	6,955
Black Mountain Expwy	scenario_D	10,510	6,612,747		93,907	2,776	15,239
I-15 NB	scenario_D	293,290	108,978,872		1,120,279	33,379	249,102
I-15 NB	scenario_D2	297,320	109,779,783		1,129,933	33,453	252,169
I-15 NB	scenario_E	286,463	105,920,289	-2.81%	1,084,187	32,254	242,596
I-15 NB	scenario_E_Incr	281,058	105,558,896	-3.14%	1,063,220	31,957	241,460
I-15 NB	scenario_E2	286,324	106,184,196	-3.28%	1,085,910	32,348	243,117
I-15 NB	scenario_E2_Incr	278,526	103,421,845	-5.79%	1,057,423	31,706	235,818
I-15 SB	scenario_D	416,604	208,120,832		1,918,518	76,583	419,330
I-15 SB	scenario_D2	414,197	211,701,360		1,929,704	80,855	410,968
I-15 SB	scenario_E	430,183	182,615,160	-12.26%	1,831,966	62,389	397,495
I-15 SB	scenario_E_Incr	431,949	209,535,741	0.68%	1,905,049	76,875	421,994
I-15 SB	scenario_E2	410,096	186,308,356	-11.99%	1,862,559	64,489	403,501
I-15 SB	scenario_E2_Incr	431,949	211,652,264	-0.02%	1,939,376	77,573	427,985

Table 42. I-15 Traffic simulation results with increased demand, incident scenarios (continued).

9:00 a.m. to 9:00 a.m.			Emissions				
Route	**Scenario**	**VMT**	**CO_2**	**CO_2 Relative to Base**	**CO**	**HC**	**NO_x**
Pomerado Rd	scenario_D	34,917	17,214,891		231,881	7,049	37,527
Pomerado Rd	scenario_D2	31,381	21,087,603		243,132	9,221	42,131
Pomerado Rd	scenario_E	38,660	18,930,927	9.97%	251,358	7,707	41,510
Pomerado Rd	scenario_E_Incr	33,226	16,979,567	-1.37%	227,540	6,998	36,845
Pomerado Rd	scenario_E2	38,750	18,952,848	-10.12%	251,671	7,727	41,691
Pomerado Rd	scenario_E2_Incr	34,473	17,251,432	-18.19%	231,422	7,153	37,424
Total, All Highways	scenario_D	854,724	398,780,996		4,161,531	144,340	847,496
Total, All Highways	scenario_D2	847,565	409,479,626		4,192,276	152,289	848,306
Total, All Highways	scenario_E	870,298	373,213,303	-6.41%	4,084,703	130,084	826,647
Total, All Highways	scenario_E_Incr	861,320	400,813,116	0.51%	4,146,083	144,830	851,656
Total, All Highways	scenario_E2	850,810	379,940,855	-7.21%	4,142,905	133,500	838,856
Total, All Highways	scenario_E2_Incr	855,124	396,178,359	-3.25%	4,116,733	143,475	841,704

Note: VMT for the increased demand scenarios were lower than the target values developed by the MTC regional model; see text for explanation.

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

CONCLUSIONS

This study examined the effects that operations strategies have on demand and emissions, especially greenhouse gas emissions, in both the short and long terms. Many past studies have documented the positive effect of operations strategies immediately after implementation – the so-called "opening-day effect" – due to their ability to reduce delay at modest investment costs. The findings of this study reinforce that earlier work. However, a major reason for undertaking the study was to determine the extent to which opening-day emissions would endure potential increases in travel demand resulting from improved travel conditions.

Past studies of induced demand have not specifically addressed the effect of operations strategies. Rather, most have focused on the effect of how changes in a supply variable (e.g., lane-miles) result in changes in travel demand, the idea being that additional highway supply results in lower transportation costs by reducing travel times. However, adding supply (whether it be lane-miles or other form of effective capacity) will only lower travel times for an existing facility during times that the facility is congested, making highway supply a crude indicator of how travel times will change. Because of this indirect linkage, some studies have looked at the direct relationship between travel times and demand.

Past studies distinguish between short-term and long-term effects. Short-term effects include diverted trips (route, temporal, and destination shifts) and new or longer trips resulting from latent demand and mode shift. In the long term, relationship is more complex. Improvements in travel time lead to changes in development patterns, which in turn lead to changes in residential and commercial location choice, and car ownership. Many authors have argued that diverted trips are not true induced demand. In general the size of the long-term effect, in terms of the elasticity of demand with a supply variable, has been found to be higher than the short-term effect.

The applicability of past studies of induced demand to operations strategies is dubious for several reasons:

- Relationships based on areawide lane-mile additions versus VMT changes are too crude for judging operations strategies. Operations strategies are only going to be invoked when congestion is present on specific facilities, most often during peak periods, while it is impossible to tell where and when the areawide lane-miles in the studies were applied. There also is the problem of equating operations strategy effects to lane-miles, but this tractable.

- Relationships based on travel time changes versus VMT are based on travel times for an entire trip. Operations strategies are a concentrated on higher order facilities, and therefore a trip will only be partially exposed. This means that the travel time savings on the operations-improved facility is less than the overall trip travel time, and therefore an adjustment would have to be made. This is important because the study is concerned specifically with the long-term effects of a deployed operations strategy.

The issue of operations influence on travel-time reliability also is often cited as a reason that historical induced demand relationships do not apply. While it is true that operations strategies do improve reliability, it also is true that other types of highway improvements do as well. Do travelers respond differently to reliability changes than they do to changes in typical travel times? Recent research from the SHRP 2 program suggests that both typical travel time and reliability are components of total transportation cost (i.e., travelers' utility) and that they respond similarly to changes in them. Accounting for reliability as an extra component of total travel cost would be a desirable feature not just for this project but for any analysis that encompasses traveler behavior.

In his 2001 review of induced travel, Cervero noted that traditional four-step travel demand models are ill-equipped to capture induced demand because of the lack of feedback to trip generation and land use.[(63)] Much has changed in the intervening decade with the advent of activity-based models, especially those that are linked to land use models. An exploratory analysis of the induced demand effect of operations was presented in Chapter 2 (White Paper #2). Elasticities were pulled from a previous study in 2005 of induced demand using the Portland, Oregon tour-based travel demand model. The effect of improved signal timing in a corridor was used to replicate the effect of arterial operations strategies (e.g., traffic adaptive control systems). The performance was worsened with the induced demand but is still better than the baseline conditions. A 3 percent increase in volumes worsens travel time performance by only 1.2 percent; even a 10 percent increase in through volumes has a better performance than baseline conditions with existing signal settings. The 3 percent volume increase represents the use of the tour-based model elasticities, which account for trip generation effects (as well as route and time-of-day shifts) but not longer term effects such as land use and car ownership shifts.

A second case study was undertaken using empirical data from the Atlanta metro area. The study was based on calculating facility travel times using continuously collected speed data from ITS sensors and automatic traffic recorders, in a before/after operational deployment setting with control sections. The results found that at several locations, ramp metering (one of the operations strategies used) did not have an appreciable effect on travel times. In locations where the operations strategies did improve travel times, no discernible increase in VMT occurred, based on an after period of more than one year. This finding corresponds to several studies of matched facility pair comparisons in the literature.

The results of the above case studies coupled with the fact that several agencies are now using advanced modeling frameworks, led the study to consider the use of a modeling framework as the primary way of getting at the demand implications of deploying operations strategies. Originally, the use of the SHRP 2 C10B modeling framework developed in Sacramento, CA was planned. This framework links an activity-based travel model with a mesoscopic simulation traffic simulation model. Such a framework provides more refined estimates of network performance than traditional traffic assignment procedures, but this framework treats land use as

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[63] Cervero, Robert, *Induced Demand: An Urban and Metropolitan Perspective*, paper prepared for: Policy Forum: Working Together to Address Induced Demand, March 2001.

a fixed input. Due to delays in the SHRP 2 C10B schedule, it turned out that it could not be used for this project.

An alternative modeling framework was selected – the MTC travel model in use in the San Francisco, CA, Bay Area. This model is used for all of MTC's travel forecasting needs, unlike the SHRP 2 C10B model which was the product of a research product and not in "production" mode yet. The MTC model links an advanced iterative land use simulation model (UrbanSim) with an activity-based travel model, so that a more comprehensive treatment of demand effects is possible. Its shortcoming is that it uses traditional traffic assignment procedures, which means the performance estimates are cruder. (A review of other advanced modeling frameworks around the U.S. revealed none fulfilled all the requirements for this project, namely, an integrated land use model, activity-based travel model, and dynamic traffic assignment based on mesoscopic simulation.)

One of the project's original objectives was to account for the effect of reliability on demand. To this end, original research was conducted with the UrbanSim model and data from the Bay Area. The results found that development patterns are affected by changes in reliability in additional to typical travel times. This finding mirrors that of the SHRP 2 research that found traveler behavior also is influenced by both travel time and reliability. Essentially, reliability is an extra congestion-related cost that heretofore has not been accounted for in traveler behavior analyses. The relationships developed by the research were imbedded in a special version of UrbanSim for use in this project.

The enhanced UrbanSim version of the MTC modeling framework was used to conduct tests of deploying operations strategies. This framework includes feedback loops for travel time to the activity model and for both travel time and reliability to the land use model. Congestion in the network was high. Results show that the deployment of operations strategies increases regional VMT, and the increase is proportional to the travel time savings. For the network that was tested, which was significantly congested, for strategies that represent a reasonably high impact on congestion (e.g., bundles of strategies) the VMT increase does not fully erode the CO_2 emissions benefits of operations; small benefits remain after accounting for both short-term and long-term demand effects at the regional level. Strategies that have a lower congestion impact (e.g., ramp metering deployed alone), a marginal increase in CO_2 emissions was found.

The long-term demand increases observed in the MTC model were used to update the I-15 traffic simulation runs. Results showed that the increased demand runs showed less benefit than the original runs, but for the majority of cases, the emissions benefits were preserved. The demand adjustment procedure used was crude, but necessary given that an integrated model capable of estimating demand changes and refined speed/delay estimates currently is not available.

All of the review and analysis conducted in this study points to several overall conclusions:

1. Operations strategies have an effect on short-term and long-term demand patterns, based on the regional modeling conducted. Because operations strategies improve travel time, there is no *a priori* reason to expect them to behave any differently than capital expansion projects in this regard. However, the strategies tested in this study were all supply-related. Traveler

information, which affects demand, was tested using a simulation model, but the results were deemed to be problematic. In the short term, traveler information may reduce demand on congested facilities by allowing travelers to make different choices for destinations, modes, or to forego a trip altogether. (Shifts in routes and departure times effected by traveler information are likely to have a negligible impact on demand.) However, in the long term, to the degree that traveler information has the global effect of reducing travel times, we would expect it to have similar demand characteristics of other strategies.

2. An empirical before/after analysis of operations deployment (ramp metering and incident management) revealed neither significant changes in travel time or demand. This may be due to relatively small decrease in travel times observed (compared to what would be achieved through capacity expansion or bottleneck removal), indicating that travelers require a significant change in travel time before they adjust their short-term behaviors.

3. Travel-time reliability affects land use decisions. Recent SHRP 2 research found that reliability affects traveler behavior and that, along with typical travel time, is part of the overall disutility associated with trip-making. This project has extended that finding to include the behavior household and business land use decisions. Because reliability is affected by many factors – including disruptions, demand, and their interaction with physical capacity – we expect that other improvements beyond operations would have a similar effect.

4. A microsimulation model, TransModeler previously calibrated for the Integrated Corridor Management Analysis in the I-15 corridor in San Diego, was used to gauge the effects of operations strategies. Individual vehicle trajectories were obtained from the model runs and converted to operating mode distributions for input the MOVES model to produce emissions estimates. This approach was deemed to be superior to using average speeds for MOVES input because it captures vehicle modal activity. However, there has been recent skepticism about the ability of microsimulation-based vehicle trajectories to replicate real-world trajectories. The reason is that the models have been internally calibrated to reproduce macrolevel performance, not individual vehicle performance. This discrepancy is a major concern for trying to obtain an absolute number for emissions; it is probably not as important for judging the relative differences in strategies, as done here.

5. Under the assumption that there is no short- or long-term change in demand, operations strategies produce emissions benefits at the ***corridor*** level, including the primary greenhouse gas, CO_2. The reductions in emissions range from two to nine percent, depending on the type of operations strategy deployed. These results are based on using a microscopic simulation model to develop trajectories for the MOVES model.

6. Accounting for demand changes created by the improved travel conditions resulting from operations, the emissions benefits at the ***regional*** level are less than at the corridor level. Regional emissions varied from -1.5 to +1.0 percent, depending on the strategy deployed. This result is based on the regional modeling framework used in this study.

7. Accounting for increased demand due to the original deployment of operations at the corridor level, emissions reductions are still present, although the reductions are not as great as if no

demand increase is assumed (one to nine percent emission reductions). This result is based on using the demand shifts determined from the regional travel model and applied to the microscopic simulation/MOVES model framework. Because the simulations were unable to account for all of the additional VMT estimated by the regional modeling, we expect the emissions benefits to be overstated. Had the simulations accounted for all of the additional VMT, we believe that emissions benefits would have been either neutral or slightly positive.

8. Microsimulation models are excellent tools for assessing roadway performance in terms of travel time and delay. Our experience indicated that their handling of demand changes is more problematic. This manifested itself the most in the analyses where traveler information was implemented – some of the results appear to be counterintuitive. Also, trying to match roadway VMT targets by modifying the trip table based on a “select link” analysis is performed is a difficult task. Finally, even for routine scenarios the model’s shifting of demand makes it hard to compare the effects of one strategy versus another. VMT is an legitimate effect of network conditions, not a static input, but it is difficult to know if the model’s treatment of demand replicates reality.

9. The study stretched the limits of current modeling capability by stitching together results from one model (demand estimates from the MTC travel model) with another (speed estimates from the I-15 microscopic simulation model). The ideal modeling framework to study this problem would have a single model that has the land use and travel activity components of the MTC model with the traffic assignment portion replaced with mesoscopic simulation model. Even then, there is a question whether the vehicle trajectories produced by mesoscopic simulation adequately reflect real-world trajectories. In fact, the accuracy of microscopic simulation produced trajectories have been called into question. Until this issue is resolved, a good deal of uncertainty will remain in **any** modeling framework that is employed to study the long-term effects of operations strategies on emissions.

RECOMMENDATIONS

Based on our experience with this project, the team offers the following recommendations for future work.

- <u>Fully integrated modeling frameworks with advanced features should be promoted in order to understand the supply demand implications for alternative investments</u>. These features should include:

  - A land use model that is sensitive to changes in transportation network conditions.
  - An activity-based travel demand model.
  - Traffic assignment via simulation procedures (e.g., mesoscopic simulation) that employs dynamic traffic assignment.

- <u>Travel-time reliability should be both an output of the modeling process as well as an input</u>. Traditional travel demand and microsimulation models should produce reliability measures as output for assessing system performance. Research should be on alternative methods for doing so, including postprocessing and scenario-based analysis. Further, reliability should be part of the feedback process in the modeling chain, in the same way that typical (average) travel times currently are used. This study showed a method for incorporating reliability in land use projections; a similar effort should be undertaken to incorporate reliability into activity models, both as an adjunct to existing models and in the development of new ones.

- <u>When operations projects are evaluated, demand changes over a short-term horizon should be included</u>. Evaluations of completed projects is an important component of a performance management system. Before/after evaluations have traditionally focused on fairly short time periods. With the inclusion of reliability, the time periods must be at least one-year long. We recommend an even longer time horizon – perhaps two years – so that demand shifts can be observed and correlated with improvements in travel conditions. Challenges exist for conducting these studies, including the impact of diversion on facility traffic volumes and changes in the drivers of ambient demand such as economic fluctuations and fuel prices. These studies will add to the knowledge gained here in the Atlanta case studies.

- <u>Emissions estimates derived from simulation model trajectory outputs should be investigated further</u>. Specifically:

    - Comparison of emissions derived from simulated trajectories versus real-world trajectories.
    - Comparison of emissions derived from simulated trajectories versus the use of average speeds.

For these comparisons, determine the size of the differences and if adjustment procedures could be developed.

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